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Original Article

Application of Expert Methods for Optimizing and Predicting the Ultimate Tensile Strength of Mild Steel Weldment

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Abstract *- This research study focuses on designing models to optimize and predict the ultimate tensile strength of mild steel weldment by the use of response surface methodology and artificial neural network analyses. The input variables are current, voltage, and gas flow rate. Ultimate Tensile Strength (UTS) is the response variable. The welding method used is the Tungsten Inert Gas (TIG) welding process. Ultimate Tensile Strength (UTS) was adopted in this research study to measure weld quality, as it is a main mechanical property that can define weld joint efficiency. The adequately optimized response variable certainly will aid in achieving an improved weld with the preferred strength and quality. The response surface methodology analyses yielded the optimal solutions to be: current, 180.00Amps; voltage, 21.672Volts and gas flow rate, 15.504L/min, for the input parameters, and 579.000MPa for the response variable. These optimal solutions, the RSM analyses, gave the Global Desirability (Dg) of achieving to be 83.62%. Weld current has the most significant effect on the response variable, as shown by the variance analysis (ANOVA) result. The predicted optimal solution for the response variable is 530.077MPa by the artificial neural network analyses, with an overall strong correlation (R) between the input parameters and the response variable of 99.893%. Deductively, it is recommended that the optimal solutions be used for modeling and application, whereas the optimal solution of the artificial neural network analyses obtained is better and more robust for practical implementation considering its higher Regression (R) value. Therefore, the results are recommended for more idealistic decision-making.*

Keywords *- ANN, Mild Steel, RSM, TIG, Ultimate Tensile Strength.*

1. Introduction

Welding is a method commonly used to join materials in several industrial applications. It is a procedure used to join metals by heating to a certain degree of temperature, with or without the use of pressure, with or without the use of filler metals. Mild steel is a broadly used industrial material, and its welding is of priority importance to numerous industries [1]. TIG welding process is an arc welding process that employs a non-consumable tungsten electrode to create an arc and a filler metal wire to join the metal parts together while protecting the welding process at the same time with the use of inert gas such as helium or argon in order to shield the molten weld puddle from atmospheric contamination [7]. The decision of the shielding gas to employ depends on the materials to be joined and the impact on the welding cost, the weld temperature, the stability of the arc, the welding speed, the splatter, the electrode life, etc. It also affects the penetration depth of the completed weld and the surface geometry, porosity, resistance to corrosion, joint strength, brittleness and hardness of the weld metal [2]. Therefore, the expendable composition of the shielding gas also significantly contributes to the weld joint strength and quality. This experiment employed the use of 100% pure argon (Ar) shielding (inert) gas. It protected the electrode, the arc, and the weld puddle from atmospheric contaminants.

Ultimate tensile strength (interchangeably called "tensile strength") is the peak stress that a weld joint can accommodate prior to failure or rupture. Ultimate tensile strength is used to calculate the peak load that a weld joint can entertain without failing. Process input parameters such as current, voltage and gas flow rate have a major influence on the mechanical properties of weld joints in all welding processes. The mechanical and metallurgical characteristics of weld joints are dependent on the bead geometry, which is a subject of the process parameters. Consequently, the strength and quality of weld joints are dependent on the process parameters. The quality and efficiency of the welding process of mild steel are highly dependent on the selection of appropriate parameters. The selection of inappropriate parameters can lead to poor weldment strength and undesirable properties. Mechanical properties emphasize weld integrity, which expresses the ability of joints to withstand failure and the features of the weld under the impact of external load [11]. Tensile strength is decisively affected by variables such as welding current, welding voltage, and gas flow rate, which are the key input parameters that affect the quality, strength, efficiency, productivity, and cost of a weld joint [6]. This is the rationale and the main reason for selecting the three input variables for this novel research study and experiment. To the best of our knowledge, no present or previous researcher has combined the trio of these process input factors to optimize and model an efficient mild steel weld joint, and this is the gap that this current and novel research study seeks to cover. To combine the three process input parameters, namely current, voltage, and gas flow rate, to optimize and model an efficient mild steel weld joint of resilient strength and desired quality. Tensile strength is a vital mechanical property that defines weld joint efficiency. The UTS of a weld joint is significant as it is an assessment of the peak load that a weld joint can bear. Hence, adequate carefulness should be given when selecting welding parameters and their optimization in order to obtain the anticipated strength and quality of the weld joint. Care should be given in the selection of key welding input process parameters such as current, voltage and gas flow rate, as inappropriate welding variables and values can result in poor welds with inadequate mechanical properties such as tensile strength, toughness, hardness, etc., thus, giving rise to increased failure of structures in infrastructures [10].

Welded joints are essential parts in the stress-bearing assemblies of infrastructures. Any compromise in a welded joint can result in a tragic breakage or failure of structures. Welding parameters, such as ultimate tensile strength, crucially impart the resulting weldment strength and quality. Hence, there is a pivotal need to optimize this parameter in order to obtain the strength and quality needed for the weld joint. Response Surface Methodology (RSM) and Artificial Neural Network (ANN) are universally used in optimizing welding parameters. RSM demonstrates the values of the process input parameters at which the responses reach the optimum. Optimum could be either the minimum or maximum of a certain function with respect to the input parameter. The optimization course of this study is to maximize the response variable, Ultimate Tensile Strength (UTS). RSM employs a sequence of Design of Experiment (DOE) to deduce the optimal response(s). ANN is used mainly to model with respect to parameters of the equipment, such as current, voltage, and gas flow rate, in order to determine the efficiency of artificial neural networks for weld modeling. ANN can deliver real-time results of equal or better accuracy and reliability comparable to most traditional or trending predictive techniques.

Nevertheless, there is a need to establish a more robust optimization model that can accurately predict the optimal ultimate tensile strength and its effect on the mild steel weldment strength, which is the main objective of this research study. This will improve the quality and efficiency of the mild steel welded joint, leading to cost savings and reduced failure rates. This research study would commence with the gathering of data from the experimental welding and the mechanical tests, which were later analyzed using the RSM and ANN methods to develop the models. The data analyses deduced the optimal solutions of the process parameters that resulted in the improved strength and quality of the mild steel weld joint. This research study will investigate the effects of these welding parameters on the microstructure, as well as the mechanical properties of mild steel weld metal. The findings of this research study will benefit the welding industry as they serve as a framework for the optimization of the welding process and the prediction of the resultant weldment strength. This research study has also developed and as well as introduced a new technique for the efficient welding of mild steel. In general, the objective of this research study is to advance the quality and efficiency of welding of mild steel, which will proactively impact various industries that deal with this technological procedure and material, and which will also save cost and time and reduce failure rates in numerous industries, for example,—ship industries, structures, steel manufacturing industries, welding industries, etc.

Mild steel is a low carbon steel alloy made up of iron (Fe) and carbon (C) with a percentage carbon content between 0.20 % - 0.30%C. It is cheaper compared to other steel alloys. Hence, it is commonly and versatilely used in fabrication. It is easily forged, welded and fabricated due to its low carbon content. It is ductile and machinable and has a high melting point. All these qualities lead to a lack of hardened zones in the Heat-Affected Zones (HAZ) and in the welds of mild steel. Mild steel produces a clean and precise weld with TIG welding. Advantages of TIG welding include, but not limited to: production of high and clean quality welds chiefly due to the absence of fluxes, eliminating the possibility of slag inclusions; production of stable arc due to the use of the shielding or inert gas, which also protects the weld pool from atmospheric contamination; high reliability; welding of thin materials; low tolerance to contamination; easy to use etc. In this experimental study, the TIG welding process used is the direct current electrode positive (DCEP), where the electrode is connected to the positive terminal of the power source, and electrons flow from the work to the electrode tip. This method provides a good oxide cleaning action in the arc and also contributes to the production of the clean welds realized from the TIG welding technique. The tungsten electrode used in the experiment was the thoriated type.

A number of investigations have been performed to investigate mild steel weldment strength and quality. [8] “SMAW: The Effects of Currents and Welding Rod Diameters on Welded Joint Ultimate Tensile Strength Using the Full Factorial DOE” studied the effects of current and rod diameter on SMAW welded joint. The Mild Steel (AISI 1018) was used as the base material to be welded using the E-6013 welding rod. The experiment was constructed according to the full factorial Design of the Experiment (DOE). This project found that the current and rod diameter are the significant factors affecting the Ultimate Tensile Strength (UTS). The research showed that the interaction between current and rod diameter is significant in affecting the UTS. This interaction was also found to be more significant with current but less significant with rod diameter in affecting the UTS of the welded joint. In addition, this research showed that the tensile strength increases when the current is increased from 80A to 100A. However, the tensile strength decreased as the current was set between 110A to 130A. [4] in “Welding Penetration and Mechanical Properties of Welded Joints of V-shaped Surface Grooves”, focused on the forming quality of surface-groove backing welds of Gas Metal Arc Welding (GMAW). The Box-Behnken design in Response Surface Methodology (RSM) was used to explore the effects of welding voltages, welding currents, welding speeds, and surface radians on the properties of welded joints. Experimental results showed that the unmelted gap decreased with the increased welding voltage, welding current, welding speed, and surface radian. Tensile strength increased with the increased welding voltage and welding speed and decreased after increasing with the increased surface radian.

Elongation first increased and then decreased with the increased welding voltage, welding speed, and surface radian. [3] in her research work, “Prediction of mechanical properties as a function of welding variables in robotic gas metal arc welding of duplex stainless steels SAF 2205 welds through artificial neural networks”, found out that the quality of a weld joint of joined Dual-phase Duplex Stainless Steel (DSS) is strongly influenced by the welding conditions. It was observed from the results of the experiment that the tensile strength values of the welds were higher than that of the base metal and that this increased when the arc current was increased. [12] in “Study on microstructure evolution and mechanical properties of the similar joint of Al-Mg-Si alloy by tungsten inert gas welding”, researched to investigate mechanical properties and microstructure evolution with varying welding current. In the present work, a similar joint of the A6061 aluminium was carried out using the TIG method using an ER 5356 filler rod and current intensities (90A, 100A, and 110 A). It was clearly observed that the weld metal area has a finer grain as the intensity of weld current progresses to 110 A current in comparison with other current intensities, which is an indication of a more stronger and higher quality weld joint and ultimate tensile strength. [5] “Influence of welding parameters on optimization of the tensile strength and peak temperature in AISI 1020 alloy joints welded by SAW” focuses on maximizing the ultimate tensile strength and minimizing the peak temperature using Taguchi, Genetic Algorithm (GA), and Simulated Annealing (SA) algorithms. The input parameters in the three techniques were voltage (V), welding speed (S), and wire feed rate (F). They found out that with the increase of the welding parameters (welding speed, arc voltage, and feed rate), the ultimate tensile strength was increased. Lastly, [9] in “Optimization of Tensile Strength of Butt Joint Weldment on Mild Steel Plate Using Response Surface Methodology”, worked to predict and optimize the tensile strength of a butt joint weldment on a mild steel plate using Response Surface Methodology (RSM). The results obtained show that the current and voltage have a powerful influence on the tensile strength.

From all these cited articles and many others more reviewed, it was observed that no present or previous researcher has delved into the research on the optimization and prediction of the ultimate tensile strength of mild steel weldment using current, voltage, and gas flow rate as joint process input variables in order to establish the effects of the optimal values of the process parameters on mild steel weldment strength using RSM and ANN, from TIG welding process, using the process factor design model. This is the gap this investigative, innovative, current and novel research study covered. This research study is centered on the designing of an optimal numerical approach to study the effects of the optimal values of these parameters on mild steel weldment strength using RSM and ANN. The optimal solution from this research study is novel, as well as an innovation and improvement on the mild steel weld joint, giving birth to a more resilient and quality mild steel weld joint, which will altogether minimize failure rates in welded structures and industries. This novel and innovative study will serve as a pivot to several industries that rely on this process, aiding them to benchmark the optimization of the welding process and the prediction of the resultant weldment strength. This novel research and innovation in the welding of mild steel with the optimal solutions derived from this research study will reduce cost, save time and also minimize rates of failure in several industries, e.g. in buildings, infrastructures, welded structures, ship industries, steel, and welding industries, etc.

2. Materials and Methods

The test for the mechanical properties of the specimens, the ultimate tensile strength, in the compressive tests were conducted with the aid of a Universal Testing Machine (UTM). Twenty (20) pieces of mild steel coupons measuring

60mm X 40mm X 10mm were prepared and used for this experiment. The welded specimens were then subjected to compressive tests according to ASTM E8 standard procedure using a Universal Testing Machine (UTM). The compressive test specimens were loaded on the table of the Load frame (Loading unit) of the UTM, where the weld specimens were placed for the compressive test. Loads are applied from the control unit of the machine until the specimens permanently deform or fracture. The variations in the application of the load and the corresponding test result were obtained from the control unit of the UTM. The laboratory where the mechanical tests were conducted on the mild steel welded specimens is a state-of-the-art laboratory with the most current and updated types of equipment, and the software used for the RSM and ANN optimization analyses is the most modern and current.

The design of the experimental matrix for the process factors using Central Composite Design (CCD) for twenty (20) experimental runs was done for the Response Surface Methodology (RSM) analyses with the aid of an analytical tool, Design Expert Software 10.0.1 (DX 10.0.1). Central Composite Design (CCD) was employed in this research study owing to its simplicity and flexibility in variable adjustment and analyses of process interactions relating to process factor combinations. The process input parameters and output parameters make up the experimental matrix, and the results recorded from the weld specimens were used as the data. A Neural Network (NN) model was selected and trained and was used for the Artificial Neural Network (ANN) or Time Series (TS) analysis. The analytical method used by the neural network or the time series analyses is the Back Propagation Network (BPN).

The main process input parameters in this experimental study are current, voltage, and gas flow rate. Their ranges (lowest and highest) from the experiment runs are indicated in Table 1 below:

Table 1. Process input variables boundary limits

Factor	Unit	Symbol	Axis Low (-)	Axis High (+)
Welding Current	Amp.	A	180	210
Welding Voltage	Volt.	V	20	23
Gas Flow Rate	Lit/Min.	F	15	18

Table 1 shows the boundary ranges of the process input parameters. They are thus selected based on literature and were to develop the experimental matrix. The experimental matrix comprised of the input variables: current (Amps.), voltage (Volts.), gas flow rate (L/min.) and five (5) response variables, namely Liquidus Temperature, Weld Time, Heat Transfer Coefficient, Ultimate Tensile Strength and Percentage Elongation in their actual values, are indicated in Table 2.

Table 2. Central Composite Design (CCD) Matrix of Experimental Results and Data

Trials	Input Parameters			Output Parameter
	Current (Amp.)	Voltage (Volt.)	Gas Flow Rate (L/min)	Ultimate Tensile Strength (MPa)
1	180	20	18	526
2	195	20	15	478
3	210	20	18	494
4	180	21.5	18	574
5	180	20	16.5	579
6	195	21.5	18	542
7	210	23	18	508
8	210	23	15	542
9	180	23	15	482
10	210	21.5	18	545
11	210	23	15	520
12	210	23	15	536
13	180	20	18	544
14	195	21.5	16.5	553
15	210	23	16.5	558
16	210	23	18	578
17	180	20	18	546
18	180	23	18	548
19	210	21.5	16.5	545
20	210	20	16.5	505

Table 2 is made up of the actual values of the process parameters from the experimental trials. The values are the lowest, median, and highest of each of the process input parameters and the equivalent value of the response recorded at each level of the input factors as implemented during the actual experimental welding of the specimens. These values were implemented in the development of the Central Composite Design (CCD) matrix used for the data analyses.

3. Results and Discussion

The response surface technique deployed for the data analyses in this research study indicated a result that the selected models are more of the quadratic types, which calls for the polynomial analysis order. For flexibility and simplicity of model analysis, the Central Composite Design (CCD) expert suggests more quadratic models for the process order, which requires polynomial analysis. In this regard, the highest order polynomial, where the additional terms are significant for the process factors, and the model is not aliased and also has an insignificant lack of fit, was selected as the best-fitted model for the response variable. The selected model would also be established on the basis of the best probability value with less error, i.e., the least PRESS value, to determine the expected error in the selected model system. The selected model for Ultimate Tensile Strength is a Quadratic non-linear polynomial model with the best significance value that is less than 0.0001, i.e. < 0.0001.

Table 3. Summary statistics of the model fit for ultimate tensile strength response variable

Model	Sequential p-value	Lack-of-fit p-value	Adjusted R^2	Predicted R^2	
Linear	.2319	.0590	.0847	-.3502	
2FI	.5740	.0512	.0282	-2.2205	
Quadratic	<0.0001	.7021	.8912	.7854	Selected
Cubic	.7021		.8587		Aliased

Table 4. Summary statistics of the model for ultimate tensile strength response variable

Model	Standard Deviation	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	23.72	.2292	.0847	-.3502	15771.06	
2FI	24.44	.3351	.0282	-2.2205	37617.27	
Quadratic	8.18	.9428	.8912	.7854	2506.67	Selected
Cubic	9.32	.9777	.8587		*	Aliased

Attention should be given to the model maximizing the Adjusted R^2 and the Predicted R^2 values, i.e. the model with the highest order polynomial (having the highest values of Adjusted R^2 and Predicted R^2), and the model is not aliased, as evidenced in the selected Quadratic model for the response variable.

The summary statistics of the model show the Standard Deviation, Coefficient of Determination (R^2), Adjusted R^2, Predicted R^2 and the PRESS values of the selected Quadratic model for the Ultimate Tensile Strength response variable. To assess the strength of the selected Quadratic Model in optimizing the Ultimate Tensile Strength response variable, the Analysis of Variance (ANOVA) model below was used.

Table 5. ANOVA model summary statistics for ultimate tensile strength response variable

Model	Sum of Sqrs.	Degree of Freedom	Mean Sqr.	F-value	p-value	
Model	11011.93	9	1223.55	18.30	<0.0001	Significant
A-Current	855.46	1	855.46	12.79	0.0050	
B-Voltage	147.04	1	147.04	2.20	0.1689	
C-Gas Flow Rate	26.22	1	26.22	0.3921	0.5452	
AB	2313.22	1	2313.22	34.60	0.0002	
AC	160.94	1	160.94	2.41	0.1518	
BC	393.98	1	393.98	5.89	0.0356	
A^2	2418.57	1	2418.57	36.17	0.0001	
B^2	3333.69	1	3333.69	49.86	<0.0001	
C^2	2112.08	1	2112.08	31.59	0.0002	
Residual	668.62	10	66.86			
Lack-of-fit	407.96	7	58.28	0.6707	0.7021	Not Significant
Pure Error	260.67	3	86.89			
Cor Total	11680.55	19				

The ANOVA table shows that the developed model is significant with a significance value that is less than 0.0001 (i.e. < 0.0001). From the ANOVA table, the F-value of 18.30 of the model indicates that the model is significant. There would only be a 0.01% chance that an F-value this large could occur due to error. Suppose the Prob.>F, sometimes called p-value (see p-value column in ANOVA table above) of the model, and each term in the model does not exceed the level of significance (a = 0.05). In that case, the model may be considered adequate within the confidence interval of 100(1-a) %—values of p-value less than 0.0500 show that model terms are significant. Thus, the significant model terms from the ANOVA table above are: current (A), interaction of current and voltage (AB), interaction of voltage and gas flow rate (BC), square of the current (A^2), square of the voltage (B^2) and square of the gas flow rate (C^2). These are significant model terms in the optimization (maximization) of the ultimate tensile strength response variable estimation. For the Lack-of-Fit test, the Lack-of-Fit could be considered insignificant if the Prob.>F (p-value) of the Lack-of-Fit exceeds the level of significance. The lack-of-fit p-value of 0.7021 shows that the lack-of-fit is insignificant. The lack-of-fit F-value of 0.6707 implies that the lack-of-fit is not significant relative to the pure error. There would only be a 70.21% chance that the lack-of-fit F-value this large could occur due to error. Insignificant lack of fit is good and makes the model fit.

Table 6. ANOVA model fit summary statistics for validating model significance towards optimizing (maximizing) ultimate tensile strength and the model comparison statistics

Standard Deviation	8.18	R^2	0.9428
Mean	534.65	Adjusted R^2	0.8912
C.V %	1.53	Predicted R^2	0.7854
		Adequacy Precision	16.6186

PRESS	2506.67
-2 log Likelihood	126.95
BIC	156.90
AICc	171.39

Table 6 above shows the ANOVA model summary statistics. It indicates that the Coefficient of Determination (R^2) of the joint input and response variables for the model are significantly adequate to the model developed for the Ultimate Tensile Strength response variable. The Coefficient of Determination (R^2) of the variables indicates that 94.28% of the input factors will be explained in the response variable of Ultimate Tensile Strength. The Predicted R^2 of 0.7854 is in agreement with the Adjusted R^2 of 0.8912; i.e. the difference is less than 0.2. A higher R^2 and Adjusted R^2 values are always desirable. If the difference between R^2 and Adjusted R^2 is large enough, or when the value of Adjusted R^2 is very small, comparable to the value of R^2, it indicates that there is a probable error in the values of the results of the variables obtained from the experimental trials, and this will cause a bias/error in the system, requiring that the experimental trials be properly checkmated and be replaced if need be. Adequacy Precision measures the signal-to-noise ratio. A ratio greater than 4 is desirable. The ratio of 16.619 indicates an adequate signal. Therefore, this model can be used for real-world design and practical modeling of the Ultimate Tensile Strength response variable.

In model comparison statistics, the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AICc), which are above a thousand, are inadequate for modelling. However, the Bayesian Information Criterion (BIC) in this model developed is 156.90, and that of Akaike Information Criterion (AICc) in the model developed is 171.39. This shows that the model developed has less predicting error and is more adequate to achieve the optimum solution of the experimental results.

Based on the results of this novel, investigative and innovative research study, which was conducted on 60mm X 40mm X 10mm mild steel specimens, there is a need for further research to be conducted on larger steel plates with higher thicknesses in order to ascertain the validity of the claims of the optimal solutions obtained from this research study, putting into consideration other external and internal factors that can affect the quality of the welds in higher thickness steel plates. For instance, there would be an increased heat input requiring an adjustment of the current and voltage ranges/settings and an increased gas flow rate when welding higher thickness mild steel plates in order to achieve a better, stronger, more efficient and quality weld joint. The analytical tools used in this research study could only analyze the data obtained from the welding of the thin, mild steel plates used in this research study, which produced the optimal solutions. This is the limitation of this current research study, for with higher thickness mild steel plates, the nature and the values of the data results that would be obtained from the welding would be different.

3.1. Diagnostic Plots

The diagnostic case statistics actually give insight into the model strength and the adequacy of the optimal second-order polynomial equation.

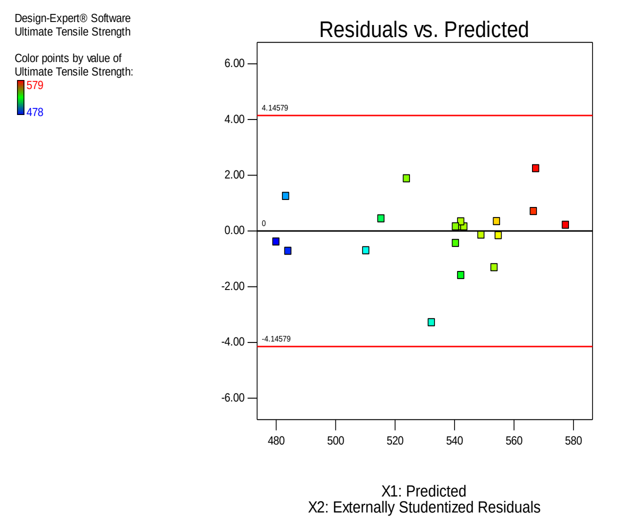

Fig. 1 Studentized residuals vs. Predicted to check for constant error

Figure 1 above is the plot of the variations of the Predicted and the Residual values to verify for constant errors. The figure shows that the errors in the Predicted and the Residuals are within values of errors that are limited and insignificant in the system. This is because all the data points of the errors, as can be seen from the figure above, lie within the acceptable range of values, -4.00 and +4.00 (the two red lines).

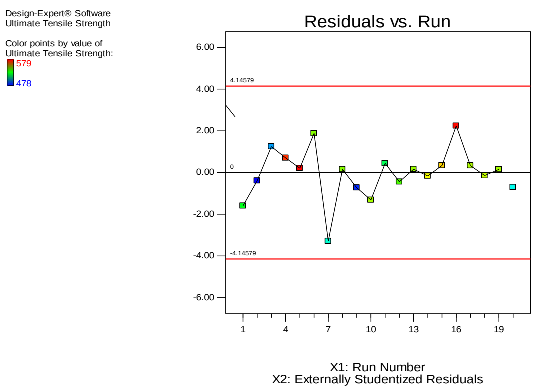

Fig. 2 Externally Studentized residuals to look for outliers, i.e., influential values

Figure 2 shows the variations in the number of runs and the residual values to verify for outliers that may cause influential points in the system. The plot shows that the influential points in the number of runs and the residuals are within a few, and the control values of the influential points are minimal and insignificant in the system.

From the figure, it is seen that all the data points lie within the acceptable range of values, -4.00 and +4.00 (the two red lines) and that no data point is of an influential value of concern to cause bias in the system.

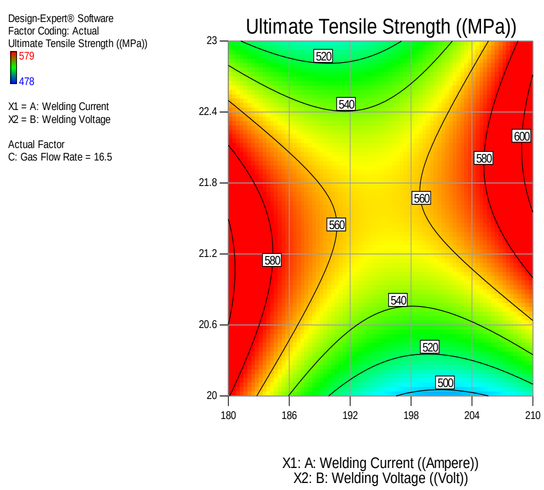

Fig. 3 Contour plot of the Ultimate Tensile Strength: Welding: Current vs. Voltage

The Contour Plot reveals the influence of the input factors on the Ultimate Tensile Strength response variable. It reveals that an increase in the welding current towards its mean slightly decreases the Ultimate Tensile Strength, while the increase of the welding current from its mean to maximum slightly increases the Ultimate Tensile Strength. Also, the increase in welding voltage towards its mean increases the Ultimate Tensile Strength, while the increase in welding voltage from its mean to maximum decreases the Ultimate Tensile Strength.

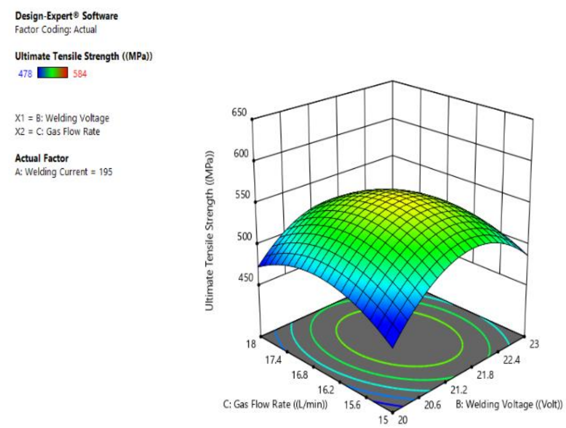

Fig. 4 3-D Surface plot revealing the effects of welding voltage and gas flow rate on the Ultimate Tensile Strength response variable

The 3-dimensional Surface Plot shows the influence of the input variables on the Ultimate Tensile Strength response variable. It reveals that the increase in the welding voltage towards its mean increases the Ultimate Tensile Strength, while the increase in welding voltage from its mean to maximum decreases the Ultimate Tensile Strength response variable. Also, the increase in gas flow rate towards its mean slightly increases the Ultimate Tensile Strength, but an increase in gas flow rate from its mean to its maximum will slightly decrease the Ultimate Tensile Strength in the system.

3.2. Optimal Solutions

The optimization analysis produced twenty (20) optimal solutions from the twenty (20) experimental runs. The optimal solutions from the RSM analysis for the process input factors indicate that the optimal solutions for welding current are 180.00Amps, welding voltage is 21.672Volts gas flow rate is 15.504L/min, and the optimal solution for the response variable, Ultimate Tensile Strength is 579.000MPa., indicating that the experimental trials are good and fit to predict the feasible response of Ultimate Tensile Strength response variable in the system. Therefore, this model can be used for modeling and practical application.

3.2.1. Artificial Neural Network (ANN) or Time Series (TS) Analyses

ANN has input and output data layers and works like the human brain.

Artificial Neural Network analyses take place in stages and through layers of neural networks consisting of neurons.

Stage 1: Data Selection

An ANN model is first selected and trained using historical data. The trained predictive model is then used to analyze the current data (real data from the experiment) to predict future outcomes. The current data (real data from the experiment) fed into the neural network for analyses are both the input and output parameters recorded from the experimental trials (See Table 2). The artificial neural network will select and analyze the data (the individual records) and predict outcomes for each of the experimental results.

Stage 2: Training of Data, Validation of Data, and Testing of Data

Artificial Neural Network (ANN) randomly shares the 100% target time steps (real data) into three sets: data training (70%), data validation (15%) and data testing (15%). The network is trained with seventy percent (70%) of the data, and the network is adjusted according to the errors of the data. The network uses fifteen percent (15%) of the data to measure generalizations from the analyses and to stop the training of the data when the generalizations stop improving.

This is called data validation. Testing of the data uses the remaining fifteen percent (15%) of the data. It has no effect on the training of the data, but it's used as an independent measure of the performance of the network during and after the data training. The Backpropagation Network (BPN) of the neural network analyses was used for the data training/analyses.

Data training automatically stops when generalizations stop to improve, as we can see in this analysis by an increase in the Mean Square Error (MSE) of the samples for data validation. If training is done several times, it will also generate different results due to different initial boundary conditions and sampling.

Mean Square Error (MSE) is the average squared difference between outputs and targets. The smaller the mean square error value (MSE), the better the predicted result, while a Mean Square Error (MSE) of zero (0) means that there is no error. Regression (R) values measure the correlation between the output and the target values. A regression (R) value of one (1) means a close relationship, but an R-value of zero (0) means a random relationship.

Stage 3: Results of the Trained Data of the Neural Network Analyses

The Neural Network (NN) then indicates the least Mean Square Error (MSE) value that gives the best-fit data (the predicted optimal or target results). The data performance in this study reveals that the lowest value of the Mean Square Error (MSE) in the data is very insignificant, with an average value of 4.35x 10^{-26} units at the eighth (8) iteration of the training of the data which is the best-fit data result.

The best validation of the performance result is 2382.3681 units at the eight (8) iterations of the training of the data. The validation performance data value, testing data and the best-fit data are closely related. However, the best-fit data is obtained at the eight iterations of training of the data with the least MSE in the system.

Stage 4: Results of the Regression of the Artificial Neural Network Data Analyses

Results of the trained Artificial Neural Network data analyses revealed that the trained output variable has a regression correlation (R) value of unity (1). The validation data or the fit data generated in the system has a regression correlation (R) value of 0.99646 units. The testing data generated also have a regression correlation (R) value of 0.99791 units. However, the Overall regression correlation (R) value of the predicted optimal (target) result data is 0.99893 units. This indicates that the process input variables and the process output variables have strong correlations at an average of 0.99893 units (99.893%). This is an indication that the data used in the research study are good and fit for statistical analysis and modeling.

Table 7. Predicted results of ANN analyses

	Predicted Output	Predicted Residual
S/N	Ultimate Tensile Strength (MPa)	Ultimate Tensile Strength (MPa)
1	425.9874	94.01259
2	636.1302	-101.13
3	558.6603	-73.6603
4	589.8437	-5.84368
5	518.0085	50.99145
6	528.1659	-36.1659
7	419.2361	128.7639
8	672.3808	-190.381
9	653.9527	-161.953
10	526.9483	-1.94829
11	619.8479	-69.8479
12	664.1948	-128.195
13	618.2879	-94.2879
14	575.3584	-12.3584
15	464.7805	93.21951
16	637.5148	-139.515
17	570.247	-52.247
18	566.8626	-18.8626
19	491.1547	-6..15468
20	530.077	48.923

Table 7 above is the Artificial Neural Network (ANN) predicted results for the Ultimate Tensile Strength response variable. The result shows that the predicted optimal solution for the Ultimate Tensile Strength response variable is 530.077MPa.

The ANN predicted result reveals that the process input parameters and the process output parameters have strong Regression or Coefficient of Determination (R) of the variables with an average of 0.99893 units (i.e. 99.893%). This is an indication that the data used in the study are good and fit for adequate modeling and practical application. Therefore, the predictive model used is suitable for statistical analyses and modeling.

4. Discussion of Results

This research study involves using the Response Surface Methodology (RSM) and Artificial Neural Network (ANN) to optimize and predict weld parameters. The aim of the optimization process is to determine the most appropriate percentage combination of the ultimate tensile strength (response variable) with the optimum values of each of the input variables, namely welding current (Amps), welding voltage (Volts) and gas flow rate (L/min.) needed to adequately optimize (maximize) the ultimate tensile strength content in the mild steel weldment. The overall target of the optimization model was to determine the most appropriate percentage combination of each of the response variables, namely the liquidus temperature, Welding Time, Heat Transfer Coefficient, Ultimate Tensile Strength, and Percentage Elongation in the mild steel weldment, with the optimum values of each of the input variables, namely: welding current, welding voltage and gas flow rate needed to adequately optimize (minimize) liquidus temperature, weld time and heat transfer coefficient response variables in the weldment, and adequately optimize (maximize) ultimate tensile strength and percentage elongation response variables in the mild steel weldment.

During the experimental welding of the mild steel specimens, ranges of values of the input variables and the output variables were observed and recorded, which made up the experimental data for the analysis. A statistical Design of the Experiment (DOE) using the Central Composite Design (CCD) was generated. An experimental matrix consisting of twenty (20) experimental runs was developed. The input variables and the output variables make up the experimental matrix. The RSM tool used for the Design of the Experiment (DOE) is the Design Expert Software 10.0.1 (DX.10.0.1). Central Composite Design was employed in this study owing to its simplicity and flexibility to variable adjustment and analyses of process interaction relating to process factor combinations. It’s also used because of its multi–intput–output process factor design analysis.

The results of the model analyses revealed a Quadratic model for the process order requiring the polynomial analyses selected for each of the response variables. The Quadratic models selected, which are also the best-fit models, proved to be the highest-order polynomials where the additional terms are significant for the process factors and the model is not aliased. Also, the selected Quadratic models have an insignificant lack of fit. Models with a significant lack of fit cannot be employed for optimization or prediction. The Quadratic models were selected due to there is a reasonable agreement between the p-value, the Coefficient of Determination (R^2) value, the Predicted R^2 value, the Adjusted R^2 value, and the PRESS value. The summary of the model design indicates the following for the ultimate tensile strength response variable: minimum value of 576.379MPa, maximum value of 600.996MPa, mean value of 534.65MPa, and a standard deviation of 8.18MPa. The optimal solution of the response surface methodology revealed that the optimum solution of the ultimate tensile strength response variable is 579.000MPa. The model has a high signal-to-noise ratio with a value of 16.6186. To assess the strength of the Quadratic Model in optimizing (maximizing) the ultimate tensile strength response variable, a one-way Analysis of Variance (ANOVA) table was generated for the response variable, and the results derived are shown in Table 5. The Analysis of Variance (ANOVA), Table 5, indicates that the Welding Current (WC) process input variable has a more significant effect on the ultimate tensile strength response variable. However, the RSM analyses indicate that the desirability of achieving the optimum solution results is 83.62%.

In validating the adequacy of the Quadratic model based on its ability to maximize the ultimate Tensile Strength response variable, the model fit statistics summary, Table 6, was employed.

The Coefficient Estimation Analyses of the models showed that the models possess low standard error ranging. Standard errors should be similar within the type of coefficient; however, the smaller the standard error, the better the design result. Variance Inflation Factor (VIF) lies between one (1) and three-point forty five (3.45) for all the Quadratic models selected in this research study, indicating that the Coefficient of Estimation of the input variables to the response variables is adequate, good, and as well as fit for more appropriate statistical modeling of the system. When VIF is greater than ten (10), it can cause bias (error) in the modeling system, and there would be a need to checkmate such variables or even replace the experimental trial. But VIF close to unity is good and fit for adequate modeling of the response variable. When the calculated VIF is less than 10.00 for all the terms in the design system, it indicates a significant model in which the input variables are well correlated with the response.

The ANN analyses in this study were conducted with predictive modeling software called Neural Power Algorithm, Version 2.5, which uses the Backpropagation Network (BPN). The rationale for using the backpropagation algorithm is because it can perform multiple data training and analyses for a complex data set. Using the time series or Artificial Neural Network (ANN) modeling, results shown in Table 7, it was observed that the predicted optimal solution for the welding would produce a weldment with an ultimate tensile strength of an optimum value of 530.077MPa. The ANN analyses produced an overall strong correlation (R) of 99.893% between the input variables and the output variables.

This research study has successfully demonstrated and established that a Response Surface Methodology (RSM) and

Artificial Neural Network (ANN)) Algorithms can be used efficiently to optimize and predict mild steel weld metal variables. This research study employed the use of welding input variables design to determine the optimal solutions of the response variables of the mild steel weldment.

In this research study, the development of a second-order polynomial solution was successfully achieved, authenticated by statistical and graphical results such as calculated Standard Error, VIF, Normal Probability Plot, Cook's Distance plot, etc. Hence, a scientific methodology to establish the cause-and-effect relationship between the process variables using expert systems was successfully established and well-determined in this research study.

In testing the accuracy of the models in actual application, conformity tests were conducted by assigning different values for process variables within their working limits but different from the design matrix. These tests conducted revealed that the models developed are good and adequate for proper statistical modeling of the system and real-world application and can be employed in manufacturable qualities, steel manufacturing companies and industrialization generally. Hence, the optimal solutions determined by the modeling systems in this research study can be adopted for real-world applications and will influence the activities of mild steel production and usage. Therefore, the application of the optimal solutions from this research study will be of strategic economic value to the utilizing companies and in the material usage. This research study will serve as a reference guide to the users of mild steel material and its application in welding and industrialization in general.

5. Conclusion

This research study conducted experiments and data analyses to produce the optimization and prediction models that will establish the optimal values of liquidus temperature, welding time, heat transfer coefficient, ultimate tensile strength and percentage elongation, which are weld metal response variables from welding current, welding voltage, and gas flow rate as input variables in TIG welding process using RSM and ANN techniques. The thesis is "Experimental Investigation of the Effects of Optimal Process Parameters on Mild Steel Weldment Strength using Response Surface Methodology and Artificial Neural Network," and the topic of this research study is: "Application of Expert Methods for Optimizing and Predicting the Ultimate Tensile Strength of Mild Steel Weldment."

The design of the experimental matrix for the process input variables using Central Composite Design (CCD) for the RSM analyses was done for twenty (20) experimental runs using the Design Expert Software 10.0.1 (DX10.0.1). Both the input and the response parameters made up the experimental matrix. The mild steel specimens were welded for the experiment. Results were recorded from the weld specimens used as the experimental data for the data analysis. The Universal Testing Machine (UTM) was used to determine the mechanical properties of the mild steel weldments. The Artificial Neural Network (ANN) analyses were done using the software Neural Power Algorithm, Version 2.5. From the RSM analyses, the optimal solutions of the process input variables are: welding current, 180.00Amps; welding voltage, 21.672Volts and gas flow rate, 15.504L/min, while the optimal solutions of the response variables are: liquidus temperature, 1484.783^{0}c; welding time, 44.000secs; heat transfer coefficient, 238.819w/m^{2o}c; ultimate tensile strength, 579.000mpa and percentage elongation, 22.111%. The RSM analyses produced the "Desirability" of achieving the optimal solutions to be 83.62%. The RSM analyses suggested only the Quadratic models for each of the five responses.

The models have a high significance with the p-values of all the five response variables less than 0.05 (i.e. $p < 0.05$), and all the five response variables possessed Variance Inflation Factor (VIF's) that is less than 10 (i.e. $VIF < 10$). This affirms that the models have a high Goodness of Fit (GOF). Results of the ANN analyses produced the predicted optimal solutions of each of the response variables to be: liquidus temperature, 1464.490˚c; welding time, 53.7132sec; heat transfer coefficient, 256.663w/m^{2o}c; ultimate tensile strength, 530.077mpa and percentage elongation, 18.504%. The input factors and the response variables have an overall strong Regression (R) of 99.893%. Conclusively, the results obtained from the two analytical techniques suggest that both analytical tools can be employed for the effective optimization and prediction of the weld factors, but the optimal solutions of the ANN analyses proved to be better and more robust than those of the RSM analyses because of its higher Regression or Coefficient of Determination (R) value of 99.893% from the ANN analyses when compared with 83.62% produced from the RSM analyses. Hence, the ANN model is recommended for ideal application and use and systematic decision-making. This is a great and innovative improvement in the mild steel weld quality.

The findings in this study also underscore part of the innovative and novel aspect of this research study, and it hinges on the optimal solutions and the desirability of achieving the optimal solutions as given by each of the analytical tools deployed in this research study and as seen in the analyses. From the results of the RSM analyses, the optimal solutions of the process input variables are: welding current, 180.00Amps; welding voltage, 21.672Volts and gas flow rate, 15.504L/min, while the optimal solutions of each of the five response variables are liquidus temperature, 1484.783^{0}C; welding time, 44.000Secs; heat transfer coefficient, 238.819W/m^{2o}c; ultimate tensile strength, 579.000MPa and percentage elongation, 22.111%. The RSM analyses produced the "Global Desirability (Dg)" of achieving the optimal solutions to be 83.62%. From the ANN analyses, the predicted optimal solutions for each of the five response variables are: liquidus temperature, 1464.490˚C; welding time, 53.7132Secs; heat transfer coefficient, 256.663W/m^{2o}c; ultimate tensile strength, 530.077MPa and percentage elongation, 18.504%. The input factors and the response variables have an overall strong Regression (R) of 99.893%. Another key finding from this research study is that the Welding Current (WC) process input variable has the most significant effect on the ultimate tensile strength response variable of the mild steel weldment.

Based on the results of this novel, investigative and innovative research study, which was conducted on 60mm X 40mm X 10mm mild steel specimens, there is a need for further research to be conducted on larger steel plates with higher thicknesses in order to ascertain the validity of the claims of the optimal solutions obtained from this research study, putting into consideration other external and internal factors that can affect the quality of the welds in higher thickness steel plates. For instance, there would be an increased heat input requiring an adjustment of the current and voltage ranges/settings and an increased gas flow rate when welding higher thickness mild steel plates in order to achieve a better, stronger, more efficient and quality weld joint. The analytical tools used in this research study could only analyze the data obtained from the welding of the thin, mild steel plates used in this research study, which produced the optimal solutions. This is the limitation of this current research study, for with higher thickness mild steel plates, the nature and the values of the data results that would be obtained from the welding would be different.

Finally, the main goal of this research study is to improve the quality and efficiency of welding, which will positively impact innumerable industries that rely on this process, save the cost and time of welding, and also drastically lessen the rate of failures in various industries. The models developed from this research study are laudable, and thus, they're suggested for industrial application and systematic decision-making. The models and the optimal solutions from this research study can be adopted in numerous industries, including for example, ship industry, structures and steel manufacturing industries, welding industries, etc., that make use of the steel material and apply the industrial process.

5.1. Recommendation

Recommendation is made for the use of other data analytical tools, e.g. Taguchi method, Genetic Algorithm, TOPSIS, Particle Swarm Optimization (PSO), Optimized Particle Swarm Optimization (OPSO), Simulated Annealing (SA), etc., for the same weld parameters optimization and prediction in order to achieve a more broad and integrated knowledge and information on the welding process optimization, and for comparative study, and also to address any limitations presented by this research study and the analytical methods employed.

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