Journal of Inventive Engineering and Technology (JIET)
ISSN: 2705-3865
Volume-3, Issue-3, pp-13-24
www.jiengtech.com
Research Paper Open Access

OPTIMIZATION AND PREDICTION OF LIQUIDUS TEMPERATURE OF MILD STEEL WELD METAL USING RSM AND ANN

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ABSTRACT : *This study is focused on the optimization and prediction of Liquidus Temperature 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 Liquidus Temperature. The final solution of the optimization process is to determine the most appropriate percentage combination of the Liquidus Temperature with the optimum values of Current, Voltage and the Gas Flow Rate that will adequately optimize (minimize) the Liquidus Temperature of the Mild Steel weld metal. 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 R^2 for Liquidus Temperature are 94.69% and 89.92% 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, Liquidus Temperature is 1484.783^{0}C. From the analysis of variance (ANOVA), it was observed that welding current (WC) input parameter has more significant effect on the Liquidus temperature response variable.
The ANN analysis predicted an optimal solution for the Liquidus temperature response variable to be 1464.49, 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.

KEYWORDS*: TIG, Mild Steel, Liquidus Temperature, RSM, ANN*

Date of Submission: 05-07-2023 Date of acceptance: 14-07-2023

I. 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 liquidus temperature 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 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 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 liquidus temperature 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.

Each material has many different physical and chemical properties which can be altered after welding. Strength can be altered drastically by welding. If the weld is made with too little heat, little penetration will occur. If the weld is made with too much heat we could destroy the microstructure of the base material. Welding temperature varies depending on the melting temperature of the metals to be fused. Welding current and welding voltage controls the heat input to the weld joint. In Gas metal arc welding, welding voltage affects the arc length. Increase in arc length consequently leads to increase in the arc voltage due to the fact that extension of the arc exposes the entire arc column to the cool boundary of the arc (Fan et al. (2013). Prediction and Optimization of Heat Affected Zone (HAZ) width for SAW process shows that the HAZ has various regions which influence the ability of the joint to provide crack resistance and uniform strength in both the directions of the weld (Singh, 2013). Liquidus is the lowest temperature at which an alloy is completely liquid. The liquidus temperature, TL or Tliq, specifies the temperature above which a material is completely liquid (Askeland, D. R. and Wright, W. J, 2014) and the maximum temperature at which crystals can co-exist with the melt in thermodynamic equilibrium. It is mostly used for impure substances (mixtures) such as glasses, alloys and rocks. The Liquidus Temperature factor is a very important parameter considered to determine the quality and strength of a welded joint (Ojika, H.O. and Achebo, J.I., 2020). Liquidus Temperature is a significant parameter, not only for processes of melting and hot forming, but also for steel welding. For the sake of optimizing the existing processes of steel manufacturing, it is important to know phase transformation temperatures, or temperatures at which steel loses its plasticity or strength (Zhuang et al., 2015). Works toward optimizing the process of solidification of heavy forging ingots (Merder, T., 2014) were implemented in the casting and solidification of steel. Finally, an attention is focused on the fluid flow behavior of steel flow in the tundish (Merder, T. (2014). The methods of study of metallurgical processes are also based on knowledge of thermodynamic properties of materials occurring in a given technology nodes. Knowledge of the Liquidus and Solidus temperatures are critical parameters necessary for the optimal production of steel products. Correct setting of physical or numerical models are equally important for achieving the best steel melting and fabrication processes. The correct determination of these temperatures significantly influences the quality and properties of semi-finished products (Khosravifard et al., 2013).

According to Bansal et al. (2015), Tungsten inert gas (TIG) welding is a thermal process that depends upon heat conducted through the weld joint materials. 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, A.K. , Sachin, A.M. ,2015).

A critical study of numerous related literatures has revealed that the optimization and prediction of Liquidus Temperature 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.

II. MATERIALS AND METHODS

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. 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. A thermocouple was connected to the weld specimen to take temperature readings. 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 parameters 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.

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)	Liquidus Temp. (^{o}C)
1	180	20	18	1450
2	195	20	15	1348
3	210	20	18	1475
4	180	21.5	18	1453
5	180	20	16.5	1378
6	195	21.5	18	1434
7	210	23	18	1397
8	210	23	15	1535
9	180	23	15	1496
10	210	21.5	18	1484
11	210	23	15	1504
12	210	23	15	1541

13	180	20	18	1468
14	195	21.5	16.5	1449
15	210	23	16.5	1485
16	210	23	18	1398
17	180	20	18	1465
18	180	23	18	1438
19	210	21.5	16.5	1448
20	210	20	16.5	1462

III. RESULTS 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 Liquidus Temperature response variable

Source	Sequential p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	0.1944	0.0854	0.1077	-0.4524	
2FI	0.0544	0.6267	0.8391	0.6336	
Quadratic	**< 0.0001**	**0.8728**	**0.8992**	**0.7690**	**Suggested**
Cubic	0.8728		0.8202		Aliased

The Table 3 above shows the selected model fit summary of the response variable, Liquidus Temperature. The selected model is based on the best probability value with less error in the selected model system. The selected model for Liquidus Temperature is Quadratic non-linear model with a significance value that is less than 0.0001.

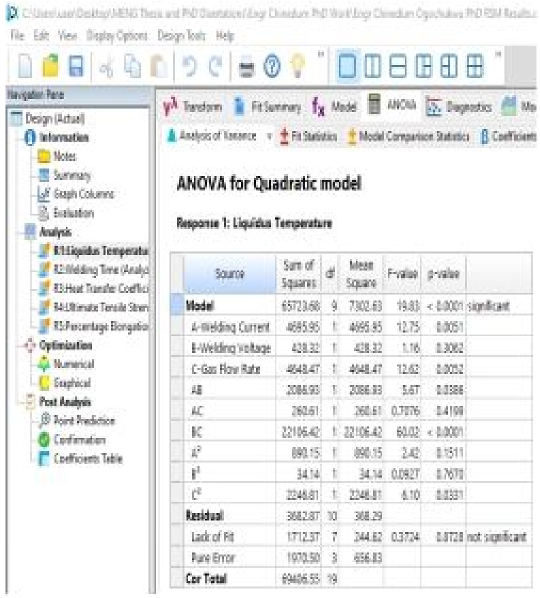
Table 4: Model Summary Statistics

Source	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	57.09	0.2486	0.1077	-0.4524	1.008E+05	
2FI	24.25	0.8899	0.8391	0.6336	25433.07	
Quadratic	**19.19**	**0.9469**	**0.8992**	**0.7690**	**16033.24**	**Suggested**
Cubic	25.63	0.9716	0.8202		*	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 (minimizing) the Liquidus Temperature response variable, one-way analysis of variance (ANOVA) was employed as shown in Fig.1.



ANOVA for Quadratic model

Response 1: Liquidus Temperature

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	65723.68	9	7302.63	19.83	< 0.0001	significant
A-Welding Current	4695.95	1	4695.95	12.75	0.0051	
B-Welding Voltage	428.32	1	428.32	1.16	0.3062	
C-Gas Flow Rate	4648.47	1	4648.47	12.62	0.0052	
AB	2086.93	1	2086.93	5.67	0.0386	
AC	260.61	1	260.61	0.7076	0.4199	
BC	22106.42	1	22106.42	60.02	< 0.0001	
A²	890.15	1	890.15	2.42	0.1511	
B²	34.14	1	34.14	0.0927	0.7670	
C²	2246.81	1	2246.81	6.10	0.0331	
Residual	3682.87	10	368.29			
Lack of Fit	1712.37	7	244.62	0.3724	0.8728	not significant
Pure Error	1970.50	3	656.83			
Cor Total	69406.55	19				

Fig.1: ANOVA Model Statistical Summary for Liquidus Temperature.

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 19.83 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, C^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 0.37 implies the Lack -of-Fit is not significant relative to the pure error. There is an 87.28% 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 5: Fit Statistics for validating model significance towards minimizing L.T.

Std. Dev.	19.19	**R^2**	0.9469
Mean	**1466.35**	Adjusted R^2	**0.8992**
C.V. %	**1.31**	Predicted R^2	**0.7690**
PRESS	**16033.24**	Adeq Precision	**20.8083**

In Table 5 above, the model fit summary statistics shows that the Coefficient of Determination (R^2) of the input factors and the response variable for the model are significantly adequate to the model developed for the Liquidus Temperature response variable. The Coefficient of Determination of the variables shows that 94.69% of the input factors will be explained in the response variable of Liquidus Temperature. The **Predicted R^2** of 0.7690 is in reasonable agreement with the **Adjusted R^2** of 0.8992; i.e. the difference is less than 0.2. **Adequacy Precision** measures the signal-to-noise ratio. A ratio greater than 4 is desirable. The ratio of 20.808 indicates an adequate signal. This model can be used to navigate the design space.

A. Diagnostic Plots

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

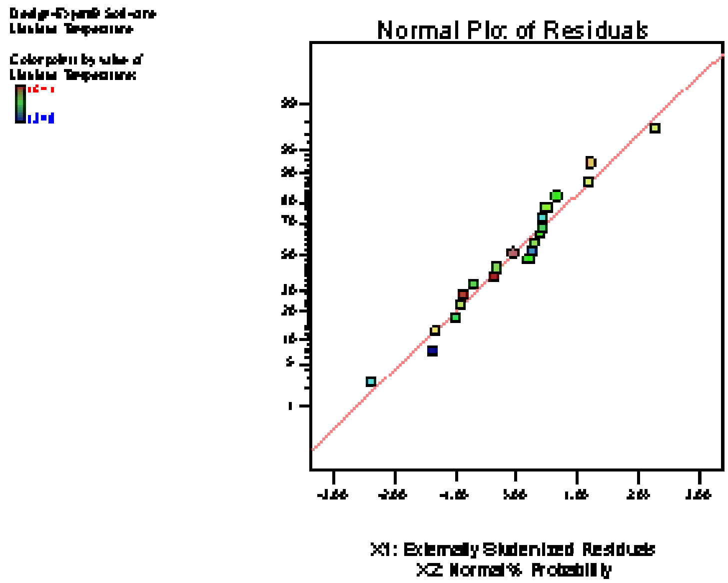


Fig.2: Normal Probability Plot of Studentized Residuals

Fig. 2 above shows the Normal Probability Plot of the residuals for the Liquidus Temperature to check for normality of the residuals on the response variable. The plot shows that the residuals are normally distributed on the response.

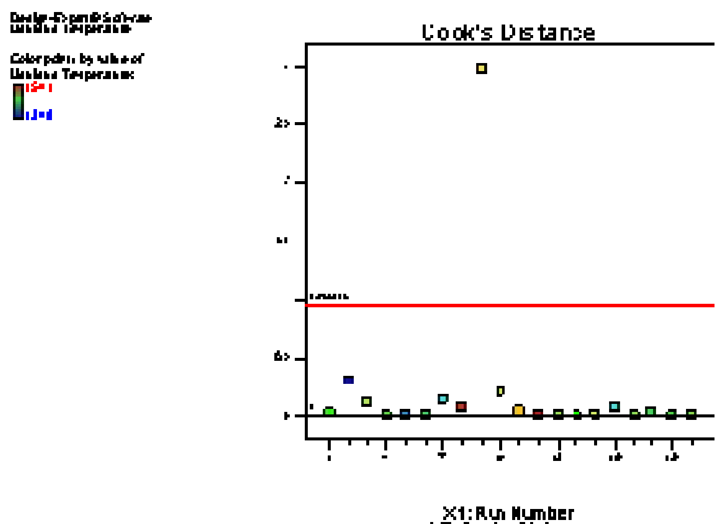


Fig.3: The Diagnosis of the Cook's Distance for Liquidus Temperature

The Fig. 3 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 only one of the experimental trials cause bias. The cook's distance is a measure of how much the regression would change if the outlier is omitted from the analysis. The single point that has a very high distance value relative to the other points should be carefully monitored or investigated to ensure that it didn't cause bias in the system. However, the other experimental trials are good and fit to predict the feasible response variable in the system. The cooks distance falls within the range of 0 and 1 indicating that there is only one outlier in the data making the optimal solution strongly accepted.

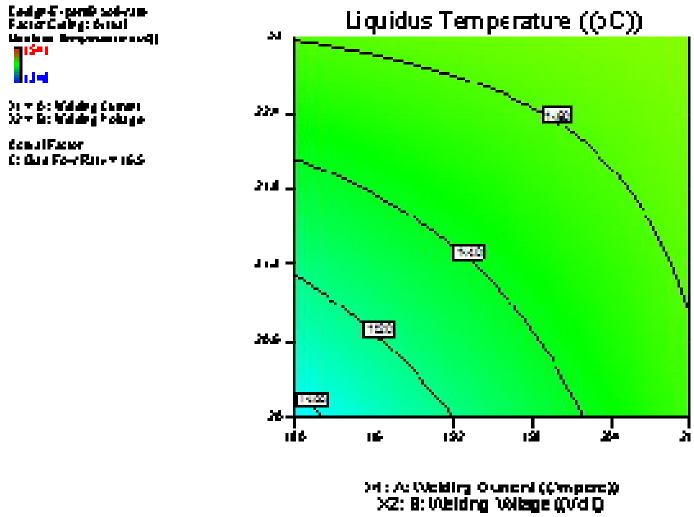


Fig. 4: Predicting Liquidus Temperature using Contour Plot

The Contour Plot in Fig.4 shows the influence of the input factors on the Liquidus Temperature response variable at the highlighted points.

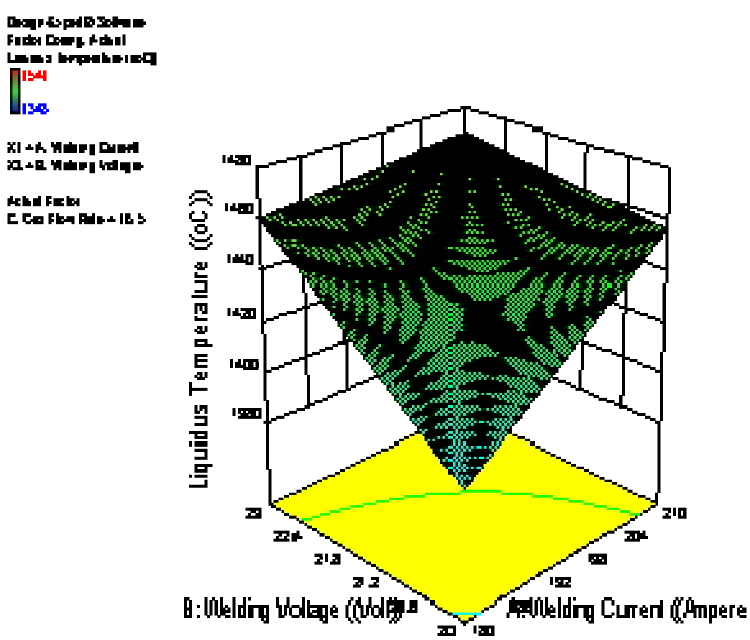


Fig.5: 3-D Surface Plot showing effects of Current and Voltage on L.T. response variable

Fig.5 shows 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 indicates 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.

B. 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 Liquidus Temperature response variable is 1484.783^0C, 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.

1. 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 2). 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 4.35×10^{-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.

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 6: ANN Predicted Results

	Predicted Output	**Predicted Residual**
S/N	Liquidus Temp.(^{o}C)	Liquidus Temp. (^{o}C)
1	1252.823	197.1769
2	1355.894	194.1055
3	1036.969	338.0311
4	1300.915	152.0854
5	1251.534	126.4657
6	1216.718	187.2819
7	1111.689	278.3108
8	1315.207	119.7927
9	1405.108	-9.10773
10	1382.936	101.0643
11	1554.218	-50.2182
12	1487.518	44.48238
13	1592.888	-104.888
14	1509.781	-36.7814
15	1354.555	30.4445
16	1437.192	-39.1922
17	1417.276	47.72365
18	1299.032	138.9682
19	1390.212	57.78845
20	1464.49	-2.49

Table 6 shows the Artificial Neural Network (ANN) predicted results of the Liquidus Temperature response variable. The result shows that the predicted response parameter for Liquidus Temperature is 1464.49^{0}C. 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.

C. 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 Liquidus Temperature with the optimum values of Welding Current (Amps.), Welding Voltage (Volts.) and Gas Flow Rate (L/min) that will adequately optimize (minimize) the Liquidus Temperature 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 Liquidus Temperature is 1427.442^0C, with a maximum value of 1488.893^0C, mean value of 1466.35^0C, and standard deviation of 19.19. The Optimal Solution for the response variable, Liquidus Temperature is 1484.783^0C.The model has a high signal-to-noise ratio of 20.808. 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. 1. From the analysis of variance (ANOVA); Fig. 1, it was observed that welding current (WC) input parameter has more significant effect on the Liquidus temperature response variable.
To validate the adequacy of the Quadratic Model based on its ability in minimizing Liquidus Temperature, the goodness of fit statistics presented in Table 5 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 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 6 observed that the Predicted Optimal Solution for the welding will produce a weldment with a Liquidus Temperature optimal value of 1464.49˚C. 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.

IV. 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 Liquidus Temperature 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 Liquidus Temperature of 1484.783^0C with a Coefficient of Determination (R^2) of 94.69% 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 Liquidus Temperature response variable is 1464.49^0C. 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 Liquidus Temperature 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 Liquidus Temperature and optimized input parameters obtained from this study be utilized by users of the mild steel components and its applications for more economic value.

REFERENCES

Askeland, D. R., Wright, W. J (2014). "Essentials of Materials Science and Engineering." Cengage Learning. p. 329. ISBN 978-1-11157685-1.

Bansal, J., Umed, K. K., Deepak, K. (2015). *"Optimize the Various Effects of Welding Parameters of AL Plate by TIG Welding."* Gas 4.2,2015.

Fan, F.Q., Zhang,m, Z. D., Liu, L. M. (2013). *"Oxide Contribution on Arc Plasma in Tungsten Inert Gas Welding of Magnesium Alloy."* Journal of Science and Technology of Welding and Joining Vol. 18, Issue 5, pp. 434-440.

Khosravifard, A., Hematiyan, M.R., Wrobel, L.C. (2013). *"Simultaneous Control of Solidus and Liquidus Lines in Alloy Solidification."* Engineering Analysis. Boundary Elements 2013, issue 34, pp 211–224

Merder, T. (2014). *"Validation of Numerical Model of a Liquid Flow in a Tundish by Laboratory Measurements."* Metalurgical . Vol. 53, issue 3/2014. p. 323-326. ISSN 0543-5846.

Ojika, H.O., Achebo, .J.I (2020). *"A Cooks Distance Approach to Obtain Optimum Liquidus Temperature of TIG Mild Steel Weld."* International Journal of Scientific and Research Publications, Volume 10, Issue 12.

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

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.

Singh, V. (2013). *"An Investigation for Gas Metal Arc Welding Optimum Parameters of Mild Steel AISI 1016 Using Taguchi Method."* International Journal of Engineering and Advanced Technology (IJEAT) ISSN 2249 – 8958, Volume-2, Issue-6.

Zhuang, C. L., Liu, J. H., Bernhard, C., Presoly, P. (2015). "Analysis of Solidification of High Manganese Steels Using Improved Differential Thermal Analysis Method." J. Iron Steel Res. Int. 22, 709–714.