UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 3(5), December (2024), 1434-1446
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

Experimental investigation of the effects of optimal weld time on mild steel weldment strength using expert methods

Chukwunedum Ogochukwu Chinedum, Godspower Onyekachukwu Ekwueme and Nkemakonam Chidiebube Igbokwe.
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
This research study aims to develop models for the optimization (minimization) of the weld time of mild steel weldment using response surface methodology and artificial neural network. The input factors used in this research study are: current, voltage, and gas flow rate. The output parameter is the weld time. The welding process used for the experimental welding is the tungsten inert gas (TIG) welding.. Weld time adequately optimized will produce a quality weld with the desired strength. The RSM analysis gave the optimal solutions for each of the input factors with current as 180.00Amps, voltage as 21.672Volts, and gas flow rate as 15.504L/min. The optimal solution for the output factor, weld time is 44.000secs. The optimum results were achieved with a desirability of 83.62%. Analysis of variance results indicated that gas flow rate input factor has the most significant effect on the output variable under consideration. The artificial neural network predicted an optimal solution for the weld time response factor as 53.71292Secs, and showed an overall strong correlation (R) between the input factors and the output parameter to be 99.893%. Therefore, the models are recommended to be used for design and application. However, the optimal solution of the artificial neural network analyses will produce a better and more quality weld because of its higher Regression (R) value, and thus, suggested for practical application and systematic decision making.

Keywords: TIG, Mild Steel, Weld Time, RSM, ANN.

1.0 Introduction

Various industrial applications use welding as the most common industrial method of joining materials. Mild steel is a widely used material in many different industries; therefore, the welding of mild steel is particularly important as it is. Welding is a fabrication process whereby two or more parts are fused together by means of heat, pressure or both forming a joint as the parts cool. Welding is usually used on metals and thermoplastics but can also be used on wood. The completed welded joints may be referred to as weldment (TWI Ltd., 2024). It's advantages over other metal joining processes is in its flexibility, low fabrication cost, simple set up and production of very efficient joints Bansal et al (2021). The increasing demand for welding new materials or large or thicker materials has made the ordinary initial gas flame welding originally used by welding engineers obsolete and unable to meet up with demand, hence giving rise to improved welding technologies and processes, for e.g. the tungsten inert gas welding (TIG), also known as the gas tungsten arc welding (GTAW), electron beam welding (EBW), laser beam welding (LBW), plasma welding (PW) etc. Kumar et al (2017). Arc welding uses a welding power source to create and maintain an arc between the electrode and the base metal to melt and join the metals at the point of welding. Weld Time as a welding variable contributes immensely to the properties of the resultant weldment, improving the mechanical and metallurgical properties of a weld if adequately controlled, hence, the need to adequately optimize this parameter.

Techniques that are commonly used in optimization and prediction of welding variables are the response surface methodology (RSM) and artificial neural network (ANN). RSM mathematical models can be used to study and optimize the direct and interaction effects of weld input parameters to the output. Major use of the ANN has been in identifying trends and relationships in complex data sets that depend upon a number of parameters. The aim of this research study was to employ RSM and ANN techniques to optimize and predict the weld time and its consequential effect on mild steel weldment strength. This research study would start with the collection of data on the welding process which would be used to develop the optimization and prediction models. The data analyses of the models generated the optimal welding parameters that will result in the weld joint of desired strength. This research study will be useful in investigating the effects of the welding parameters on the microstructure of the mild steel weld metal, as well as the mechanical properties.

The total time during which current is passed through the joint of workpieces in order to form a cohesive bond or weld joint is known as the weld time. The standard measurement of weld time is in cycles of line voltage as are all timing functions. A cycle can be 1/60 of a second in a 60Hz power system or 1/50 of a second in a 50Hz power system depending on the country. Frequency used in this experiment was 60Hz. Weld time has been a convenient measuring criterion for the duration of weld heat. That is to say, the total amount of heat generated during welding a workpiece is directly proportional to the weld time. Weld time could be said to be long when it took a longer time than specified for the job to weld the workpiece, all other conditions being constant. Weld time can also be said to be short when welding current (heat application) is put off too soon, Pasau et al (2024). Weld time too long can cause high indentation, excessive expulsion, and electrode sticking. The worst case scenario will lead to "burn-through", a condition whereby metal between the electrode is completely melted and displaced, giving rise to a hole in the parts to be welded. That is, the heat of the electrode melts through the workpieces expunging the portion of base metals which ought to be welded together from the workpieces and thereby creating a hole in the part of the base metals which ought to be welded together. Weld time too short can lead to a small nugget size, a situation where the size or area on the base materials that are formed where the two metals were joined will be very small or narrow.

In the worst-case scenario, there would be a missing weld, where the weld seam is hardly seen or very insignificant, or a stuck weld can result, where weld metal are only on a portion of the base metal and not uniformly distributed along the path of the intended weld joint. Prashant and Sachin (2015). High welding current (heat input) and short weld time will give shallow bead penetration, while sufficient welding current and weld time will produce a good weld of deeper bead penetration. Since the strength and quality of a good weld is characterized by a deeper bead penetration, it infers that sufficient current (heat input) and enough welding time would be required to make a deeper bead penetration, a characteristic of a good and quality weld of adequate strength. Sufficient current and enough weld time will increase the nugget size and give a deeper bead penetration and thus, increasing the strength and quality of the weld. Proper and adequate optimization of the weld time factor is one sure way of having a good weld of desirable strength and quality. Adequate optimization of the weld time factor applied with the right process and welded according to the weld time specification, will produce a stronger and of more adequate quality weld joint with the right and required properties, and will contribute immensely to reduction of failure rates in industries and in welded structures.

The choice and preference of TIG welding process for this research study is based on the high quality welds produced from TIG welding process. With TIG, mild steel produces a clean and precise weld. TIG welding process is easy to use and reliable. TIG welding process can be used to weld thin, light, and dissimilar materials. In TIG welding, a non-consumable tungsten electrode is used so that there is an absence of fluxes, eliminating the possibility of slag inclusions, which makes TIG welding process have a low tolerance to contamination, without impurities and contributing to the high quality welds produced from TIG process. An inert shielding gas e.g. argon, helium, etc., but 100% pure Argon was used in this experiment, protects the electrode, the arc, and the molten weld pool from atmospheric contamination. Inert gases do not chemically combine with other elements, and therefore are used to exclude the reactive gases such as O_2 and N_2 from forming compounds that could be detrimental to the weld quality. The major advantages of TIG are in its high quality weld, ability to weld thin materials, and production of stable arc as a result of the shielding gas used. Also, the consumable composition of the shielding gas contributes to the strength and quality of the weld. The melting temperature necessary to weld materials in the TIG welding is obtained by automatically initiating an arc between the tungsten electrode and the work piece at high frequency. The tungsten electrode used for this study was the thoriated type.

Mild steel is a ferrous metal made from iron (Fe) and carbon (C). It is a low carbon steel alloy with percentage carbon content usually between 0.25 – 0.30%C. It has a high melting point, and it is commonly used in fabrication because of its low cost and it is easily welded compared with other steel alloys. It is ductile, machinable, and easily forged. These qualities of mild steel leads to a lack of hardened zones in the heat affected zones (HAZ) and welds. With TIG welding, mild steel produces a clean and precise weld. Several researchers have studied and researched on the importance of proper and specified weld time to the production of quality welded joints. Some of these research studies are cited below: Wicaksono and Hendrawan (2024), "Effect of welding time on the structure and strength of the spot-welded mild steel and aluminum with zinc powder as filler." In the study they discovered by macro photo testing method that the variation of welding time affects the nugget size diameter. Chen et al (2022), "Investigation on shearing strength of resistance spot-welded joints of dissimilar steel plates with varying welding current and time." In the research they investigated the effects of welding current and welding time on the shear strength of resistance spot-welded joints of low-carbon steel and stainless steel plates. They examined the macro characteristics, microstructure and micro-hardness of the welded joints. They found out that the diameter of welded joints and nuggets increased with increasing welding current and welding time. Li et al (2022), "Effect of welding time on the joint organization and mechanical properties of 6063 aluminum alloy." The study showed that the spreading performance of the weld joint gradually increases with the welding time, and the shear strength of the 6063-aluminum alloy joint increased first, and then decreases with the increase of the welding time.

Dwibedi et al (2020), "To investigate the influence of weld time on joint characteristics of Hastelloy X weldments fabricated by RSW process." In the experimental investigation, they explored the influence of weld time on joint strength, nugget size, mode of fracture of Hastelloy X weldments fabricated by resistance spot welding process, and determined the parameters and root cause of the failure by the use of Fractography. They discovered in the experimental study that, the elevation in weld time led to a significant increase in weld dimension. They also evaluated the relationships between mechanical properties and weld nugget dimensions with weld time. The vital results infer that the nugget diameter broadens with increasing weld time and the strength of resistance spot welded metal improves with increasing weld time up to an optimum value. Beyond an optimum value of weld time, instantaneous crack initiation takes place during welding itself due to excessive heat input and electrode pressure subjected on the metal. Singh et al (2018), "Effect of parameters involved in arc welded mild steel plates." From all these articles cited above and many other related articles reviewed and studied in the course of this research study, it was observed that the prediction and optimization of the weld time of mild steel weld metal using current, voltage and gas flow rate as joint process input factors from gas tungsten arc welding (GTAW) using process factor design model in order to determine the optimal weld time for the mild steel weldment has not been investigated or established to the best of our knowledge.

This gap and the optimization techniques, RSM and ANN, employed in the analyses of this study to determine the optimal solutions of the process parameters are the basis of this novel and innovative research. The optimal solutions derived from this study will improve the strength and quality of welds, thus leading to a drastic reduction of failure rates in welded structures and in steel industries that rely on this process and make use of the mild steel material. This study will be of significant value to the welding industries that deals on the mild steel material as the findings from this study will serve as a reference guide for optimizing the welding process and for predicting the strength of the resultant weld. Also, a new and innovative approach and technology for obtaining a stronger mild steel weld joint would've been possible through the optimal solutions of this research study. Conclusively, the major contribution of this research study is to develop a novel and innovative solution to enhance the quality and efficiency of welding of mild steel, which will have a positive impact on various industries that utilize this process, will save cost and time, and will also reduce failure rates in various industries, for e.g. in ship industries, welded structures, steel industries, and welding industries, etc.

2.0 Materials and methods

Mild steel coupons, twenty (20) pieces in number measuring 60mm X 40mm X 10mm was prepared and used for the experimental study and for the analyses. With the aid of a welder's stop watch the varying weld times were measured. For flexibility and ease of model analyses, the central composite design (CCD) was used for the response surface methodology (RSM) analyses designing for twenty (20) experimental runs. The values of the input parameters and output parameters recorded from the experimental welding trials served as the data for the analyses. A Neural Network (NN) analyses using the Back Propagation Network method (BPN) was trained used for prediction in the time series (TS) analyses. The major input parameters in this research study are: Current, Voltage, and gas flow rate. Their ranges from the experimental trials are given in Table 1:

Table 1: Range of Input Variables

Factor	Unit	Symbol	Axis Low (-)	Axis High (+)
Current	Amp.	A	180	210
Voltage	Volt.	V	20	23
G. F. R.	Lt/Min.	F	15	18

Table 1 above reveals the adopted boundary limits for the process input factors. They're the least and the highest values of each of the input factors recorded during the experimental welding of the mild steel specimens which were used to develop the design matrix for the data analyses. The bases of selecting the boundary limits are based on literature. An experimental matrix having the three input parameters: current (Amps.), voltage (Volts.) and gas flow rate (Lt/Min) and five response parameters: weld time, liquidus temperature, heat transfer coefficient, ultimate tensile strength and percentage elongation and their experimental values are presented below:

Table 2: Central Composite Design (CCD) Matrix with the Experimental Results and Data

Run	Input Parameters			Output Parameter
	Current (Amp.)	Voltage (Volt.)	G.F.R. (Lt/min)	Weld Time (Sec)
1	180	20	18	59
2	195	20	15	56
3	210	20	18	68
4	180	21.5	18	52
5	180	20	16.5	49
6	195	21.5	18	52
7	210	23	18	51
8	210	23	15	48
9	180	23	15	62
10	210	21.5	18	47
11	210	23	15	46
12	210	23	15	45
13	180	20	18	60
14	195	21.5	16.5	59
15	210	23	16.5	53
16	210	23	18	44
17	180	20	18	61
18	180	23	18	50
19	210	21.5	16.5	51
20	210	20	16.5	62

Table two is made up of the values of the input parameters and the response variable recorded during the actual experimental welding of the mild steel specimens. The values represent the least, medium and highest values of each of the input factors as implemented in the experimental welding of the specimens and the corresponding values of the response variable recorded at each setting of the input factor during the experimental welding of the mild steel specimens. The values were used to develop the design matrix, (CCD) for the data analysis as seen in table 2 above.

3.0 Results and Discussion

The results of the response surface technique employed in this research study showed that the suggested models are more of the quadratic types which demand the polynomial analyses order. Usually, the highest order polynomial where the additional terms are significant for the process factors is selected as best fit model for the response variable. The suggested models must also not be aliased and its lack-of-fit value must be insignificant. The suggessted model would be on the basis of the best probability value with the least error (least PRESS value) in the suggested model. The selected model for Weld Time in this study is a Quadratic model having the best significance value of 0.0002 units.

Table 3: Statistics Summary of the Model Fit for Weld Time Response Variable

Model	Sequential P value	Lack of fit P value	Adj. R^2	Pred. R^2	
Linear	.1364	.0107	.1515	-.4256	
2FI	.0038	.0319	.6153	-.1194	
Quadratic	.0002	.2615	.9224	.8338	**Suggested**
Cubic	.2615		.9598		Aliased

Table 4: Statistical Summary of the Model for Weld Time Response Variable

Model	Standard. Deviation	R^2	Adj. R^2	Pred. R^2	PRESS	
Linear	6.03	.2855	.1515	-.4256	1160.19	
2FI	4.06	.7368	.6153	-.1194	910.93	
Quadratic	**1.82**	**.9591**	**.9224**	**.8338**	**135.22**	**Suggested**
Cubic	1.31	.9937	.9598		*	Aliased

Interest should be on the maximization of the Adjusted R^2 and the Predicted R^2 values, i.e. the highest order polynomial that has the highest values of the Adj. R^2 and Pred. R^2 and is not aliased as we see in the suggested Quadratic model. The summary of the model's fit statistics displays the Standard Deviation, the Coefficient of Determination (R^2), Adj.R^2, Pred. R^2 and the PRESS value of the suggested Weld Time Quadratic model.
To test the adequacy of the Quadratic Model suggested in optimizing (minimizing) the Weld Time response variable, analysis of variance table shown below was used.

Table 5: ANOVA Model Statistical Summary for Weld Time Response Variable

Model	SS	Deg. of freedom	MS	F value	P value	
Model	780.55	9	86.73	26.08	<0.0001	Significant
A-Current	87.22	1	87.22	26.23	0.0004	
B-Voltage	8.46	1	8.46	2.54	0.1419	
C-G.F.R.	148.44	1	148.44	44.64	<0.0001	
AB	101.92	1	101.92	30.65	0.0002	
AC	0.9061	1	0.9061	0.2725	0.6130	
BC	168.28	1	168.28	50.60	<0.0001	
A^2	69.72	1	69.72	20.97	0.0010	
B^2	130.17	1	130.17	39.14	<0.0001	
C^2	88.21	1	88.21	26.53	0.0004	
Residual	33.25	10	3.33			
Lack of fit	28.09	7	4.01	2.33	0.2615	Not Significant
Pure Error	5.17	3	1.72			
Cor Total	813.80	19				

The Model's F-value of 26.08 revealed by the ANOVA table above indicates that the model is significant. It would take only a 0.01% chance for an F-value this large to occur due to error. The model developed as can be seen from the ANOVA table is significant with a significance value that is less than (<) 0.0001. By standard measurement of the software employed, if the Probability of F value (also called the P value) of the model and of each term in the regression model does not exceed the level of significance (say a = 0.05) then the model may be considered adequate within the confidence interval of 100(1- a) %. Hence, the model terms with Probability of F values (P value) less than 0.05 indicate that the model terms are significant. The model terms that are significant in this case as can be seen from the ANOVA table are: Current (A), Gas Flow Rate (C), interactions of Current and Voltage (AB), interactions of Voltage and Gas Flow Rate (BC), square of Current (A^2), square of Voltage (B^2), and square of Gas Flow Rate (C^2). By the standard measurement of the analytical tool, the Lack-of-Fit could be considered insignificant if the Probability of F value (P value) of the Lack-of-Fit exceeds the level of significance (0.05). The Lack-of-fit P value of 0.2615 indicates that the Lack-of-fit is insignificant and also, there is a 26.15% chance that a Lack-of-Fit F-value of 2.33 could occur due to error. F value of 2.33 for the Lack-of-fit indicates that the Lack-of-fit is not significant relative to the pure error. The non-significant Lack-of-Fit makes the model to fit.

Table 6: ANOVA Model Fit Statistical summary for Weld Time Response Variable.

Standard Deviation	1.82	**R^2**	0.9591
Mean	53.10	**Adjusted R^2**	0.9224
C.V %	3.43	**Predicted R^2**	0.8338
		Adeq Precision	15.1235

Table 6 above shows that the Coefficient of Determination of the variables (R^2) for Welding Time response is 0.9591 (or 95.91%). The Pred. R^2 of 0.8338 is in concordance with the Adj. R^2 of 0.9224; the difference is less than 0.2, which is within acceptable limit. 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 be replaced completely. Adequacy Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 15.1235 indicates an adequate signal. This model can be used for further statistical modeling of the Weld time response variable.

Diagnostic Plots

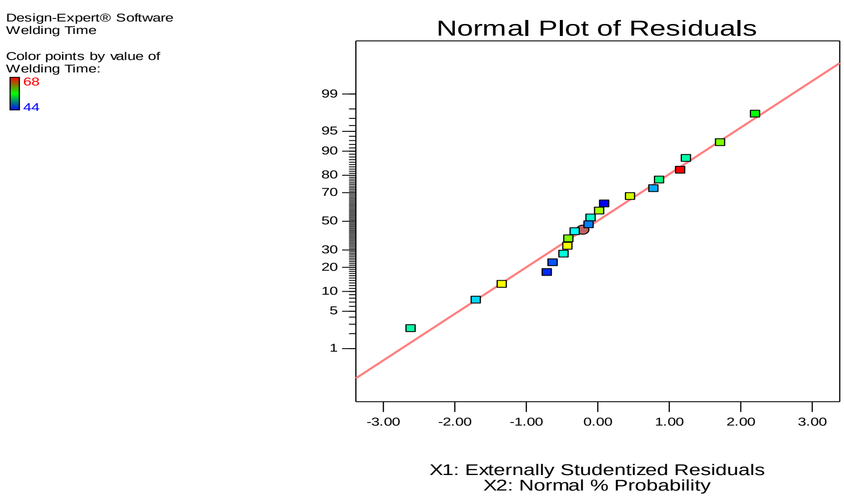

Figure 1: Normal Probability Plot of Studentized Residuals.

Figure 1 shows the Normal Probability Plot of the residuals. Residuals or errors are the difference between the actual values (real data) and the predicted (or target) values. The Normal Probability Plot shows that the residuals are normally distributed in the response variable and are insignificant or negligible in the system. The data points are around the 45^0 diagonal lines, with the majority of the data points within the boundary -0.50 and 1.00, which accounts for about eighty – five (85%) percent of the total data population or experimental trials.

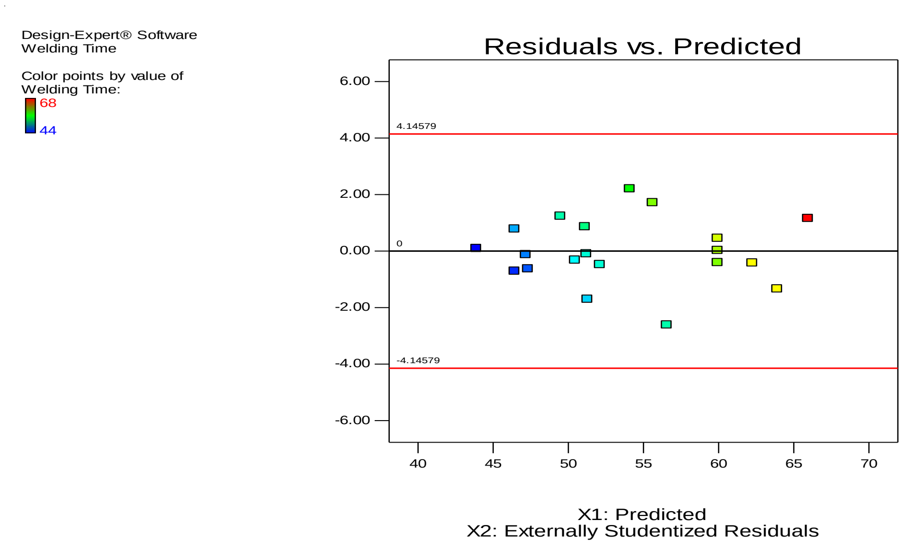

Figure 2: Studentized Residuals vs. Predicted to check for constant error.

Figure 2 above shows the plot of the variations of the predicted values and the residual values to check for constant errors. The plot shows that the errors in the Predicted and the Residuals 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 the default range indicated by the red lines, i.e. between -4.00 and +4.00

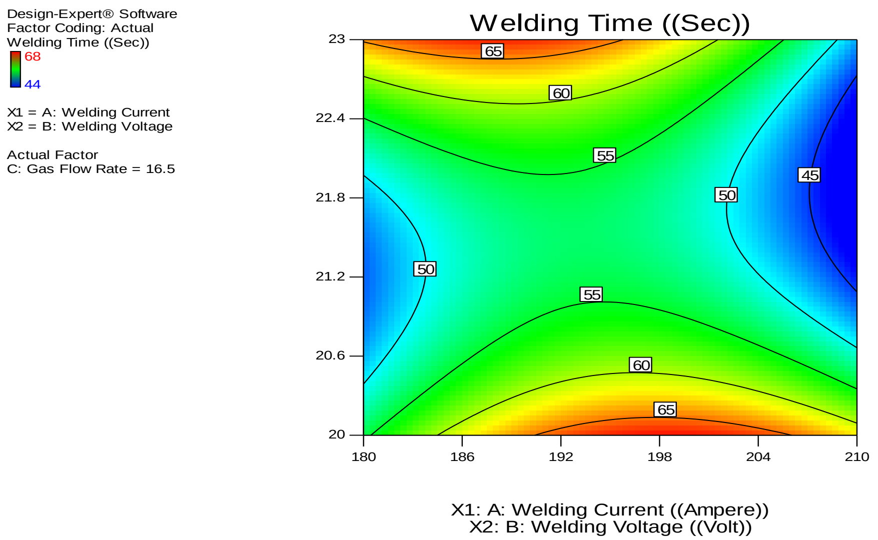

Figure 3: Predicting Welding Time using Contour Plot.

The contour plot of the current versus the voltage reveals that a decrease in current slightly decreases the Welding Time in the system. The increase in voltage towards its mean decreases the Welding Time, but increase in voltage from its mean to its maximum increases the Welding Time in the system.

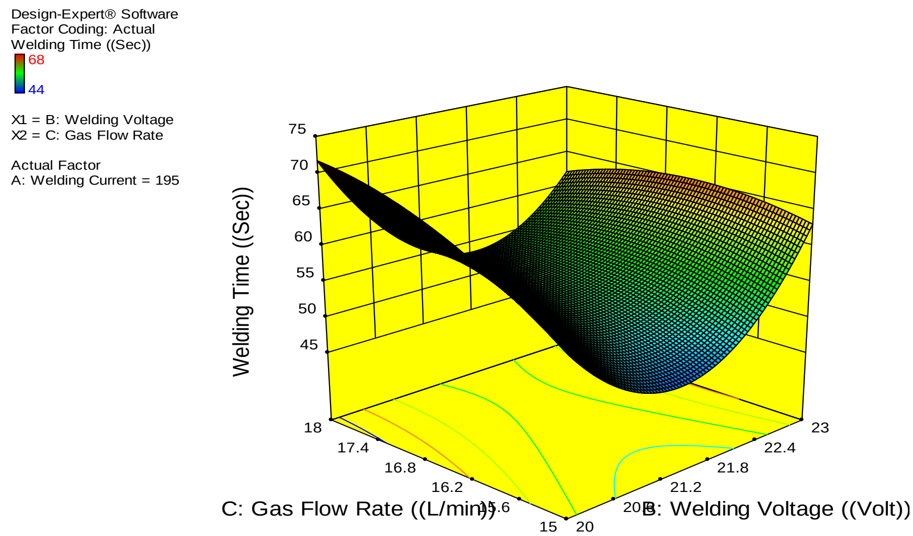

Figure 4: 3-D Surface Plot showing effects of voltage and gas flow rate on Weld Time response variable.

The 3-Dimensional Surface Plot reveals that an increase in voltage towards its mean decreases the Welding Time, but increase in voltage from its mean to its maximum increases the Welding Time in the system. Also, a decrease in gas flow rate slightly decreases the Welding Time in the system, while increase in the gas flow rate slightly increases the Welding Time.

Optimal Solutions

The results of the optimization analysis generated twenty (20) optimal solutions. The RSM analysis produced optimal solutions for each of the input factors with welding current as 180.00Amps, welding voltage as 21.672Volts and gas flow rate as 15.504L/min, and the optimal solution for the Welding Time response variable as 44.000Secs, which shows that the experimental trials are good and fit for the prediction of the feasible response of the welding time response variable in the system, and thus, indicating that the optimal solutions can be used for practical application.

Artificial Neural Network (ANN) Analyses

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 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 this 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 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. 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 data training method used in this study is the back propagation network (BPN) which is good and efficient in analyzing complex data sets that depends upon a number of parameters. 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. Training several times will generate different results due to different initial boundary conditions and sampling. 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 was 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 fit 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.

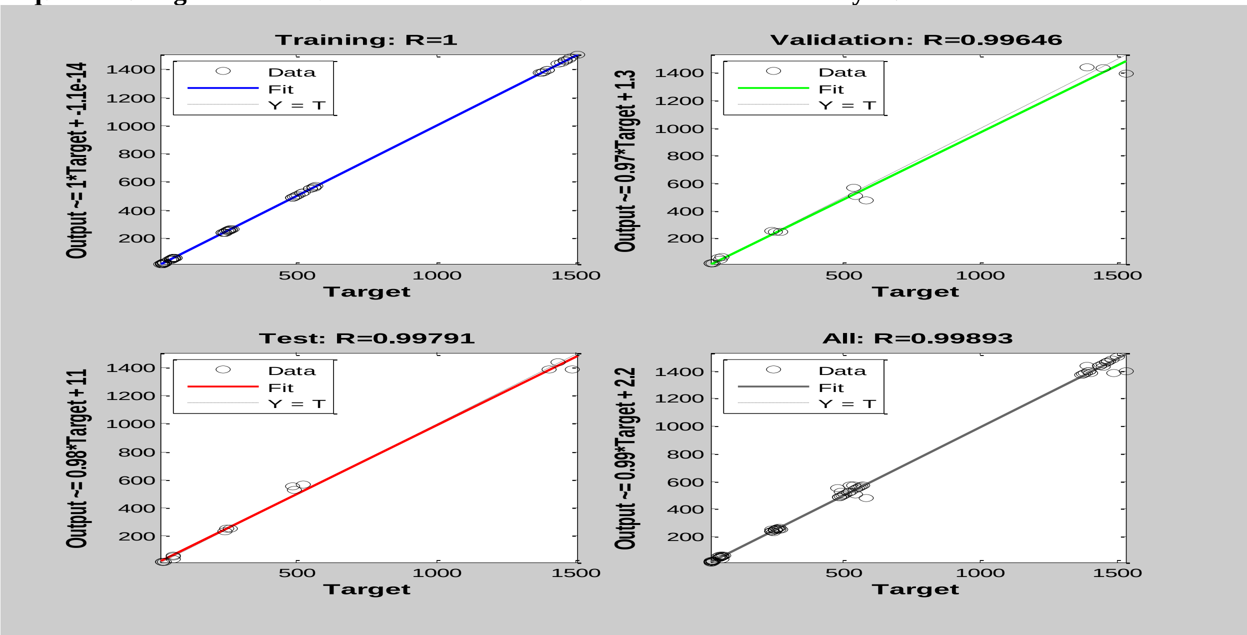

Figure 5: Regression results of the trained data analysis from the Artificial Neural Network (ANN) algorithm.

The result of the artificial neural network analysis reveals that the trained data analyses have a Regression Correlation (R) value of unity (1). The validation data analyses generated a Regression Correlation (R) value of 0.99646 units. The testing data analyses generated a Regression Correlation (R) value of 0.99791 units. Thus, the Overall Regression Correlation (R) value of the target result is 0.99893 units showing that the process input factors and the output parameters have strong correlation of 0.99893 units which is 99.893%. This indicates that the data used in the system are good and fit for statistical analysis and for modeling.

Table 7: ANN Predicted Results

S/N	Predicted Output Welding Time (sec)	Predicted Residual Welding Time (sec)
1	87.35373	-31.3537
2	149.8705	-87.8705
3	173.124	-125.124
4	113.9794	-59.9794
5	125.717	-75.717
6	220.1935	-165.194
7	61.95053	-15.9505
8	177.4656	-124.466
9	96.50894	-36.5089

10	121.2381	-73.2381
11	114.3624	-70.3624
12	159.4982	-107.498
13	110.1013	-55.1013
14	137.9158	-88.9158
15	74.25691	-21.2569
16	142.3118	-86.3118
17	75.13029	17.1303
18	156.8149	-100.815
19	16.74131	42.25869
20	**53.713**	**-9.713**

Table 7 above shows the artificial neural network (ANN) analyses predicted results for the Weld Time response variable. The result shows that the predicted response parameter for Weld Time is 53.713Secs. The ANN result shows that the input 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. Hence, the predicted model can be used for decision making and for practical application.

4.0. Discussion of Results

This study undertakes the use of response surface methodology (RSM) and artificial neural network (ANN) for the optimization and prediction of the parameters of a mild steel weldment. The objective of the optimization analyses is to determine the most appropriate combination of the weld time and each of the process input factors, namely: current (Amps.), voltage (Volts.) and gas flow rate (Lt/min) that will adequately optimize (minimize) the weld time content in the mild steel weldment. The final solution of the optimization process was to determine the most appropriate percentage combination of each of the response variables, namely: liquidus temperature in the weldment, weld time in the weldment, heat transfer coefficient in the weldment, ultimate tensile strength in the weldment and percentage elongation in the weldment with the combined values of each of the input factors, namely: current, voltage and gas flow rate, that will adequately optimize (minimize) the following response variables: liquidus temperature, weld time and heat transfer coefficient, and adequately optimize (maximize) the following response variables: ultimate tensile strength and percentage elongation, while determining the optimal values of each of the process input factors in the weldment.

In the course of the experiment, ranges of values of the input factors and response variables were obtained which makes up the data for the experimental analyses. Design of experiment (DOE) was developed using the central composite design method (CCD), and an experimental matrix consisting of twenty (20) experimental runs was generated for the RSM analyses. The input parameters and the output parameters make up the experimental matrix. The design of experiment (DOE) was done with the statistical tool, Design Expert Software 10.0.1 (DX.10.0.1). Central Composite Design was employed in this study because of its simplicity and flexibility to variable adjustment and analyses of process interaction relating to process factor combinations.

The results of the response surface technique showed that a Quadratic Model for the process order which demand the polynomial analyses was suggested for each of the response variables. For flexibility and ease of model analysis, the central composite design (CCD) expert recommends more of the Quadratic models for the process order which demand the polynomial analysis. The response surface technique will usually suggest the highest order polynomial where the additional terms are significant for the process factors and the model is not aliased as the best fit model. Additionally, the selected models must have insignificant Lack-of-Fit. The reasons for the suggestion of the Quadratic Models was as a result of the conformity between the P-value, R^2 value, the Pred. R^2 value, Adj. R^2 value and the PRESS value. The summary of the model design reveals that the least value of the response variable, weld time is 39.984 Sec., with a maximum value of 47.046Sec, mean value of 53.10 Sec, and standard deviation of 1.82Sec. Optimal solution for the response variable, weld time revealed 44.000Sec.The signal-to-noise ratio of the model is high, with a value of 15.1235. In testing the adequacy of the suggested Quadratic Model in optimizing (minimizing) the target response, weld time, ANOVA table was generated, and the results obtained are presented in Table 5. The ANOVA table, Table 5, revealed that gas flow rate (GFR) input factor has the most significant effect on the response variable, weld time. From the optimal solutions generated by the response surface technique, the

Desirability of achieving the optimum solutions was 83.62%. The model fit statistical summary for the response variable, weld time, is shown in table 6.

The Coefficient of Estimation analyses of the models revealed that the models possess low standard errors. The smaller the standard error the better the result of the model designed. Variance Inflation Factor (VIF) lies between one (1) and three point forty five (3.45) in this experimental study which shows that the Coefficient of Estimation of the input factors to the response parameters in this experiment are adequate, good, and as well as fit for further adequate modeling of the system. VIF greater than ten (10) can cause error in the system and there would be need to checkmate such factor or even replace the experimental trial. Meanwhile, VIF that is close to unity is good and fit for an adequate modeling of the response variable. The software or prediction tool used for the ANN analysis is the Neural Power Algorithm, Version 2.5 which uses the back propagation network (BPN) analyses. The advantage of using the back propagation algorithm is that it can perform multiple data training and analysis for a complex data set. Using Artificial Neural Network algorithm or the Time Series analyses, the result of Table 7 revealed that the predicted optimal solution for the welding will produce a weldment with a Weld Time of optimal value of 53.713Sec. The input factors and the response variable have an overall strong correlation (R) of 99.893%.
This research study successfully employed and established a response surface methodology (RSM) and artificial neural network (ANN) algorithms for the optimization and prediction of mild steel weldment parameters. In this study, the application of the welding input parameters design was used to determine the optimal solutions of the response variables of the mild steel weldment.

The development of a second order polynomial solution has been successfully achieved in this study, validated by graphical and statistical results such as the 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. To test the accuracy of the models in actual application, conformity tests were conducted by assigning different values for process variables within their working limits but different from design matrix. These tests revealed that the developed models can be put into practical application as regards the optimal solutions derived, mostly in the optimization of manufacturable qualities and quantities in establishments that utilize the mild steel material e.g. steel and manufacturing industries, welding industries, and in industrialization generally. Therefore, the optimal solutions and the models developed in this study 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 and advantage to the utilizing companies and in the material usage. This research study will also serve as a reference guide to the users of the mild steel material and its application in Tungsten Inert Gas (TIG) welding process and in industrialization generally.

5.0 Conclusion

This research study conducted an optimization and proposed a prediction model to determine the optimal values of liquidus tempearture, welding time, heat transfer coefficient, ultimate tensile strength and percentage elongation as the response variables based on current, voltage, and gas flow rate as the input factors in TIG welding process using RSM and ANN. The research topic worked on is: "Experimental Investigation of the Effects of Optimal Weld Time on Mild Steel Weldment Strength using Expert Methods." While 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," For the RSM analyses, design of the experimental matrix for the input variables using the central composite design (CCD) for twenty (20) experimental trials was done using Design Expert Software 10.0.1 (DX10.0.1). The experimental matrix was made up of both the input variables and the response variables. Specimens of the mild steel weldment were produced for the experiment. Results obtained from the specimens of the weldments during and after welding were used as the data for the analysis. The mechanical properties (strength) of the mild steel weldments were determined using Universal Testing Machine (UTM) in a laboratory. ANN analysis was done with the aid of the software - Neural Power Algorithm, Version 2.5. The optimal solutions of the process input factors derived from the RSM analyses gave, current as 180.00Amps; voltage as 21.672Volts and gas flow rate as 15.504L/min.

The optimal solutions of the response variables determined from the RSM analyses gave, liquidus temperature as 1484.783^{0}C, weld time as 44.000secs, heat transfer coefficient as $238.819 W/m^{2o}C$, ultimate tensile strength as 579.000MPa and percentage elongation as 22.111%. The RSM analyses determined that the Desirability of achieving the optimum solution is 83.62%. Quadratic models were suggested by the RSM analyses for each of the five response variables, each model possessing a high significance value, with all their p-values less than 0.05 ($p < 0.05$). Also, all the suggested Quadratic models possessed Variance Inflation Factor (VIF) that is less than 10 ($VIF < 10$). This confirms that the models possessed high goodness of fits. The predicted optimal solution from the ANN analyses for each of the five response variables gave, liquidus temperature as 1464.490˚C, weld time as 53.7132sec, heat transfer coefficient as 256.663W/m^{2o}C, ultimate tensile strength as 530.077MPa and percentage elongation as 18.504%. The input factors and the response variables have an overall strong Regression or Coefficient of Determination (R) of 99.893%. Finally, it can be deduced that from the results obtained from the two analytical methods, 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 with 83.62% of the RSM analysis. Therefore, the ANN model is recommended for practical 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 given by each of the analytical tools employed in this research study and as stated above. Also, another major finding of this research study is that gas flow rate (GFR) has the most significant effect on the response variable, weld time of the mild steel weldment. In conclusion, the main objective of this research study is to enhance 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. The models and optimal solutions derived from this study are commendable, and therefore recommended for industrial use and practical application, and for systematic decision making. The models and the optimal solutions obtained from this research study can be practically implemented in more of the listed industries: ship industry, steel structures, steel manufacturing industries, welding industries, etc. that relies on this process and makes use of the mild steel material.

5.0 Recommendation

It is recommended that the application of other data analytical tools like Taguchi method, Genetic Algorithm, Ansys, Particle Swarm Optimization (PSO) etc.be deployed 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 employed analytical tools.

References

Bansal et al (2021). Effect of welding parameter on mechanical properties of TIG welded AA6061. *Materialstoday: Proceedings,* 37(2): 2126-2131, Chennai, India. Available from: https://www.sciencedirect.com [28 February 2021]

Chen et al (2022). Investigation on shearing strength of resistance spot-welded joints of dissimilar steel plates with varying welding current and time. *Journal of Materials Research and Technology,* Volume 16: 1021-1028, Zhejiang, PR China. Available from: https://www.sciencedirect.com [January–February 2022].

Dwibedi et al (2020). To investigate the influence of weld time on joint characteristics of Hastelloy X weldments fabricated by RSW process. *Materialstoday: Proceedings,* 26(2): 2763-2769, India. Available from: https://www.sciencedirect.com [6 March 2020].

Kumar et al (2017). Experimental investigation and optimization of Tig welding parameters on aluminum 6061 alloy using firefly algorithm. *IOP Conference Series: Materials Science and Engineering. International Conference on Materials, Alloys and Experimental Mechanics (ICMAEM-2017)*, Volume 225, Narsimha Reddy Engineering College, India. Available from: https://iopscienec.iop.org [3-4 July 2017].

Li et al (2022). Effect of welding time on the joint organization and mechanical properties of 6063 aluminum alloy. *Journal of Physics: Conference Series: 2nd International Conference on Advanced Materials and Mechatronics (ICAMM 2022),* Volume 2343, Dali City, China. Available from: https://iopscience.iop.org [24-26 June 2022].

Pasau et al (2024). Effect of welding time variation in resistance spot welding on mechanical properties of dissimilar joints on mild steel and AISI 304 stainless steel. *Journal of Physics: Conference Series: 3rd International Symposium on Advances and Innovation in Mechanical Engineering (ISAIME 2022),* Volume 2739, Makassar, Indonesia. Available from: https://iopscience.iop.org [13-14 October 2022].

Prashant and Sachin (2015). Optimization of welding parameters to reduce distortion in welding of SA 203 GRADE-E by ANOVA. *IJSTE - International Journal of Science Technology & Engineering,* 1(12): 181-185, Mumbai, India. Available from: https://www.academia.edu [June 2015]

Singh et al (2018). Effect of parameters involved in arc welded mild steel plates. *IOP Conference Series: Materials Science and Engineering*, *International Conference on Mechanical, Materials and Renewable Energy,* Volume 377, Sikkim, India. Available from: https://iopscience.iop.org [8-10 December 2018].

The Welding Institute (TWI). Copyright © 2024. TWI Ltd, UK.

Wicaksono and Hendrawan (2024). Effect of welding time on the structure and strength of the spot welded mild steel and aluminum with zinc powder as filler. *Proceedings of the 8th International Conference on Engineering, Technology, and Industrial Applications 2021 (8th ICETIA 2021): Engineering, Environment, and Health: Exploring the Opportunities for the Future,* 2838 (1), *Surakata, Indonesia*. Available from: https://pubs.aip.org. [23 February 2024]