



Optimization and Prediction of Solidus Temperature of Mild Steel Weldment, Using Response Surface Methodology

Sibete.G¹ and Eyitemi. T²

¹Doctor, Department of Mechanical Engineering, Niger Delta University, Wilberforce Island, Bayelsa State, Nigeria.

²Engineer, Nigeria Maritime University, Okerenkoko, Delta State, Nigeria.

ABSTRACT

Solidus temperature is one of the significant parameters considered in the welding of alloy in Tungsten Inert Gas (TIG) welding when assessing the performance and integrity of an alloy. In the field of welding and metallurgy, a good solidus temperature results in the formation of high quality alloy. In order to achieve a good solidus temperature, the optimization and prediction of solidus temperature of the mild steel weldment, employing response surface methodology (RSM) is studied. The aim of this study therefore is to develop model that would minimize solidus temperature. The design of experimental matrix was developed, using the design expert software. This is determined by the input factors and its parametric levels. The Response Surface Method was employed to analyze the data collected from the experiment. The second order of polynomial model was adopted having current, voltage, welding speed, welding time and feed rate as input factors, solidus temperature is the target response. To test for the model significance, adequacy and validity, the analysis of variance (ANOVA) was done and goodness of fit was determined. From the result, the P-value of solidus temperature, model is 0.001, which is lower than 0.05, reveals that the model developed is significant. The determination coefficient (R²), which measures the goodness of fit for solidus temperature is 0.895956. The result shows that a combination of current 160.2A, voltage 25.03V, welding speed 57.72 mm/s, welding time 80sec, feed rate 70.11mm/s will produce optimal solidus temperature 1,301.509oC at a desirability 0.739.

Keywords : Optimization, prediction, solidus, solidus temperature, mild steel, weldment.

1. Introduction and Literature Review

The welding industry as a whole incorporates several means and methodologies of completing welding projects. MIG welding, soldering and arc welding are just the start of an extensive list. Another way to fuse metals come in the form of TIG welding. Tungsten Inert Gas is a method that utilizes a tungsten electrode to heat the metal that is being welded. To shield the weld from being contaminated throughout the entire time of the welding operation, protecting in the form of inert gas, like argon is utilized and can be utilized for any metals /thickness.

TIG welding is highly recognized as result of its quality, versatility and applicability. Indeed, the operation can be employed to more metals than any other methods, with the ability to weld metals like brass, bronze, copper, magnesium, nickel, steel, aluminium and gold.

Gadewar et al (2010) researched the effect of operation parameters of TIG welding like weld current, gas flow rate, thickness of work piece on the bead geometry of SS304. It was discovered that the operation parameters considered had influence on the mechanical properties to a great extent.

Esme et al (2009) researched the multi-response optimization of TIG welding for an optimal parametric combination to produce favourable bead geometry of joints welded utilizing the Grey relational analysis and Taguchi Method.

Kishore et al (2010) analysed the effect of operation parameters for the welding of AA6351, employing TIG welding. Different and separate control factors were discovered to influence weld quality predominantly. The percentage contributes from each parameter were computed through which optimal parameters were identified. ANOVA method was used to check the adequacy of the data obtained.

According to Myers et al (1989) many industries today, now apply the Response Surface Methodology in formulating new products, especially in the chemical engineering industries, where there is need for the process optimization.

2. Methodology and Theory

The method of achieving the objectives of the research is explained in this chapter. It comprises of research design, population, sampling techniques, method of data collection, and method of data analysis.

2.1 Research Design

2.2 Population

This research study focused on heat input of mild steel weldment, using response surface methodology, to optimize and predict the output. The input process parameters are current, voltage, welding speed, welding time and feed rate. The method was employed because of its capability to accommodate complex experimental designs.

The Central Composite Design (CCD) was developed for this study, using the design expert software. This design is for any input parameters considered within the range of 3-5 levels.

160 pieces of mild steel coupons measuring 60mm×40mm×10mm was used for the experiments, the experiment was performed 32times, using 5 specimen for each run.

2.3 Samples and Sampling Techniques

Mild steel plate 10 mm thickness was selected for the experiment. The mild steel work piece was cut to 60mm X 40mm dimension using power hacksaw and the edges ground to evenness with a grinding tool. The TIG equipment was used to weld the plates after the edges have been beveled. The welding process uses a shielding gas to shield the weld specimen from atmospheric interaction, 100% pure Argon gas was utilized in this study.

The diagnostic case statistics which shows the experimentally obtained values of solidus temperature against the predicted values is presented as shown in table 1 below.

Table 1: Diagnostic Case Statistics

Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residual	Externally Studentized Residual	Influence on Fitted Value DFFITS	Cook's Distance	Run Order
1410	1437.382	-27.3819	0.191853	-0.86586	-0.86049	-0.41926	0.01618	1
1235	1262.789	-27.789	0.434759	-1.05072	-1.05346	-0.9239	0.077196	2
1215	1217.515	-2.51509	0.53907	-0.10531	-0.1028	-0.11117	0.001179	3
1420	1449.197	-29.1965	0.058371	-0.8553	-0.84962	-0.21154	0.004123	4
1430	1434.314	-4.31402	0.502569	-0.17388	-0.16981	-0.17069	0.002777	5
1490	1466.627	23.37257	0.509163	0.948347	0.94597	0.963468	0.084813	6
1230	1205.462	24.53779	0.470701	0.958771	0.956841	0.902323	0.074316	7
1560	1513.396	46.6041	0.195983	1.477479	1.523212	0.752033	0.048373	8
1408	1440.585	-32.585	0.19077	-1.0297	-1.03126	-0.50071	0.022723	9
1320	1328.216	-8.21551	0.501879	-0.3309	-0.32377	-0.32499	0.010029	10
1380	1347.842	32.15767	0.507311	1.302351	1.325625	1.345152	0.158769	11
1420	1460.674	-40.6735	0.188138	-1.28322	-1.30448	-0.62796	0.03469	12
1450	1481.419	-31.4187	0.184353	-0.98893	-0.98839	-0.46989	0.020095	13
1440	1449.197	-9.19652	0.058371	-0.26941	-0.26337	-0.06557	0.000409	14
1420	1425.923	-5.92345	0.478691	-0.23322	-0.22789	-0.21838	0.00454	15
1405	1449.197	-44.1965	0.058371	-1.29473	-1.31719	-0.32795	0.009447	16
1490	1449.197	40.80348	0.058371	1.195328	1.208352	0.300851	0.008052	17
1320	1348.686	-28.6863	0.530038	-1.18952	-1.20206	-1.27658	0.145076	18
1311	1314.55	-3.54988	0.528682	-0.14699	-0.14352	-0.152	0.002203	19
1430	1418.214	11.78632	0.189274	0.37211	0.364345	0.176044	0.002939	20
1300	1333.299	-33.2987	0.352298	-1.17617	-1.18761	-0.87587	0.068404	21
1380	1392.13	-12.1304	0.181844	-0.38123	-0.37334	-0.17601	0.002937	22
1548	1548.6	-0.59955	0.516022	-0.0245	-0.02391	-0.02469	5.82E-05	23
1496	1457.667	38.33319	0.189944	1.21073	1.225082	0.593227	0.031247	24
1389	1412.258	-23.2578	0.506381	-0.94103	-0.93835	-0.9504	0.082585	25
1519	1449.197	69.80348	0.058371	2.044876	2.229916	0.555196	0.023564	26
1380	1391.268	-11.2675	0.496597	-0.45144	-0.44271	-0.43971	0.018277	27
1350	1309.295	40.70458	0.458422	1.572327	1.633601	1.502964	0.190238	28
1290	1277.983	12.0169	0.51522	0.490625	0.481569	0.496458	0.023257	29
1407	1406.135	0.864821	0.474905	0.033926	0.03311	0.031488	9.46E-05	30
1360	1336.816	23.18368	0.418852	0.864508	0.859099	0.729341	0.048969	31
1530	1517.973	12.02737	0.454424	0.462885	0.454052	0.414389	0.016224	32

2.4 Method of Data Collection

In this study, the CCD was undertaken, using the factor ranges in Table 1 below.

Table 2: Welding Parameters and their levels

F a c t o r s	U n i t	S y m b o l	L o w (- 1)	H i g h (+ 1)
W e l d i n g C u r r e n t	A m p e r e	I	1 6 0	2 4 0
W e l d i n g V o l t a g e	V o l t s	V	2	3
W e l d i n g S p e e d	m m / s e c	S	3	5
W e l d i n g t i m e	S e c o n d s	T	5	8
F e e d R a t e	m m / s e c	F R	7	1 4

A design matrix for the response surface analysis was generated as shown in Table 3. The equivalent design matrix in actual factors is shown table 4.

Tables 3 and 4 can be inter-converted by using the relation (Myers et al, 2009)

$$\text{Coded} = \frac{\text{Actual Value} - \text{Mean}}{\text{half of range}} \quad (1)$$

Table 3: Design Matrix in coded factors

I	V	S	T	F	R
0	0	- 1 . 7 5	0	0	
1 . 7 0	0	0	0	0	
- 1	1	1	1	- 1	
0	0	0	0	0	
1	- 1	1	- 1	1	
1	1	1	- 1	- 1	
- 1 . 7 2 5	0	0	0	0	
0	- 1 . 8	0	0	0	
0	0	0	0	- 1 . 7 4 3	
1	1	- 1	- 1	1	
1	1	- 1	1	- 1	
0	0	1 . 7	0	0	
0	0	0	- 1 . 7 3 3	0	
0	0	0	0	0	
- 1	1	1	- 1	1	
0	0	0	0	0	
0	0	0	0	0	
- 1	1	- 1	1	1	
1	- 1	- 1	1	1	
0	0	0	1 . 6 6 7	0	
- 1	- 1	- 1	- 1	- 1	
0	1 . 6	0	0	0	
1	- 1	1	1	- 1	
0	0	0	0	1 . 7 1 4	
- 1	- 1	1	1	1	
0	0	0	0	0	
- 1	- 1	- 1	1	- 1	
- 1	1	- 1	- 1	- 1	

Table 4: Design Matrix in actual factors

R u n s	I	V	S	T	F	R
1	2 0 0	2 5	2 0	6 5	1 0 5	
2	2 6 8	2 5	5 5	6 5	1 0 5	
3	1 6 0	3 0	7 5	8 0	7 0	
4	2 0 0	2 5	5 5	6 5	1 0 5	
5	2 4 0	2 0	7 5	5 0	1 4 0	
6	2 4 0	3 0	7 5	5 0	7 0	
7	1 3 1	2 5	5 5	6 5	1 0 5	
8	2 0 0	1 6	5 5	6 5	1 0 5	
9	2 0 0	2 5	5 5	6 5	4 4	
1 0	2 4 0	3 0	3 5	5 0	1 4 0	
1 1	2 4 0	3 0	3 5	8 0	7 0	
1 2	2 0 0	2 5	8 9	6 5	1 0 5	
1 3	2 0 0	2 5	5 5	3 9	1 0 5	
1 4	2 0 0	2 5	5 5	6 5	1 0 5	
1 5	1 6 0	3 0	7 5	5 0	1 4 0	
1 6	2 0 0	2 5	5 5	6 5	1 0 5	
1 7	2 0 0	2 5	5 5	6 5	1 0 5	
1 8	1 6 0	3 0	3 5	8 0	1 4 0	
1 9	2 4 0	2 0	3 5	8 0	1 4 0	
2 0	2 0 0	2 5	5 5	9 0	1 0 5	
2 1	1 6 0	2 0	3 5	5 0	7 0	
2 2	2 0 0	3 3	5 5	6 5	1 0 5	
2 3	2 4 0	2 0	7 5	8 0	7 0	
2 4	2 0 0	2 5	5 5	6 5	1 6 5	
2 5	1 6 0	2 0	7 5	8 0	1 4 0	
2 6	2 0 0	2 5	5 5	6 5	1 0 5	
2 7	1 6 0	2 0	3 5	8 0	7 0	
2 8	1 6 0	3 0	3 5	5 0	7 0	
2 9	2 4 0	3 0	7 5	8 0	1 4 0	
3 0	2 4 0	2 1	3 5	5 0	7 0	
3 1	1 7 0	2 0	7 5	5 0	7 0	
3 2	1 7 0	2 0	3 5	5 0	1 4 0	

2.5. Method of Data Analysis

In this study, the RSM was employed to optimize and predict heat input. RSM is a gathering of mathematical and statistical methods which optimizes a targeted response from several input variables.

2.5.1. Fitting an Approximating Function

Let the linkage between the factors and responses be represented by

$$y = f(X_i) + \varepsilon \quad (2)$$

$$\text{Where } \mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} I \\ V \\ S \\ T \\ FR \end{bmatrix}$$

The true nature of the functional relationship is not known. We attempt to fit a second order polynomial to the experimental data. Applying Taylor's series expansion through second order to equation 2, we obtain

$$\begin{aligned}
 y &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 \\
 &+ \beta_{44} X_4^2 + \beta_{55} X_5^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{14} X_1 X_4 + \beta_{15} X_1 X_5 + \beta_{23} X_2 X_3 \\
 &+ \beta_{24} X_2 X_4 + \beta_{25} X_2 X_5 + \beta_{34} X_3 X_4 + \beta_{35} X_3 X_5 + \beta_{45} X_4 X_5 \quad \dots \quad (2.1a) \\
 &= \beta_0 + \sum_{i=1}^5 \beta_i X_i + \sum_{i=1}^5 \beta_{ii} X_i^2 + \sum_{i < j=2}^5 \beta_{ij} X_i X_j \quad \dots \quad (2.1b)
 \end{aligned}$$

Equation 3.2 is a second order response surface model to be fitted to the experimental data.

To develop the model for the solidus temperature, the sequential sum of squares is determined and the results are shown in table 5 below.

Table 5: Sequential Sum of Squares

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob> F	
Mean vs Total	62532540	1	62532540			
Linear vs Mean	45443.46	5	9088.691	1.156507	0.3567	
2FI vs Linear	88315.8	10	8831.58	1.218028	0.3498	
Quadratic vs 2FI	95368.87	5	19073.77	10.16401	0.0008	Suggested
Cubic vs Quadratic	11371.79	7	1624.542	0.700928	0.6809	Aliased
Quartic vs Cubic	0	0				Aliased
Fifth vs Quartic	0	0				Aliased
Sixth vs Fifth	0	0				Aliased
Residual	9270.8	4	2317.7			
Total	62782311	32	1961947			

Different degree polynomial models were examined in order to choose a fitting model for the data set. The statistics computed for the various models are as shown in table 5.

In accessing the strength of the quadratic model towards minimizing the solidus temperature, the one way analysis of variance (ANOVA) was done, the result is presented as shown in the table below.

Table 6: ANOVA for Ts

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob> F	
Model	223783.5	10	22378.35	18.08372	< 0.0001	Significant
A-I	4829.818	1	4829.818	3.902927	0.0615	
B-V	28154.16	1	28154.16	22.75109	0.0001	
C-S	1030.385	1	1030.385	0.832644	0.3719	
D-T	7769.705	1	7769.705	6.278619	0.0205	
E-FR	552.6593	1	552.6593	0.446598	0.5112	
AC	18289.66	1	18289.66	14.77969	0.0009	
AE	50818.73	1	50818.73	41.0661	< 0.0001	
BD	9158.442	1	9158.442	7.400844	0.0128	
DE	9529.156	1	9529.156	7.700414	0.0113	
A^2	94623.85	1	94623.85	76.46457	< 0.0001	
Residual	25987.21	21	1237.486			
Lack of Fit	16716.41	17	983.3183	0.424265	0.9052	not significant
Pure Error	9270.8	4	2317.7			
Cor Total	249770.7	31				

The Model F-value of 18.08 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise.

Values of "Prob> F" less than 0.0500 indicate model terms are significant. In this case B, D, AC, AE, BD, DE, A² are significant model terms.

The "Lack of Fit F-value" of 0.42 implies the Lack of Fit is not significant relative to the pure error. There is a 90.52% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good -- we want the model to fit.

Table 7 below shows the summary statistics of the various polynomial model. Here the focus is on the model maximizing the "Adjusted R-Squared" and the "Predicted R-Squared".

Table 7: Model Statistics

Std. Dev.	35.17792		R-Squared	0.895956
Mean	1397.906		Adj R-Squared	0.846411
C.V. %	2.516472		Pred R-Squared	0.789736
PRESS	52517.89		Adeq Precision	16.63705

The "Predicted R-Squared" of 0.7897 is in reasonable agreement with the "Adjusted R-Squared" of 0.8464.

"Adequate Precision" determines the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 16.637 indicates an acceptable signal. This model can be employed to navigate the design space.

To obtain the optimal solution we first considered the coefficient statistics as presented in table 8 below.

Table 8: Estimated Model Coefficients

Final Equation in Terms of Coded Factors:

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	1449.197	1	8.499002	1431.522	1466.871	
A-I	14.90602	1	7.545125	-0.78493	30.59697	1.011253
B-V	-35.6663	1	7.477514	-51.2167	-20.116	1.012492
C-S	6.751195	1	7.398625	-8.63509	22.13748	1.01377
D-T	-18.5897	1	7.418914	-34.0182	-3.16123	1.011715
E-FR	4.941006	1	7.393615	-10.4349	20.31687	1.013511
AC	34.29642	1	8.921052	15.74407	52.84876	1.035021
AE	-57.0088	1	8.89611	-75.5093	-38.5083	1.029241
BD	-23.6647	1	8.698812	-41.7548	-5.57451	1.016273
DE	-23.9094	1	8.616131	-41.8277	-5.99121	1.017968
A ²	-73.2691	1	8.378974	-90.6942	-55.8441	1.005727

Table 8 gives the estimated model coefficient in coded form

The variance inflation factor (VIF) values indicate that there is little multicollinearity between the data sets. The variance of the coefficients of the regression are only marginally inflated and are therefore stable.

There is 95% confidence that the true intercept between 1431.522 and 1466.871.

The confidence interval of -0.78483 to 30.59697 indicates that the current coefficient is not very different from zero (0) and is probably not having a statistically significant effect on the response.

The same is true for the welding speed and feed rate coefficients.

The optimal equation which shows the individual effects and combine interactions of the selected factors against the measured response (Solidus temperature) is presented base on the coded variables and the actual factors has shown in the following equations.

$$T_s = 1449.20 + 14.91*A - 35.67*B + 6.75*C - 18.59*D + 4.94*E + 34.30*A*C - 57.01*A*E - 23.66*B*D - 23.91*D*E - 73.27*A^2$$

Final Equation in Terms of Actual Factors:

$$T_s = 1438.67694 + 20.60771*I + 13.37612*V - 8.23654*S + 11.43080*T + 11.24550*FR + 0.042871*I*S - 0.040721*I*FR - 0.31553*V*T - 0.045542*T*FR - 0.045793*I^2$$

To study the effects of combine input variables on the response, solidus temperature, 3D surface plot is presented in Figure 1 below.

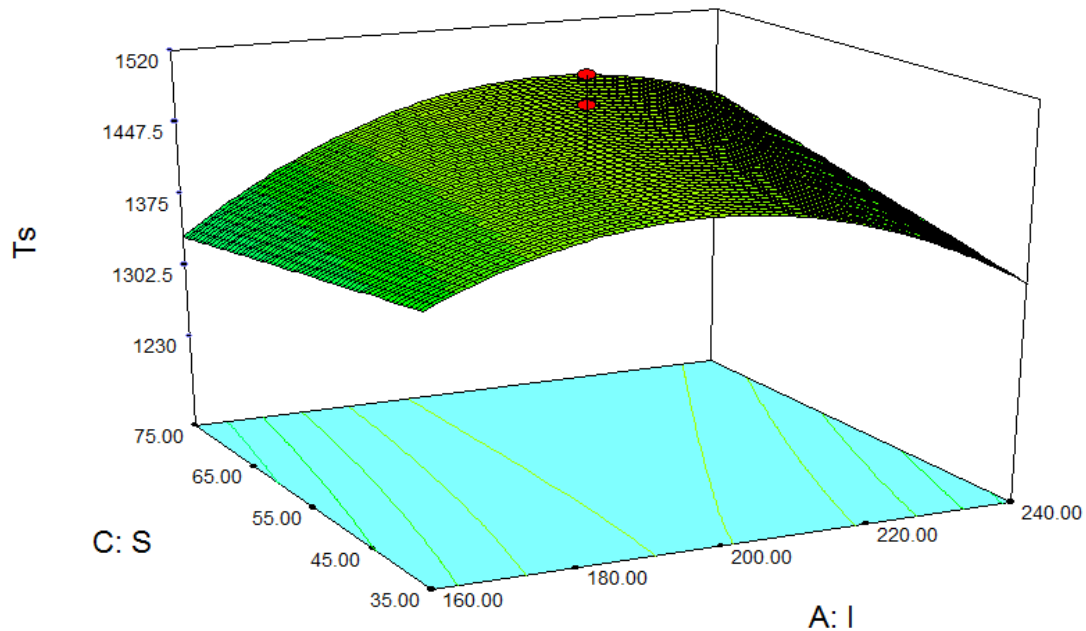


Figure 1: Effect of current and welding speed on solidus temperature

3. Result and Discussion

In this study, the Response Surface Methodology was used to predict the solidus temperature of TIG welds. The model had P-value less than 0.05 which reveals that the model is significant and “Predict R-squared” value of 0.7898 is in reasonable agreement with the “Adj R-squared” of 0.8464. ANOVA was done and the result showed that the model is significant and possess a very good fit.

To validate the significance and adequacy of the model, a coefficient of determination (R-squared) of 0.8960 indicating the appreciable strength of the model. The computed signal to noise ratio of 16.6371 as observed in table 7 indicates an acceptable signal. This model can be employed to navigate the design space and adequately predict the solidus temperature. The model graph show the interactions of the combine variables on the measured response, solidus temperature as presented in a 3-dimensional surface plot.

4. Conclusion

The integrity of a weld is determined by the quality of the weld bead geometry. Solidus temperature is a very important factor considered in assessing the integrity of an alloy. In this study, model to optimize and predict solidus temperature of mild steel has been developed. In this study, an approach using the RSM for optimizing and predicting weld solidus temperature of mild steel weldment to improve the integrity of welded joints has been successfully introduced and its effectiveness and efficiency well demonstrated.

References

- Kishore, K; Gopal Krishna, P.V., Veladri, K and Kiran Kumar, G. (2010): Analysis of defects in gas shielded Arc welding at AA6351 using Taguchi Method, International Journal of Applied Engineering Research, Vol.5, PP 393-399.
- Gadewar, Paravliswaminadhan, M.G. Harkare, S.H. Gawande, “Experimental investigation of weld characteristics for a single pass TIG welding with SS304”. International Journal of Engineering Science and Technology, Vol 2 (8) 2010, 3676-3686.
- Myers, R.H, Khuri, A.I. and Carter, W.H (1989). Response Surface Methodology: 1966-1988. Technometrics 31, 137-157 MR1007291.
- Myers, R.H. Montgomery, D.C., & Anderson-Cook, C.M.,.. Response Surface Methodology product, process optimization employing Designed Experiments (Fourth.ed). Willey, 2016.

Na.S.J,S.L(1987). A study on the three dimensional Analysis of the Transient Temperature Distribution in Gas Tungsten Arc Welding. Journal of Mechanical Engineering, 201133, 149-156.