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Expert Method Application for the Prediction and Optimization of the Percentage Elongation of Mild Steel Weldment

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KEYWORDS

TIG, Mild Steel, Percentage Elongation, RSM, ANN

ABSTRACT

This research study is centered on the optimization and prediction of Percentage Elongation of Mild steel weld metal using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) from Tungsten Inert Gas (TIG) welding process. Welding Current, Welding Voltage and Gas Flow Rate are the process input parameters and the response variable is Percentage Elongation. The final solution of the optimization process is to determine the most appropriate percentage combination of the Percentage Elongation with the optimum values of Current, Voltage and the Gas Flow Rate that will adequately optimize (maximize) the Percentage Elongation of the Mild Steel weld metal. Percent elongation is a mechanical property of a metal that indicates the degree to which a metal may be bent, stretched or compressed before it ruptures. It's an important quality for metals used in welding, as they need to be able to withstand the high temperatures and stresses involved in the welding process. Optimizing this process is one sure way of producing a quality weld. The RSM model produced the numerical optimal solution for the weldment of Mid Steel (MS). The model Coefficient of Determination (R^2) and Adjusted R2 for Percentage Elongation are 93.48% and 87.61% respectively. The Optimal Solutions for the input parameters are; Welding Current, 180.00Amps, Welding Voltage, 21.672Volts and Gas Flow Rate, 15.504L/min. The Optimal Solution for the response variable, Percentage Elongation is 22.111%. From the analysis of variance (ANOVA), it was observed that Gas Flow Rate (GFR) input parameter has more significant effect on the Percentage Elongation response variable. The ANN analysis predicted an optimal solution for the Percentage Elongation response variable to be 18.5044%, with an overall strong correlation (R) between the input factors and the response variable to be 99.89%. Therefore, it is advised that the models be used to navigate the design space.

1. Introduction

Welding is a commonly used method of joining materials in various industrial applications. Welding of mild steel is particularly important, as it is a widely used material in many different industries. Welding parameters, such as Percentage Elongation significantly affect the resulting weldment strength and quality. Therefore, there is a need to optimize this parameter in order to achieve the desired strength and quality of the weld joint. In the process industry welding is very widely used by metal workers in fabrication, maintenance and repairs of parts and structures. Welding is the most convenient, economical, efficient and rapid way of joining two or more metals together to form a monolithic structure (Carry, 1998). Its advantages over other metal joining processes is in its flexibility, low fabrication cost, simple set up and production of very efficient joints (Armentani et al., 2007))

In optimizing the welding parameters, response surface methodology (RSM) and artificial neural network (ANN) models are commonly used. RSM is a statistical approach that can be

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used to optimize the welding process by analyzing the relationship between the input parameters and the output responses. ANN is a computational technique that can be used to model complex relationships between the input and output variables. This research study aims to optimize and predict the percentage elongation and its effect on mild steel weldment strength using RSM and ANN. The study will start by collecting data on the welding process, which will be used to develop RSM and ANN models. The models will be used to determine the optimal welding parameters that will result in a weld joint with the desired strength. The study will also investigate the effects of the welding parameters on the microstructure of the weldment, as well as the mechanical properties.

Percent elongation is a mechanical property of a metal that indicates the degree to which a metal may be bent, stretched or compressed before it ruptures. It is a measure of ductility, which provides the confidence that metal can be formed without cracking or fracturing. It is also a measure of toughness of a metal. Therefore, percent elongation, especially at fracture, is of engineering importance not only as a measure of ductility but also as an index of the quality of the metal. It is one of the essential mechanical properties for weld joints (frepd.com, 2010) and can be affected by welding parameters (Bang et al., 2008; Tewari et al., 2010).

In GTAW also known as TIG process while some work has been done to investigate the effect of welding parameters on the strength of welded joints (Edi et al., 2018; Rajeev, 2014; Rohit and Jha, 2014). very limited attempt has been made on the effects of these parameters on percent elongation especially on mild steel weld joints, and this is the basis of this study. In TIG welding, a non-consumable tungsten electrode of diameter between 0.5 to 6.5 mm is employed with an inert shielding gas (Rishi et al., 2017). The shielding gas used in this experiment is 100% pure Argon. It protects the weld pool from atmospheric contamination with free gases of the air that could be detrimental to the weld quality. The consumable composition of the shielding gas also directly influences the strength and quality of a weld, and thereby, contributes immensely to weld metal properties (strength and quality). TIG welding is very reliable process for improving quality characteristics of weld pool. A mathematical model was developed for the prediction of TIG weld bead characteristics (Prashant and Sachin, 2015).

A critical study of numerous related literatures has revealed that the optimization and prediction of Percentage Elongation of mild steel weld metal using Welding Current (WC), Welding Voltage (WV) and Gas Flow Rate (GFR) jointly as process input factors from Tungsten Inert Gas (TIG) welding process, using process factor design model has not been established to the best of our knowledge, and this is the gap this research study covered. The findings of this study will benefit the welding industry by providing a framework for optimizing the welding process and predicting the resulting weldment strength. The study will also contribute to the development of new technologies and techniques for welding of mild steel. Overall, this study aims to improve the quality and efficiency of welding, which will have a positive impact on various industries that rely on this process.

2. Material and Methods

Thirty (30) pieces of mild steel coupons measuring 60mm x 40mm x 10mm was prepared and used for this experiment. The experiment was performed only twenty (20) times. The welded specimens were prepared and then subjected to tensile tests according to ASTM E8 standard procedure using a Universal Testing Machine (UTM). The tensile test specimens were fastened to tapered slots with a pair of racked jaws at the center of the upper and lower crossheads of the loading unit of the UTM to grip the tensile test specimens. When the load is applied from the control unit of the UTM, there’s a relative movement of the lower and upper crossheads of the UTM as a result of the extension of the specimen. Loads are applied until the specimens permanently deform or fractures. The extension is measured by an elongation scale which is provided along with the loading unit. The percentage elongation is determined using the following expression:

$$\%\text{Elongation} = \frac{increase\ in\ length}{original\ length}\ \text{X}\ 100$$

The central composite design (CCD) matrix was developed for the response surface methodology (RSM), using the design expert software, producing twenty (20) experimental runs. The input parameters and output parameter make up the experimental matrix and the responses recorded from the weld samples were used as the data. An artificial neural network (ANN) was selected and trained and was used for the neural network analysis.

The key parameters considered in this work are Welding Current (WC), Welding Voltage (WV) and Gas Flow Rate (GFR). The range of the process input parameters obtained from the experiment is shown in Table I.

Table 1: Input Factors Boundary Limit.

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

The table 1 above shows the adopted boundary conditions of the input process factors used in this study**.** The bases of selecting the boundary conditions are based on experimental values. The experimental matrix comprising of the three input variables namely; 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 real values is presented in Table 2 below.

Table 2: Central Composite Design (CCD) Matrix showing Experimental Results & Data.

Run	**Input Parameters**			**Output Parameter**
	Welding Current (Ampere)	Welding Voltage (Volt.)	Gas Flow Rate (L/min)	Percentage Elongation. (%)
1	180	20	18	15
2	195	20	15	14
3	210	20	18	21
4	180	21.5	18	17
5	180	20	16.5	14
6	195	21.5	18	19
7	210	23	18	15
8	210	23	15	23
9	180	23	15	25
10	210	21.5	18	20
11	210	23	15	25
12	210	23	15	22
13	180	20	18	16
14	195	21.5	16.5	18
15	210	23	16.5	15
16	210	23	18	14
17	180	20	18	16
18	180	23	18	17
19	210	21.5	16.5	19
20	210	20	16.5	21

3. Result and Discussion

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

Table 3: Model Fit Summary Statistics for Percentage Elongation response variable.

Source	Sequential p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	0.0372	0.0508	0.2901	-0.1508	
2FI	0.0003	0.2433	0.7871	0.1615	
Quadratic	**0.0385**	**0.4349**	**0.8761**	**0.7244**	**Suggested**
Cubic	0.4349		0.9014		Aliased

The table above shows the selected model fit summary of the response variable, Percentage Elongation. The selected model is based on the best probability value with less error in the selected model system. The selected model for Percentage Elongation is Quadratic non-linear model with a significance value of 0.0385

Table 4: Model Summary Statistics.

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	3.52	0.4022	0.2901	-0.1508	381.77	
2FI	1.93	0.8543	0.7871	0.1615	278.18	
Quadratic	**1.47**	**0.9348**	**0.8761**	**0.7244**	**91.44**	**Suggested**
Cubic	1.31	0.9844	0.9014		*	Aliased

Focus on the model maximizing the Adjusted R^2 and the Predicted R^2.

The model summary statistics of model's fit shows the Standard Deviation, the R^2, Adj.R^2, Pred. R^2 and the PRESS values for each complete model. In assessing the strength of the Quadratic Model towards optimizing (maximizing) the Percentage Elongation response variable, one-way analysis of variance (ANOVA) was employed as shown below:

Table 5: ANOVA Model Statistical Summary for Percentage Elongation.

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**P-value**	
Model	310.11	9	34.46	15.92	<0.0001	significant
A-Welding Current	9.28	1	9.28	4.29	0.0652	
B-Welding Voltage	4.73	1	4.73	2.19	0.1701	
C-Gas Flow Rate	36.43	1	36.43	16.84	0.0021	
AB	24.75	1	24.75	11.44	0.0070	
AC	0.6324	1	0.6324	0.2923	0.6006	
BC	45.83	1	45.83	21.18	0.0010	
A^2	0.2249	1	0.2249	0.1039	0.7538	
B^2	11.80	1	11.80	5.45	0.0417	
C^2	3.07	1	3.07	1.42	0.2608	
Residual	21.64	10	2.16			
Lack of Fit	16.47	7	2.35	1.37	0.4349	Not significant
Pure Error	5.17	3	1.72			
Cor. Total	331.75	19				

Analysis of variance (ANOVA) was needed to check whether or not the model is significant and also to evaluate the significant contributions of the linear term coefficients, the interactive term coefficients and the quadratic sum term coefficients on the response. The model F-value of 15.92 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant.

In this case A, C, AB, BC, B^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (not counting those required to support hierarchy), model reduction may improve the model. The Lack of Fit F-value of 1.37 implies the Lack-of-Fit is not significant relative to the pure error. There is a 43.49% chance that a Lack-of-Fit F-value this large could occur due to noise. Non-significant lack of fit is good as it indicates a model that is significant.

Table 6: Fit Statistics for validating model significance towards maximizing P.E

Std. Dev.	**1.47**	R^2	**0.9348**
Mean	**18.75**	Adjusted R^2	**0.8761**
C.V. %	**7.85**	Predicted R^2	**0.7244**
PRESS	**91.44**	Adeq Precision	**13.4885**

In Table 6 above, the model Fit summary statistics shows that the Coefficient of Determination (R^2) of the input factors and the response variables for the model are significantly adequate to the model developed for the Percentage Elongation response variable. The Coefficient of Determination of the variables shows that 93.48% of the input factors will be explained in the response variable of Percentage Elongation. The Predicted R-Squared of 0.7244 is in reasonable agreement with the Adjusted R-Squared of 0.8761, that is the difference is less than 0.2. Adequate Precision measures the signal-to-noise ratio. A ratio greater than 4 is desirable. The ratio of 13.489 indicates an adequate signal. This model can be used to navigate the design space for Percentage Elongation.

Diagnostic Plots.

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

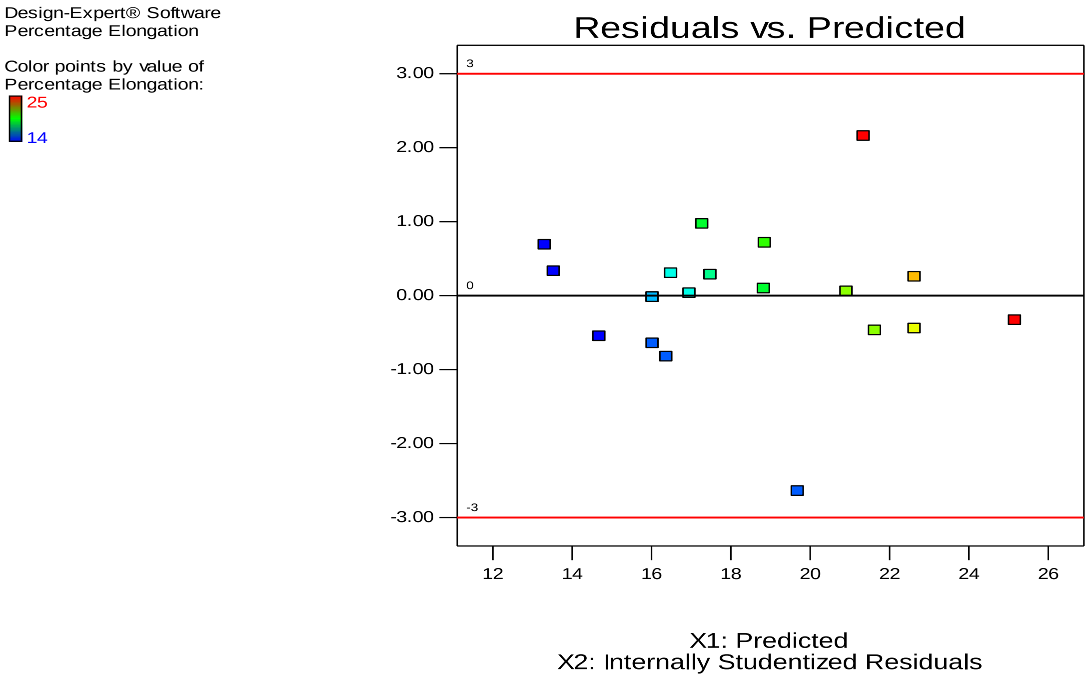

Figure 1: Studentized Residuals vs. Predicted to check for constant error.

The figure 1 above shows the plot of residuals vs. predicted responses in the Percentage Elongation response variable, and it is clear from the figure that the actual and predicted values are closer to each other having small residuals. The plot shows that the errors in the predicted and the residuals are within limited values of errors that are insignificant in the system.

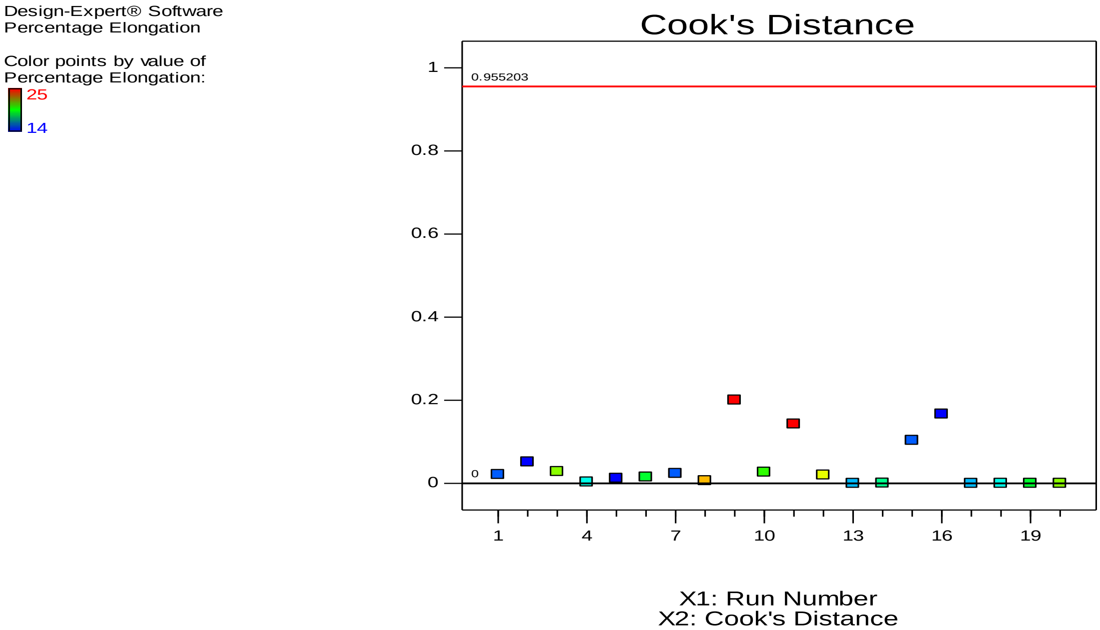

Figure 2: The Diagnosis of the Cook's Distance for Percentage Elongation.

The figure above shows the diagnosis of the input factors and the response variable to check and to look for outliers that will cause the influential values in the system. The Cook's Distance shows that none of the experimental trials cause bias in the system. All the experimental trials are good and fit to predict the feasible response variable of Percentage Elongation in the system. The cooks distance for all the experimental trials falls within the range of 0 and 1 indicating that there is no outlier in the data making the optimal solution strongly accepted.

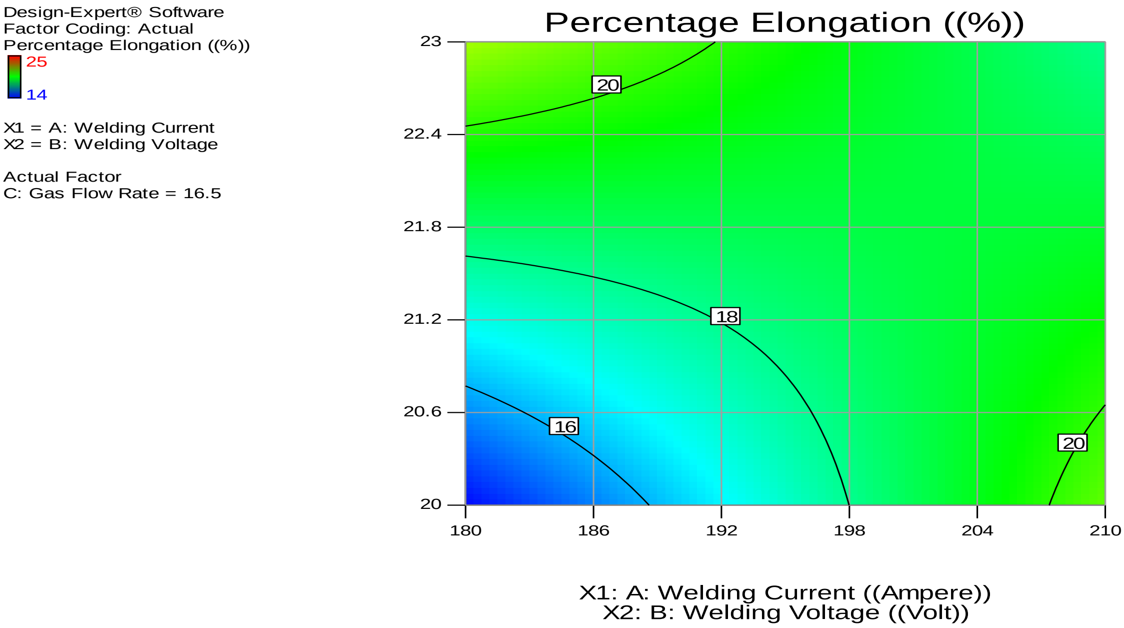

Figure 3: Predicting Percentage Elongation using Contour Plot.

The Contour Plot shows the influence of the input factors on the Percentage Elongation response variable at the highlighted points.

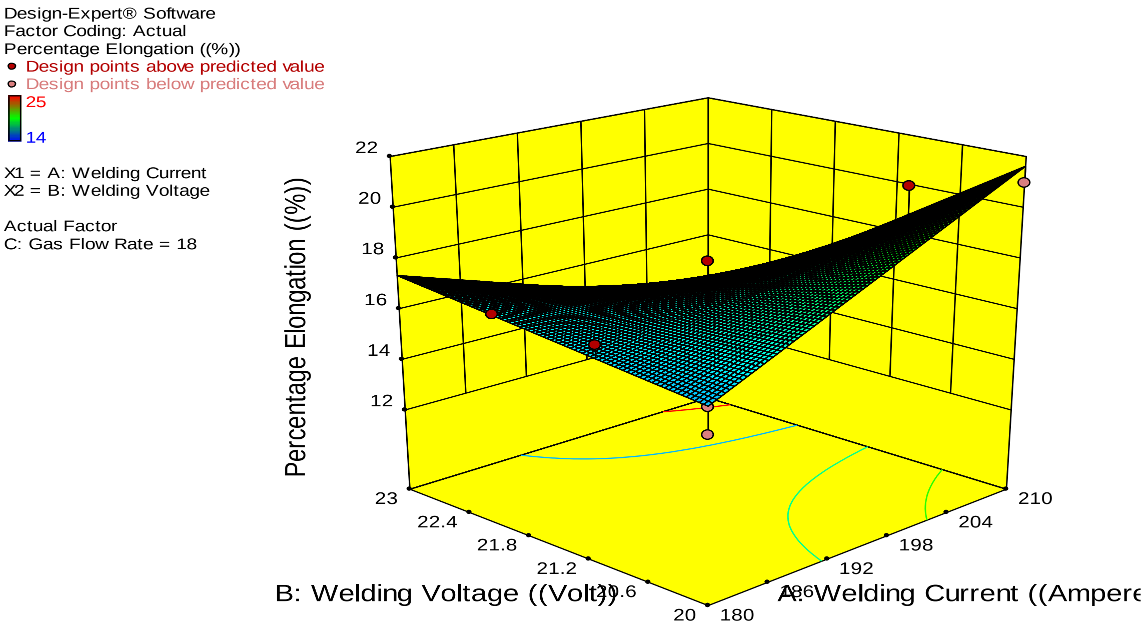

Figure 4: 3-D Surface Plot showing effects of Current and Voltage on P.E. response variable.

Figure 4 show the influence of the input variables (Welding Current, Welding Voltage and Gas Flow Rate) on the Percentage Elongation response variable. The edges of the surface plots indicate the corresponding values of the response variables (Weld Time, Liquidus Temperature, Heat Transfer Coefficient, Ultimate Tensile Strength and Percentage Elongation) at the coordinate levels of the input variables.

Optimal Solutions

The numerical optimization produced twenty (20) optimal solutions. The Optimal Solutions for the input process parameters indicate that the optimal solutions for Welding Current is 180.00Amps, Welding Voltage is 21.672Volts and Gas Flow Rate is 15.504L/min, and the optimal solution for the Percentage Elongation response variable is 22.111%, indicating that the experimental trials are good and fit to predict the feasible response variable in the system. Therefore, the model can be used to navigate the design space.

4. Artificial Neural Network (ANN) Algorithm.

Artificial Neural Network analysis occurs in sequences and via neural network layers made up of artificial neurons.

Sequence 1: Data Selection.

Neural Network analysis starts with the selection and training of an ANN model using a historical data. Real data from the experiment is then fed into the trained predictive model for analysis in order to predict future outcomes. The data fed into the neural network for analysis are both the input and output parameters generated as a result of experimental trials conducted in the research (See Table 7). The artificial neural network will select and analyze the data and predict outcomes for each of the experimental trials.

Sequence 2: Data Training, Validation and Testing.

In the analysis of the data, Artificial Neural Network (ANN) randomly by default divides the 100% target timesteps (Real data) into three sets: Training Data (70%), Validation Data (15%) and Testing Data (15%). Seventy percent (70%) of the data are presented to the network during training and the network is adjusted according to the data errors. Fifteen percent (15%) of the data are used by the network to measure generalizations from the analysis, and to halt the data training once generalizations stop improving. And this is referred to as data validation. Fifteen percent (15%) of the remaining data used for testing has no effect on the data training, but serves as an independent measure of network performance during and after training of the data.

The Artificial Neural Network (ANN) is trained to fit the input process variables and the output response variables. The type of data training method used in this research study is Levenberg-Marquardt back propagation. Training of the data automatically stops when the generalizations stops improving as indicated by an increase in the mean square error (MSE) of the validation samples. The 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 at all. Regression (R) values measure the correlation between the output values 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.

Sequence 3: Trained Results of Neural Network Data Analysis.

The neural network (NN) then reveals the least Mean Square Error (MSE) value that gives the best fit data (that is, the predicted results). The data performance in this study shows that the least 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 eight (8) iteration of the data training which is the best fitted data result.

The best validation of the performance result is 2382.3681 units at the eight (8) iterations of the trained data. The Validation performance data value, Testing data and the Best fit data are closely related. However, the Best fit data is generated at the eight iterations with the Least Mean Square Error in the system.

Sequence 4: Regression Results of the Artificial Neural Network Data Analysis.

Table 7: ANN Predicted Results

	Predicted Output	**Predicted Residual**
S/N	Percentage Elongation. (%)	Percentage Elongation. (%)
1	60.62277	-45.6228
2	113.7397	-99.7397
3	148.4978	-127.498
4	86.63008	-69.6301
5	103.1488	-89.1488
6	207.558	-188.558
7	26.82108	-11.8211
8	153.6502	-130.65
9	76.80446	-52.8045
10	90.21177	-70.2118
11	102.2986	-77.2986
12	138.4174	-116.417
13	90.47311	-74.4731
14	136.9269	-118.927
15	57.67407	-42.6741
16	123.7579	-107.758
17	58.87403	-42.874
18	121.0224	-104.022
19	-5.26993	24.26993
20	18.50438	2.49562

The result of the Trained Artificial Neural Network data analysis shows that the trained data output parameter has a Regression Correlation (R) of unity (1). The Validation Data generated in the system has Regression Correlation (R) of 0.99646 units. The Testing Data generated also have a Regression Correlation (R) of 0.99791 units. However, the Overall Regression Correlation (R) of the data is 0.99893 units. This shows that the input process factors and the output process parameters have strong correlations at an average of 0.99893 units. This shows that the data used in the system are good and fit for statistical analysis.

Table 7 above shows the Artificial Neural Network (ANN) or Time Series (TS) analysis for the predicted result of the Percentage Elongation response variable. The result shows that the predicted response parameter, Percentage Elongation has a value of 18.50438%. The ANN result shows that the input process factors and the output process parameters have strong Coefficient of Determination (R) of the variables with an average of 0.99893 units (i.e. 99.89%). This shows that the data used in the system are good and fit for adequate statistical analysis. Therefore, the predictive model can be used to navigate the design space.

5. Discussion of Results.

In this study, the response surface methodology (RSM) and artificial neural network (ANN) was used respectively to optimize and predict weld parameters. The goal of the optimization process is to determine the most appropriate percentage combination of the Percentage Elongation with the optimum values of Welding Current (Amps.), Welding Voltage (Volts.) and Gas Flow Rate (L/min) that will adequately optimize (maximize) the Percentage Elongation content in the mild steel weld metal. In the course of the experiment, ranges of values of the input parameters and output parameters were observed and recorded which makes up the data (that is, the results from the weld specimens). A statistical design of experiment (DOE) using the central composite design method (CCD) was developed. Then, an experimental design matrix having twenty (20) experimental runs was generated. The input parameters and the output parameters make up the experimental matrix. Both the experimental matrix designed and the optimization analyses were executed with the aid of statistical tool called Design Expert Software 10.0.1 (DX.10.0.1).

The result of the model analysis shows that a Quadratic Model for the process order which requires the polynomial analysis was selected for the response variables. The highest order polynomial where the additional terms are significant for the process factors, the model was selected as the best fitted model. In addition, the selected models have insignificant Lack-of-Fit. Model with significant Lack-of-fit cannot be employed for prediction. The reason for selection was the reasonable agreement between the P-value, R-Square value, the Predicted R-Square value, Adjusted R-Square value and the PRESS value. The model design summary shows that the minimum value observed for Percentage Elongation is 20.655%, with a maximum value of 23.522%, mean value of 18.75%, and standard deviation of 1.47%. The Optimal Solution for the response variable, Percentage Elongation is 22.111%.The model has a high signal-to-noise ratio of 13.489. In assessing the strength of the Quadratic Model towards optimizing the target response, one-way analysis of variance (ANOVA) table was generated for the response variable and results obtained is presented in Fig. 3. From the analysis of variance (ANOVA), table 5, it was observed that Gas Flow Rate (GFR) input parameter has more significant effect on the Percentage Elongation response variable. To validate the adequacy of the Quadratic Model based on its ability in maximizing Percentage Elongation, the goodness of fit statistics presented in Fig. 4 was employed.

From the Coefficient Estimation Analyses of the models, it was observed that the models possess a low standard error ranging. Standard errors should be similar within type of coefficient; however the smaller the standard error the better the result of the design. The Variance Inflation Factor (VIF) in this research is between one (1) to three point forty five (3.45) which shows that the Coefficient of Estimation of the input factors to the response parameters are adequate and is good, and as well as fit enough for more appropriate modeling of the system. Variance Inflation Factors (VIF) greater than ten (10) can cause bias in the modeling system and there is need to checkmate such factor or even replace the experimental trial, but Variance Inflation Factors (VIF) that is close to unity is good and fit for an adequate modeling of the response parameters. Variance Inflation Factor (VIF) less than 10.00 calculated for all the terms in the design indicated a significant model in which the input variables are well correlated with the response.

Using Artificial Neural Network algorithm, the result of Table 7 observed that the Predicted Optimal Solution for the welding will produce a weldment with a Percentage Elongation of optimal value of 18.5044%. The input factors and the response variable have an overall strong correlation (R) of 99.893%. This research study has successfully demonstrated and well established a Response Surface Methodology (RSM) and Artificial Neural Network (ANN) algorithms to optimize and predict the Mild Steel weld metal parameters. In this study, the application of the welding input parameters design was used to express the optimal solutions of the response variables of the Mild Steel weldment.

The development of a second order polynomial solution has been successfully achieved, validated by graphical and statistical results such as calculated Standard Error values, Variance Inflation Factor, Normal Probability Plot and Cook's Distance plot etc. A scientific approach to determine the cause-and-effect relationship between the process parameters using expert systems has been successfully established and well demonstrated in this research study. In testing the accuracy of the models in actual application, experiment revealed that the models can be used for optimal solutions mostly in optimization of manufacturable input parameters in establishments that utilize steel materials, steel manufacturing companies and in industrialization generally. The optimal solutions and the models developed will influence the activities of Mild Steel production and usage. The application of the optimal solutions of the results will be of economic value to the utilizing companies and in the material usage. The research will serve as a reference to the users of Mild Steel and its application in Tungsten Inert Gas (TIG) welding process and in industries.

4. Conclusion

The quality and integrity of welded joints is highly influenced by the optimal combination of the welding input parameters. This research work focuses on the optimization and prediction of the Percentage Elongation of mild steel weld metal using RSM and ANN. The general research study aims to optimize and predict the Weld Time, Liquidus Temperature, Heat Transfer Coefficient and their effects on Mild Steel weldment strength using RSM and ANN. This research study developed models using expert systems (RSM) and neural network (ANN) to optimize and predict weld metal Weld Time, Liquidus Temperature, Heat Transfer Coefficient, Ultimate Tensile Strength and Percentage Elongation from input parameters namely: Welding Current (WC), Welding Voltage (WV) and Gas Flow Rate (GFR). Results from the Response Surface Methodology analysis shows that a Welding Current of 180.00Amps, Welding Voltage of 21.672Volts, Gas Flow Rate of 15.504L/min will produce an optimal solution of Percentage Elongation of 22.111% with a Coefficient of Determination (R^2) of 93.48% and with a Desirability of 0.836. Using Artificial Neural Network algorithm (ANN), the network predicted that the input process factors and the response variables has an overall strong Regression (R) or Coefficient of Determination (R-Square) of 99.89%. However, in Artificial Neural Network (ANN), the result observed that the predicted optimal value for the Percentage Elongation response variable is 18.5044%. The mathematical relationship between the optimal input parameters and the response variables obtained from this research study is an improvement in the weld joint quality, and will save cost and time, and also minimize error in the mild steel welded joint and heat affected zones (HAZ). The information gathered from this study will also aid fabrication industries and industrialists to adequately select parameters and produce appropriate materials and structures required from the mild steel material. It is therefore recommended that the optimal Percentage Elongation and the optimized input parameters obtained in this study be employed so as to achieve the desired molten weld metal, weld strength and quality and also to minimize error in the welded joint and the heat affected zones (HAZ). It is also recommended that the optimal Percentage Elongation and optimized input parameters obtained from this study be utilized by users of the mild steel components and its applications for more economic value.

In the findings from this research study, on which also is based the novelty of this study, we see from the analysis of variance (ANOVA), Table 5, that Gas Flow Rate (GFR) input parameter has the most significant impact on the Percentage Elongation response variable. The ANN analysis predicted an optimal solution for the Percentage Elongation response variable to be 18.5044%, with an overall strong correlation (R) between the input factors and the response variable to be 99.89% as against the 83.62% derived from the RSM analysis. Therefore, it is advised that the models be used to navigate the design space. But the ANN model produced the more robust model. 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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References

Armentani, E., Espositor, R., Sepe, R. (2007). The effect of thermal properties and weld efficiency on residual stresses in welding. *Journal of Achievements in Materials and Manufacturing Engineering*, Vol. 20: 319-322.

Bang, K. S., Jung, D. H., Park, C., Chang, W. S. (2008). Effects of Welding Parameters on Tensile Strength of Weld Metal in Flux Cored Welding. *Science and Technology of Welding and Joining.* 13 (6): 508-514.

Carry, H. B. (1998). Historical Development of Welding. *Modern Welding Technology, 4th Edition.* Pp. 6-7, 492-500. Prentice Hall Inc. New Jersey.

Edi, W., Iswant, I., Mirtza, A. N., Karyanik, K.. (2018). Electric Current Effect on Mechanical Properties of SMAW-3G on the Stainless Steel AISI 304. *MATEC Web of Conferences*, 197, 12003

Prashant, A. K., Sachin, A. M. (2015). Optimization of Welding Parameters to Reduce Distortion in Welding of SA 203 grade-E by ANOVA. *International Journal of Science Technology & Engineering (IJSTE),* 1 (12): Page. 57, ISSN (online): 2349-784.

Rajeev Ranjan, (2014). Parametric Optimization of Shielded Metal Arc Welding Processes by Using Factorial Design Approach. *International Journal of Scientific and Research Publications*, 4 (9): Pp. 1-4

Rishi, K., Ramesh, N. M., Santosh, R., Nitin, A., Vinod, R., AjayPalSinh, B. (2017). Experimental Investigation and Optimization of TIG Welding Parameters on Aluminum 6061 Alloy Using Firefly Algorithm. *IOP Conference Series: Materials Science and Engineering.* https://iopscience.iop.org/article/10.1088/1757- 899X/225/1/012153/pdf.

Rohit, J., Jha, A. K. (2014). Investigating the Effect of Welding Current on the Tensile Properties of SMAW Welded Mild Steel Joints. *International Journal of Engineering Research & Technology.* 3 (4): Pp.1304-1307.

Tewari, S. P., Gupta, A. and Prakash, J. (2010). Effect of welding parameters on the weldability of materials. *International Journal of Engineering Science and Technology*, 2(4): 512-516.