UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES (UJEAS)

Research Article

Numerical Prediction and Optimization of Heat Transfer Coefficient and their Effects on Low Carbon (Mild) Steel Weldments using Expert Methods

Chukwunedum, Ogochukwu Chinedum, Igbokwe, Nkemakonam C., Ekwueme, O.G.

Special Issue
A Themed Issue in Honour of Professor Clement Uche Atuanya on His retirement.

This themed issue pays tribute to Professor Clement Uche Atuanya in recognition of his illustrious career in Metallurgical and Materials Engineering as he retires from Nnamdi Azikiwe University, Awka. We celebrate his enduring legacy of dedication to advancing knowledge and his impact on academia and beyond through this collection of writings.

Edited by
Chinonso Hubert Achebe PhD.
Christian Emeka Okafor PhD.

UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 3(3), September (2024), 1005-1015
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

Numerical Prediction and Optimization of Heat Transfer Coefficient and their Effects on Low Carbon (Mild) Steel Weldments using Expert Methods

Chukwunedum, Ogochukwu Chinedum, Igbokwe, Nkemakonam C., Ekwueme, O.G.
Department of Industrial & Production Engineering, Faculty of Engineering, Nnamdi Azikiwe University, PMB 5025, Awka, Anambra State, Nigeria.
*Corresponding Author's E-mail: oc.chukwunedum@unizik.edu.ng

Abstract
The purpose of this study is to develop a model that will optimize (minimize) the heat transfer coefficient of mild steel weldment using Response Surface Methodology (RSM) and Artificial Neural Network (ANN). The process input parameters are welding current, welding voltage, and gas flow rate, while the response variable is heat transfer coefficient. Tungsten inert gas (TIG) welding process was used to produce the welded joints. Optimizing this parameter is one sure way of producing a good weld with the desired strength and quality. From the RSM analysis, the optimal solutions for the process 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 is 238.819W/m^{0}C. The Desirability of achieving the Optimum solution results is 83.62%. From the analysis of variance (ANOVA), it was observed that gas flow rate (GFR) has more significant effect on the response variable. The ANN analysis predicted an optimal solution for the response variable to be 256.663W/m^{2o}C, with an overall strong correlation (R) between the input factors and the response variable to be 99.893%. Therefore, it is recommended that the models be used to navigate the design space. But, the optimal solutions of the artificial neural network (ANN) analysis (ANN) are better and more robust because of its higher Regression (R) value, and therefore recommended for application and use, and for systematic decision making.

Keywords: Mild Steel, TIG, Heat Transfer Coefficient, RSM, ANN.

1.0 Introduction

Welding is one of the most practical techniques for assembling structures (Abid et al 2021), such as ships, automobiles, and electronic goods (Aniruddha et al 2015). Gas tungsten arc welding (GTAW) or TIG is a joining method used widely in industries. Many researchers has researched on the process to aid other researchers to explore the process, either through experiments or computer simulations (Deepak et al 2014; Farrahi et al 2020; Filho et al 2018;Jian et al 2020; Luo et al 2020; Ma et al 2015). The shielding gas used in this experiment is 100% pure Argon. The shielding gas (inert gas) shields the electrode, the arc, and the weld puddle from atmospheric contamination. 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 (Margono et al 2019).

In any welding process welding current, welding voltage and gas flow rate have influence on the mechanical properties of weld. The mechanical and metallurgical features of weld depend on the bead geometry which is directly related to the process parameters. In other words, the strength and quality of a good weld depends on the process parameters. The quality and efficiency of the welding process of mild steel is highly dependent on the selection of suitable parameters. The selection of inappropriate parameters can lead to poor weldment strength and undesirable properties. In optimizing the parameters RSM and ANN are popularly used. However, there is a need to develop a more robust optimization model that can predict the optimal welding parameters and their effects on the mild steel weldment strength accurately. This will improve the quality and efficiency of welding leading to cost savings and reduced failure rates in industries. A number of investigations have been performed to investigate mild steel weldment strength and quality. The development 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 methods is the basis of this study. Heat Transfer Coefficient is a constant that relates heat transfer to change in temperature used to calculate heat transmission by conduction, convection, and radiation through materials or structures. Heat transfer coefficient describes the flow of heat (thermal energy) due to temperature changes and the resultant temperature distribution and the changes. For solids, mild steel for an example, heat transfer is by conduction. Heat transfer in welded plates during welding is assumed to be the conductive heat transfer of semi-infinite body, and relates to Fourier's law of conduction, which states that; ''the rate of heat transfer through a single homogenous body is directly proportional to the area of the section at right angles to the direction of the heat flow and to the change in temperature with respect to the length of the path of the heat flow, expressed mathematically as:

Heat flux, $q = -k\frac{dT}{dx}$ (Fourier's law)

k, is called the thermal conductivity**.** $-k\frac{dT}{dx}$, means that temperature decreases with respect to the length of the path of the heat flow.

The basic principle of welding is heating control, and heat affects any type of material that is welded or cut by any process. How much the heat will affect the material during and after welding varies depending on the melting temperature, thickness and shape of the material being fused as well as the welding process and the amount of heat input (amperage). The most important characteristic of heat input is that it governs the cooling rates in welds and thereby affects the microstructure of the weld metal and the heat affected zones (HAZ). A change in microstructure directly affects the mechanical properties of welds. Improper rates of heating and cooling of welded materials can result in weld cracking. Therefore, the control of heat input and the minimization of the heat transfer rate to forestall improper rates of heating and cooling of welded materials is very important in welding in terms of quality control. Heating and rapidly cooling welded materials will cause weld cracking or shrinkage. Weld cracking or shrinkage is what we attempted to minimize in this research study with proper heat control.

Mild steel is a ferrous metal made from iron (Fe) and carbon (C). It is a low carbon steel with a low percentage of carbon usually between 0.25 – 0.30% carbon. It has a high melting point, and it is commonly used in fabrication because it is inexpensive and is easily welded compared with other steel alloys. It is ductile, machinable, and easily forged. This qualities leads to lack of hardened zones in the heat affected zones (HAZ) and welds. With TIG welding, mild steel produces a clean and precise weld. TIG welding has the advantages of: production of stable arc, use of inert gas, high reliability, welding of thin materials, low tolerance to contamination, easy to use, clean and high quality weld production, absence of fluxes, and it is a multi –objective and multi – factor metal fabrication technique. 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 work to electrode tip. This method provides a good oxide cleaning action in the arc, hence, contributing to the production of the clean welds. The tungsten electrode used was the thoriated type.

A critical study of numerous literatures including, Michael et al 2020, "A Study of the Heat Transfer Mechanism in Resistance Spot Welding of Aluminum Alloys AA5182 and AA6014", in which they determined thermal contact conductance and heat transfer coefficient for natural convection and thermal radiation at ambient air and forced convection inside the water cooled electrode for aluminum resistance spot welding, Pamnani et al 2016, "Investigations on the impact toughness of HSLA steel arc welded joints", a work in which they studied the impact toughness of HSLA steel weld joints fabricated by arc welding processes, and finally, Prachya 2017, ". Investigation of the effects of submerged arc welding process parameters on the mechanical properties of pressure vessel steel ASTM A283 Grade A", in which they studied the effects of submerged arc welding (SAW) process parameters on the mechanical properties of this steel etc., has revealed that the optimization and prediction of Heat Transfer Coefficient of mild steel weld metal using welding current (WC), welding voltage (WV) and gas flow rate (GFR) as joint process input variables 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 welding industry will benefit from the findings of this research study which will provide them a framework for optimizing the welding process and predicting the resulting weldment strength. This research study will also contribute to the development of new technologies and techniques for welding of mild steel. Overall, this research study aims to improve the quality and efficiency of welding, which will have a positive impact on various industries that rely on this process, will save cost and time, and also reduce failure rates in various industries for e.g. in ship industry, structures, steel manufacturing industries, welding industries, etc. that makes use of the material.

2.0 Material and methods

The TIG welding and test were conducted at the Welding Engineering and Offshore Technology Workshop, Petroleum Training Institute (PTI), Warri, Delta State, Nigeria. Twenty (20) pieces of mild steel coupons measuring 600mm X 400mm X 10mm was prepared and used for this experiment. The Heat Transfer Coefficient was calculated by dividing the thermal conductivity of the convection fluid which is 64W/m°K with different length scales, measured in $W/m^{2o}C$. A central composite design (CCD) matrix was developed for the response surface methodology (RSM) analysis using the design expert software, DX 10.0.1, producing twenty (20) experimental runs. Central composite design (CCD) was used for the design because of its multi –input multi – output process process factor design analysis. The process input parameters and output parameter make up the experimental matrix and the results recorded from the weld specimens were used as the data for the analysis. A Neural Network (NN) model was selected and trained and was used for the artificial neural network (ANN) or time series (TS) analysis. The software or prediction tool used for the ANN analysis is the Neural Power Algorithm, Version 2.5 - [Levenberg-Marquardt Back Propagation Network (BPN)].The key process input parameters considered in this research study 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 process input parameters used in this study. The bases of selecting the boundary conditions are based on literature. 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 and data

Run	Input Parameters			Output Parameter
	Welding Current (Ampere)	**Welding Voltage (Volt)**	**Gas Flow Rate (L/min)**	**Heat Transfer Coefficient ($W/m^{20}C$)**
1	180	20	18	263.85
2	195	20	15	275.95
3	210	20	18	267.53
4	180	21.5	18	253.54
5	180	20	16.5	236.22
6	195	21.5	18	252.22
7	210	23	18	238.99
8	210	23	15	273.39
9	180	23	15	270.38
10	210	21.5	18	241.70
11	210	23	15	269.32
12	210	23	15	271.79
13	180	20	18	262.63
14	195	21.5	16.5	253.16
15	210	23	16.5	257.84

16	210	23	18	234.84
17	180	20	18	259.32
18	180	23	18	250.08
19	210	21.5	16.5	252.39
20	210	20	16.5	265.62

3.0 Results and Discussions

The highest order polynomial where the additional terms are significant for the process factors and the model is not aliased, the model was selected as best fitted model for the response variable. In addition, the selected model have insignificant lack-of-fit. The selected model is based on the best probability value with less error in the selected model system. The selected model for Heat Transfer Coefficient is a Quadratic non-linear polynomial model with a significance value of 0.0450. The Quadratic model was also suggested based on the fact that the model also does have the least PRESS value to determine the expected error in the system.

Table 3: Model Fit Summary Statistics for Heat Transfer Coefficient response variable.

Source	Sequential P-value	Lack-of-fit P-value	Adjusted R^2	Predicted R^2	
Linear	0.1550	0.0944	0.1361	-0.3163	
2FI	<0.0001	0.6826	0.8489	0.6042	
Quadratic	**0.0450**	**0.9329**	**0.9091**	**0.7724**	**Suggested**
Cubic	0.9329		0.8127	*	Aliased

Table 4: Model Summary Statistics for Heat Transfer Coefficient response variable

Source	St. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	12.80	0.2725	0.1361	-0.3163	4744.96	
2FI	5.35	0.8966	0.8489	0.6042	1426.84	
Quadratic	**4.15**	**0.9522**	**0.9091**	**0.7724**	**820.59**	**Suggested**
Cubic	5.96	0.9704	0.8127			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 the Heat Transfer Coefficient Quadratic model.

In assessing the strength of the Quadratic Model towards optimizing (minimizing) the Heat Transfer Coefficient response variable, one-way analysis of variance (ANOVA) was deployed as shown below:

Table 5: ANOVA Model Statistical Summary for Heat Transfer Coefficient response variable

Source	Sum of Squares	df	Mean Square	F-value	P-value	
Model	3432.22	9	381.36	22.11	<0.0001	Significant
A-Welding Current	97.35	1	97.35	5.64	0.0389	
B-Welding Voltage	3.66		3.66	0.2125	0.6547	
C-Gas Flow Rate	302.66	1	302.66	17.55	0.0019	
AB	465.07		465.07	26.96	0.0004	
AC	472.41	1	472.41	27.39	0.0004	
BC	403.32	1	403.32	23.38	0.0007	
A^2	51.16	1	51.16	2.97	0.1158	
B^2	110.02	1	110.02	6.38	0.0301	
C^2	45.76	1	45.76	2.65	0.1344	
Residual	172.47	10	17.25			
Lack-of-fit	65.87	7	9.41	0.2648	0.9329	Not Significant
Pure Error	106.60	3	35.53			
Cor Total	3604.70	19				

Table 5 above shows that the analysis of variance model developed is significant with a significance value that is less than (<) 0.0001. The Model F-value of 22.11 implies that the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. Values of probability that is less than F value, which is less than 0.050, indicate that the model terms are significant. In this case the Welding Current (A), Gas Flow Rate (C), interaction of Welding Current and Welding Voltage (AB), interactions of Welding Current and Gas Flow Rate (AC), interaction of Welding Voltage and Gas Flow Rate (BC), and square of Welding Voltage (B^2) are all significant model terms in Heat Transfer Coefficient response parameter estimation. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve your model. The Lack-of-Fit F-value of 0.2648 implies that the Lack-of-Fit is not significant relative to the pure error. There is a 93.29% chance that the Lack-of-Fit F-value this large could occur due to noise. Non-significant lack-of-fit is good – it makes the model to fit.

Table 6: ANOVA Goodness of Fit (GOF) statistics for validating model significance towards minimizing Heat Transfer Coefficient

Std. Dev.	4.15	**R^2**	0.9522
Mean	256.04	**Adjusted R^2**	0.9091
C.V %	1.62	**Predicted R^2**	0.7724
		Adeq Precision	18.3499

Table 6 above shows the Coefficient of Determination of the input factors and the response variables for the model are significantly adequate to the model developed for the Heat Transfer Coefficient response variable. The Coefficient of Determination of the variables (R^2) shows that 95.22% of the input factors will be explained in the response variable of Heat Transfer Coefficient. The Predicted R^2 of 0.7724 is in reasonable agreement with the Adjusted R^2 of 0.9091; i.e. the difference is less than 0.2. In practical terms or as a rule of thumb, a higher R^2 and Adj. R^2 value are desirable. When the difference between them is large enough, or when the Adj. R^2 value is very small compared to the value of R^2, it indicates that there is an error in the values of the results of the variables obtained, and this will cause bias in the system, therefore, requiring that the experimental trial be properly checkmated or replaced. Adequacy Precision measures the signal-to-noise ratio. A ratio greater than 4 is desirable. The ratio of 18.3499 indicates an adequate signal. This model can be used to navigate the design space for Heat Transfer Coefficient.

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.

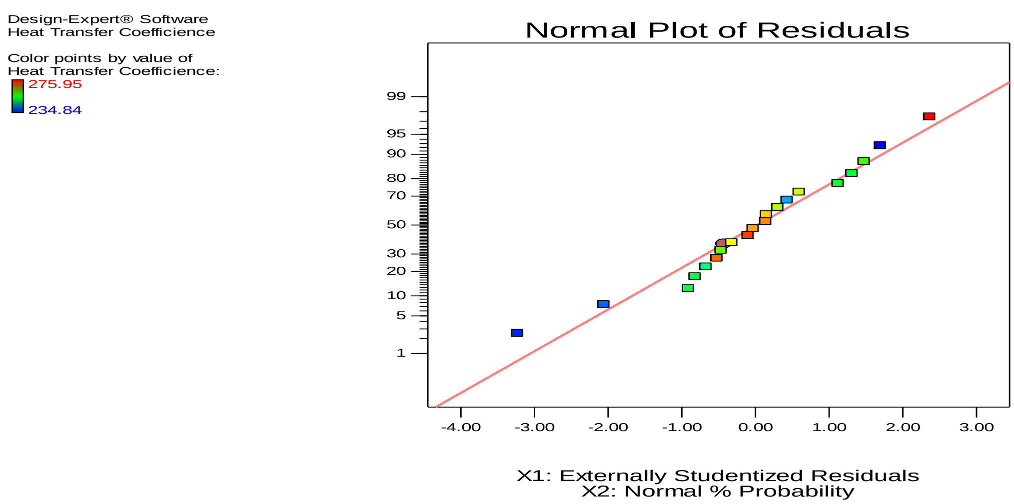

Figure 1: Normal Probability Plot of Studentized Residuals.

Figure 1 shows the Normal Probability Plot of the residuals for the Heat Transfer Coefficient to check for normality of the residuals on the response variable. The Normal Probability Plot of the residuals shows that the residuals are normally distributed in the response variable. All the data points are clustered around the 45^0 diagonal lines, with the cluster occurring between -1.00 and +2.00 accounting for about eighty - five (85%) percent of the total data population.

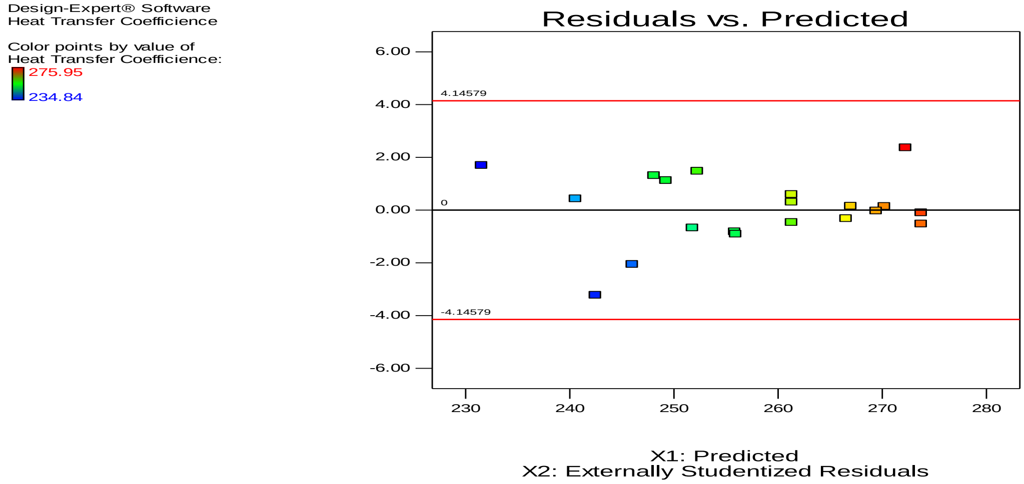

Figure 2: Studentized Residuals vs. Predicted to check for constant error.

Figure above shows the variations of the Predicted values and the Residual values of Heat Transfer Coefficient to check for the constant errors. The plot shows that the errors in the Predicted and the Residuals values are within limited values of errors that are insignificant in the system, as we can see that all the data points lies within the set or acceptable limit of default range indicated by the red lines, i.e. in-between -4.00 and +4.00.

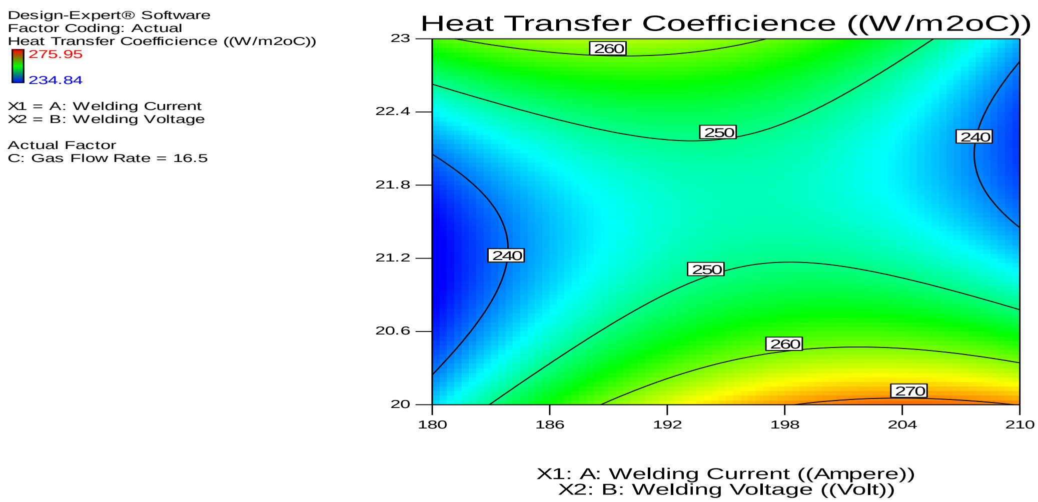

Figure 3: Predicting Heat Transfer Coefficient using Contour Plot.

The Contour Plot shows the influence of the input factors on the Heat Transfer Coefficient response parameter. It shows that the decrease in welding current decreases the Heat Transfer Coefficient. Also, the decrease in welding voltage decreases the Heat Transfer Coefficient parameter in the system.

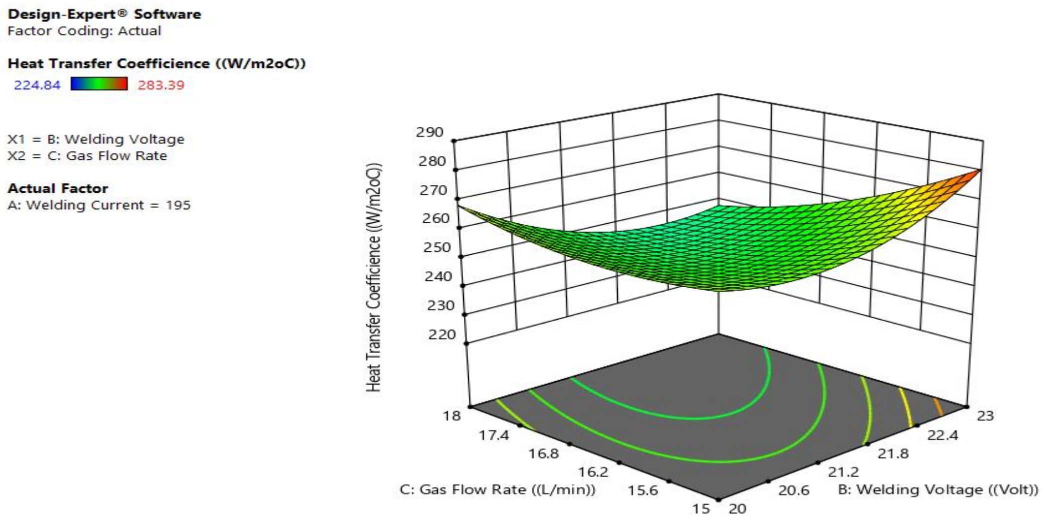

Figure 4: 3-D Surface Plot showing effects of welding voltage and gas flow rate on Heat Transfer Coefficient response variable.

The 3-Dimensional Surface Plot shows the influence of the input factors to the Heat Transfer Coefficient response parameter. The figure shows that the increase in welding voltage towards its mean decreases the Heat Transfer Coefficient, but increase in welding voltage from its mean to its maximum increases the Heat Transfer Coefficient in the system. Also, the increase in gas flow rate from its mean to its maximum slightly increases the Heat Transfer Coefficient in the system and vice versa.

3.2 Optimal Solutions

The numerical optimization analysis produced twenty (20) optimal solutions. The optimal solutions from the RSM analysis for the process input factors 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 Heat Transfer Coefficient response variable is 238.819W/m^{20}C., indicating that the experimental trials are good and fit to predict the feasible response of Heat Transfer Coefficient response variable in the system. Therefore, this model can be used to navigate the design space.

3.3 Artificial Neural Network (ANN) or Time Series Analysis (TSA)

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

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

Sequence 1: Data Selection.

Artificial 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.

Artificial Neural Network (ANN) randomly 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 when 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 type of data training method used in this research study is Levenberg-Marquardt back propagation network (BPN). Training of the data automatically stops when the generalizations stops improving as indicated in this analysis 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. 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 optimal values or target 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.

The result of the Trained Artificial Neural Network data analysis shows that the Trained Data output parameter has a Regression Correlation (R) value of unity (1). The Validation 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 shows that the process input factors and the output process parameters have strong correlations at an average of 0.99893 units (99.893%). This shows that the data used in the system are good and fit for statistical analysis.

Table 7: ANN Predicted Results

	Predicted Output	**Predicted Residual**
S/N	**Heat Transfer Coeff. ($W/m^{02}C$)**	**Heat Transfer Coeff. ($W/m^{02}C$)**
1	249.2205	**3.62955**
2	312.1502	**-36.2002**
3	281.8198	**-46.2898**
4	287.5202	-33.9802
5	280.3103	-44.0903
6	334.3302	-92.1102
7	234.0189	4.971058
8	333.2428	-83.8528
9	271.4016	-31.0216
10	269.9854	-9.28535
11	292.2279	-26.9079
12	309.8587	-38.0687
13	270.8811	-9.25105
14	300.2075	-42.1475
15	236.8099	1.030078
16	288.3894	-47.5494
17	271.7969	-15.4769
18	295.187	-48.107
19	208.1133	44.27673
20	256.663	2.156

Table 7 above shows the Artificial Neural Network (ANN) or Time Series (TS) predicted results of the Heat Transfer Coefficient response variable. The result shows that the predicted response parameter for Heat Transfer Coefficient is $256.663 W/m^{2o}C$. 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. 99.893%). 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.

4. Discussion of results.

In this study, the response surface methodology (RSM) and artificial neural network (ANN) was used respectively to optimize and predict the weld parameters. The goal of the optimization process is to determine the most appropriate percentage combination of the Heat Transfer Coefficient with the optimum values of each of the process input parameters, namely; Welding Current (Amps.), Welding Voltage (Volts.) and Gas Flow Rate (L/min) that will adequately optimize (minimize) the Heat Transfer Coefficient content in the mild steel weldment. The final solution of the optimization process was to determine the most appropriate percentage combination of the Liquidus Temperature in the weldment, most appropriate percentage combination of the Welding Time in the weldment, most appropriate percentage combination of the Heat Transfer Coefficient in the weldment, most appropriate percentage combination of the Ultimate Tensile Strength in the weldment and the most appropriate percentage combination of the Percentage Elongation in the weldment with the optimum values of the Welding Current, Welding Voltage and Gas Flow Rate that will adequately minimize Liquidus Temperature, Weld Time and Heat Transfer Coefficient, and adequately maximize Ultimate Tensile Strength and Percentage Elongation.

In the course of the experiment, ranges of values of the input parameters and output parameters were observed and recorded which makes up the experimental data (i.e. 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 a software / statistical tool called Design Expert Software 10.0.1 (DX.10.0.1). In this study Central Composite Design was employed owing to its simplicity and flexibility to variable adjustment and analysis of process interaction relating to process factor combination. Central composite design (CCD) was used for the design because of its multi –input multi – output process process factor design analysis.

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 and the model is not aliased, 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 optimization or prediction. The reason for selection of the models 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 Heat Transfer Coefficient response variable is 234.847W/m^{20}C, with a maximum value of 246.04W/m^{20}C, mean value of 256.04W/m^{20}C, and standard deviation of 4.15W/m^{20}C. The optimal solution for the response variable, Heat Transfer Coefficient is 238.819W/m^{20}C. The model has a high signal-to-noise ratio of 18.3499. 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 Table 5. From the analysis of variance (ANOVA), Table 5, it was observed that Gas Flow Rate (GFR) process input parameter has more significant effect on the Heat Transfer Coefficienmt response variable. However, the Desirability of achieving the Optimum solution results is 83.62%.

To validate the adequacy of the Quadratic Model based on its ability in minimizing Heat Transfer Coefficient, the goodness of fit statistics presented in Table 6 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) and 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.

The software or prediction tool used for the ANN analysis is the Neural Power Algorithm, Version 2.5 - [Levenberg-Marquardt Back Propagation Network (BPN)]. The advantage/rationale of using Levenberg-Marquardt back propagation algorithm is that it can perform multiple data training and analysis for a complex data set. Using Artificial Neural Network algorithm (ANN) / Time Series (TS) analyses, the result of Table 7 observed that the predicted optimal solution for the welding will produce a weldment with a Heat Transfer coefficient of optimal value of 256.663W/m$^{2 0}$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 the mild steel material, steel manufacturing companies and in industrialization generally. Therefore, the optimal solutions and the models developed will influence the activities of mild steel production and usage. Hence, the application of the optimal solutions of the results will be of economic value to the utilizing companies and in the material usage. This research study will serve as a reference to the users of mild steel and its application in Tungsten Inert Gas (TIG) welding process and in industries.

5.0. Conclusion

This research study carried out an optimization and proposed a prediction model to investigate the Liquidus Tempearture, Welding Time, Heat Transfer Coefficient, Ultimate Tensile Strength and Percentage Elongation based on Welding Current, Welding Voltage, and Gas Flow Rate in TIG welding process using RSM and ANN respectively. The dissertation is on," 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:" Numerical Prediction and Optimization of Heat Transfer Coefficient and their Effects on Low Carbon (Mild) Steel Weldments Using Expert Methods."

In this study, design of the experimental matrix for the process input factors using central composite design (CCD) for twenty (20) experimental runs was done using Design Expert Software 10.0.1 (DX10.0.1). The input parameters and the output parameters make up the experimental matrix. The weld metal specimens were produced for the experiment. The results recorded from the weld specimens were used as the experimental data for the experimental analysis. The mechanical properties of the mild steel weld metal were determined using Universal Testing Machine (UTM). ANN analysis was done with the aid of the software, Neural Power Algorithm, Version 2.5. The optimal solution of the process input factors from the RSM analysis are: Welding Current is 180.00Amps; Welding Voltage is 21.672Volts and Gas Flow Rate is 15.504L/min. While the optimal solutions of the response parameters are: Liquidus Temperature is 1484.783^{0}C; Welding Time is 44.000secs; Heat Transfer Coefficient is 238.819W/m^{2o}C; Ultimate Tensile Strength is 579.000MPa and Percentage Elongation is 22.111%. The Desirability of achieving the Optimum solution results is 83.62%. In addition, the models selected for each of the five responses have a high significance with the p-values less than 0.05 (i.e. $p < 0.05$) and also possessed Variance Inflation Factor (VIF) that is less than 10 (VIF < 10). This confirms that the models possessed high goodness of fits. The result of the ANN analysis predicted the optimal solutions to be: Liquidus Temperature is 1464.490˚C, Welding Time is 53.7132sec, Heat Transfer Coefficient is 256.663W/m^{2o}C, Ultimate Tensile Strength is 530.077MPa and Percentage Elongation is 18.504%. And the input factors and the response variables have an overall strong Regression (R) of 99.893%. From the results obtained, it was concluded that both methods, RSM and ANN are good and suitable for optimizing and predicting weld parameters, but the optimal solutions of the artificial neural network analysis (ANN) obtained are better and more robust because of its higher Regression or Coefficient of Determination (R) value of 99.893% as compared to 83.62% of the RSM analysis. Therefore, the ANN model is recommended for application and use, and for systematic decision making. This is an improvement in the weld quality.

The findings in this research study are basically the optimal solutions and the desirability of achieving the optimal solutions as given by each of the analytical tools employed in this research study and as stated above. Also, the key finding in this research study is that gas flow rate (GFR) has the most significant effect on the Heat Transfer Coefficient of mild steel weld parameter. This research study aims to improve the quality and efficiency of welding, which will have a positive impact on various industries that rely on this process, will save cost and time, and also reduce failure rates in various industries for e.g. in ship industry, structures, steel manufacturing industries ,welding industries, etc. that makes use of the material.

5.0 Recommendation

It is recommended, the application of other data analytical tools like Taguchi method, Genetic Algorithm, Ansys, Particle Swarm Optimization (PSO) etc. for the same process factor analysis in order to achieve a more robust and unified knowledge and information on the welding process optimization, and for comparative analysis, and also to address all the limitations of this research study and the analytical tools employed.

References

Abid, H. J., Khalaf, H. I., Alazawi, F. H., Ugla, A. A. 2021 Experimental investigation of the effect of spot-welding process parameters on the tensile strength of similar metal joints. *International Review of Mechanical Engineering (IREME*,. 15(2): 89-95. Available from: https://faculty.uobasrah.edu.iq [February 2021].

Aniruddha, G., Pawan, K., Arvind, K. 2015. 'Numerical analysis of heat transfer of arc welded plate'. *Advances in Material Forming and Joining. Topics in Mining, Metallurgy and Materials Engineering. Springer, New Delhi.* 273-293. [01 January 2015].

Deepak, K.Y., Swarup, B., Sukhomay, P. 2014. Heat transfer analyses in friction stir welding of aluminum alloy. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 229(10): 1-18. Available from: https://journals.sagepub.com [18 July 2014].

Farrahi, G. H., Kashyzadeh, K.R., Minaei, M., Sharifpour, A., Riazi, S. 2020. Analysis of resistance spot welding process parameters effect on the weld quality of three-steel sheets used in automotive industry: experimental and finite element simulation. *International Journal of Engineering*, 33(1): 148 – 157. Available from: https://www.ije.ir [15 January 2020].

Filho J.D.C.P., Passos E.K.D., Gonzaga R.S., Ferreira ,R.F., Santos, D.D., Juliano, D.R. 2018. Ultrasonic inspection of a 9% Ni steel joint welded with Ni-based superalloy 625: simulation and experimentation. *Metal*,. 8(10): 1-17. Available from: https://www.mdpi.com [2 October 2018].

Jian X., Wu H. 2020. Influence of the longitudinal magnetic field on the formation of the bead in narrow gap gas tungsten arc welding. *Meta*,.10(10): 1-15. Available from: https://www.mdpi.com. [9 October 2020]

Luo, C., Li, H., Song, Y., Yang, L., Wen, Y. 2020. Microstructure and performance analysis of welded joint of spray-deposited 2195 Al-Cu-Li alloy using GTAW. *Metal*, 10(9): 1-11. Available from: https://www.mdpi.com. [14 September 2020].

Ma, N, Wang, J, Okumoto, Y. 2015. Out-of-plane welding distortion prediction and mitigation in stiffened welded structures. *The International Journal of Advanced Manufacturing Technology*,. 84(5-8):1371–1389. Available from: https://link.springer.com. [15 September 2015].

Margono, B., Haikal, Atmaja, H. I., Wibowo, J., Alfayed, A., Rananto, R. F. 2019. Effect of pressure and welding time on physical and mechanical properties of dissimilar metal AISI 316 austenitic stainless steel and AISI 4140 alloy steel joints using friction welding. *Journal of Physics: Conference Series*, 1517(1): 1-6. Available from: https://iopscience.iop.org. [29 May 2020].

Michael, P., Alexandra,W., Leander, S., Vesselin, G. M., Nikolay, D., Ralf, O. 2020. A study of the heat transfer mechanism in resistance spot welding of aluminum alloys AA5182 and AA6014. *The International Journal of Advanced manufacturing Technology*, 111(1-2): 263-271. Available from: https://link.springer.com. [25 September 2020].

Pamnani, R., Jayakumar, T., Vasudevan, M., Sakthivel, T. 2016. Investigations on the impact toughness of HSLA steel arc welded joints. *Journal of Manufacturing Processes*, 21: 75-86. Available from: https://www.sciencedirect.com. [January 2016].

Prachya, P. 2017. Investigation of the effects of submerged arc welding process parameters on the mechanical properties of pressure vessel steel ASTM A283 Grade A. *Journal of Engineering*. 2017: 1-8. Available from: https://onlinelibrary.wiley.com. [05 February 2017].