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APPLICATION OF RESPONSE SURFACE METHODOLOGY TO PREDICT THE HEAT INPUT OF TIG MILD STEEL WELDS

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Abstract

Research studies have shown that there is no known particular method that can be said to be the best optimization model for welding processes. Heat input has a very critical effect on the quality of the weld and is influenced by the welding current . This research study is carried out to predict the Tungsten inert gas welding heat input, using response surface methodology. Mild steel plate was cut into dimension 60mm x 40mm x 10mm with a power hack saw, the samples were grinded and cleaned before the welding process. The TIG welding process was used to join the weld joints. The quadratic model was tested for its suitability for the heat input response which has a significant lack of fit with p value >0.05. The result of anova shows that the model is significant and has adequate strength to predict its target response.the goodness of fit statistics shows that the model has a 98.4% capacity to predict the target response.

1.0 Introduction

Tungsten inert gas welding (TIG) is one of the most important material joining processes widely used in the industry[1]. Response Surface Methodology has been developed to study the effects of input variable (i.e. current, voltage, travel speed) on output responses (i.e. reinforcement height, weld bead width, metal deposition rate).

Gas tungsten arc welding produce the high quality welds most consistently[2]. Over the years welding has improved by incorporating better suited welding methods such as Metal Inert Gas Welding, Tungsten Inert Gas Welding (TIG), and Electron and Laser Beam Welding. A new approach using experimental design matrix of experimental designs technique has been developed[3]. The artificial neural network method was used for predicting the weld bead geometric descriptors while genetic algorithm was used for optimization of process parameters.

Optimization of gas tungsten arc welding process by response surface methodology was reported in which effects of process parameters on tensile strength and hardness are evaluated[4]. The mechanical properties of AA 5456 Aluminum alloy welds has been improved on through pulsed Tungsten Inert Gas (TIG) welding process[5]. Taguchi method was employed to optimize the pulsed TIG welding process parameters of AA 5456 Aluminum alloy welds for increasing the mechanical properties.

2.0 Materials and Methods

2.1 Materials

100 pieces of mild steel coupons measuring 60mm x 40mm x 10mm were used for the experiments. The experiment was performed 20 times, using 5 specimens for each run. The tungsten inert gas welding equipment was used to weld the plates after the edges have been bevelled and machined.

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Plate 1: Welding torch

Plate 2: Welding in progress

A thermocouple is a sensor used for measuring temperature, it consists of a pair of dissimilar wires joined at one end .The type K- thermocouple is a nickel-chromium and nickel–alumel thermocouple is suitable for inert atmospheres at temperatures up to 1260^{o}c,the K-type thermocouple is shown in plate 3.

Plate 3: K-Type Thermocouple

A digital thermometer is a mercury free thermometer containing thermal sensor in them, it used to take quick and highly accurate temperature readings from the weld samples. They are easy to read with LCD display on them. The digital thermometer is shown in plate 4.

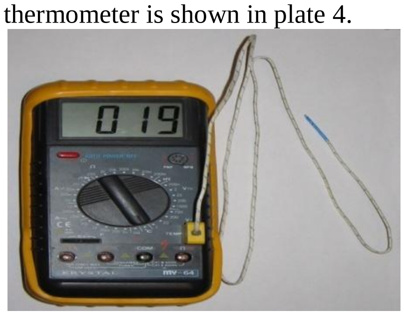


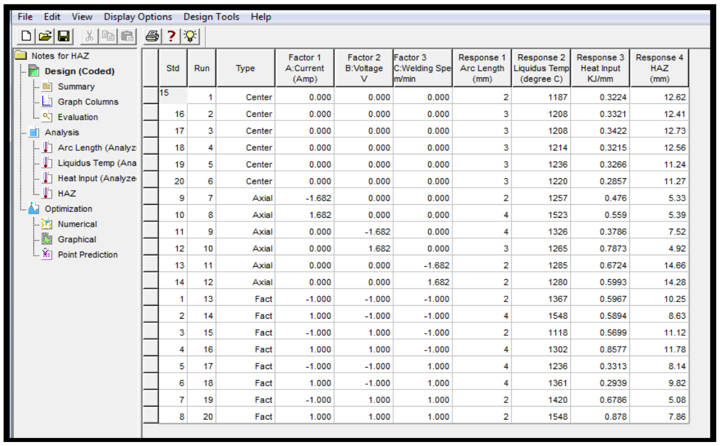
Plate 4: Digital thermometer

Table 1: Process parameters and their levels

Parameters	Unit	Symbol	Coded value	Coded value
			Low(-1)	High(+1)
Current	Amp	A	100	180
welding speed,	M/min	F	0.10	0.6
Voltage	Volt	V	16	22

3.5 Method of Data Collection

The central composite design matrix was developed, using the design expert software, producing 20 experimental runs. The input parameters and output parameters make up the experimental matrix and the responses recorded from the weld samples were used as the data. Figure 1 below shows the central composite design matrix.



Std	Run	Type	Factor 1 A:Current (Amp)	Factor 2 B:Voltage V	Factor 3 C:Welding Spe m/min	Response 1 Arc Length (mm)	Response 2 Liquidus Temp (degree C)	Response 3 Heat Input KJ/mm	Response 4 HAZ (mm)
15	1	Center	0.000	0.000	0.000	2	1187	0.3224	12.62
16	2	Center	0.000	0.000	0.000	3	1208	0.3321	12.41
17	3	Center	0.000	0.000	0.000	3	1208	0.3422	12.73
18	4	Center	0.000	0.000	0.000	3	1214	0.3215	12.56
19	5	Center	0.000	0.000	0.000	3	1236	0.3266	11.24
20	6	Center	0.000	0.000	0.000	3	1220	0.2857	11.27
9	7	Axial	-1.682	0.000	0.000	2	1257	0.476	5.33
10	8	Axial	1.682	0.000	0.000	4	1523	0.559	5.39
11	9	Axial	0.000	-1.682	0.000	4	1326	0.3786	7.52
12	10	Axial	0.000	1.682	0.000	3	1265	0.7873	4.92
13	11	Axial	0.000	0.000	-1.682	2	1285	0.6724	14.66
14	12	Axial	0.000	0.000	1.682	2	1280	0.5993	14.28
1	13	Fact	-1.000	-1.000	-1.000	2	1367	0.5967	10.25
2	14	Fact	1.000	-1.000	-1.000	4	1548	0.5894	8.63
3	15	Fact	-1.000	1.000	-1.000	2	1118	0.5699	11.12
4	16	Fact	1.000	1.000	-1.000	4	1302	0.8577	11.78
5	17	Fact	-1.000	-1.000	1.000	4	1236	0.3313	8.14
6	18	Fact	1.000	-1.000	1.000	4	1361	0.2939	9.82
7	19	Fact	-1.000	1.000	1.000	2	1420	0.6786	5.08
8	20	Fact	1.000	1.000	1.000	2	1548	0.878	7.86

Figure 1: Central Composite Design Matrix (CCD)

Method of data analysis

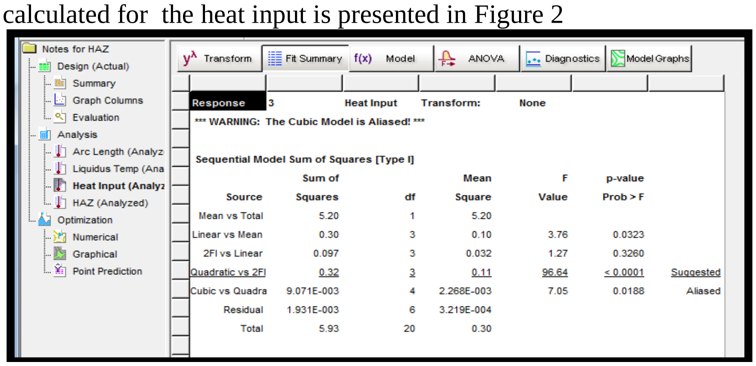
When there is a curvature in the response surface the first-order model is insufficient. A second-order model is useful in approximating a portion of the true response surface with parabolic curvature. The second-order model includes all the terms in the first-order model, plus all quadratic terms like $\beta_{11} x_{1i}$ and all cross product terms like $\beta_{13} x_{1i}$. It is usually expressed as

$$y = \beta_0 + \sum_{j=1}^{q} \beta_{jj} x_j^2 + \sum\sum_{kj} \beta_{ij} x_i x_i + \varepsilon \quad \text{……………..Equation 1}$$

Where x = $(x_{1i}, x_{2i}, \ldots, x_{iq})$, $\beta = (\beta_1, \beta_2, \ldots, \beta_q)$

Result and discussion

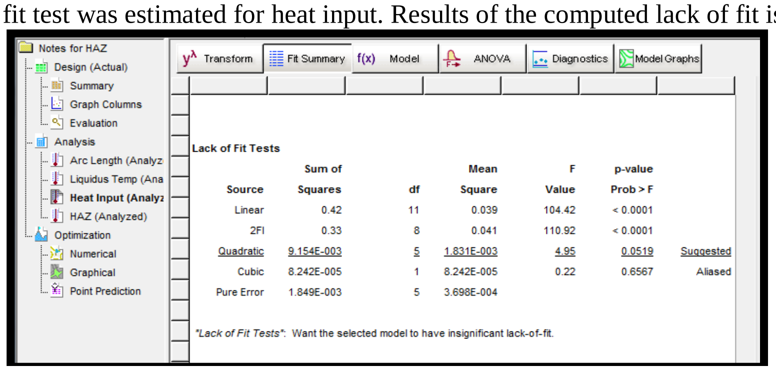
To validate the suitability of the quadratic model in analyzing the experimental data, the sequential model sum of squares was calculated for the heat input is presented in Figure 2



Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Mean vs Total	5.20	1	5.20			
Linear vs Mean	0.30	3	0.10	3.76	0.0323	
2FI vs Linear	0.097	3	0.032	1.27	0.3260	
Quadratic vs 2FI	0.32	3	0.11	96.64	< 0.0001	Suggested
Cubic vs Quadra	9.071E-003	4	2.268E-003	7.05	0.0188	Aliased
Residual	1.931E-003	6	3.219E-004			
Total	5.93	20	0.30			

Figure 2: Sequential model sum of square for heat input

To test how well the quadratic model can explain the underlying variation associated with the experimental data, the lack of fit test was estimated for heat input. Results of the computed lack of fit is presented in Figure 3



Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Linear	0.42	11	0.039	104.42	< 0.0001	
2FI	0.33	8	0.041	110.92	< 0.0001	
Quadratic	9.154E-003	5	1.831E-003	4.95	0.0519	Suggested
Cubic	8.242E-005	1	8.242E-005	0.22	0.6567	Aliased
Pure Error	1.849E-003	5	3.698E-004			

"Lack of Fit Tests": Want the selected model to have insignificant lack-of-fit.

Figure 3

Figures 3: Lack of fit test for heat input

The model statistics computed for heat input based on the different model sources is presented in Figure 4

Model Summary Statistics

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0.16	0.4135	0.3035	0.1304	0.63	
2FI	0.16	0.5463	0.3369	-0.1865	0.86	
Quadratic	0.033	0.9849	0.9713	0.8998	0.073	Suggested
Cubic	0.018	0.9973	0.9916	0.9714	0.021	Aliased

"Model Summary Statistics": Focus on the model maximizing the "Adjusted R-Squared" and the "Predicted R-Squared".

Figure 4 : Model summary statistics for heat input

In assessing the strength of the quadratic model towards minimizing the heat input one way analysis of variance (ANOVA) table was generated for minimizing the heat input and result obtained is presented in Figure 5

Response 3 Heat Input

ANOVA for Response Surface Quadratic Model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.72	9	0.080	72.34	< 0.0001	significant
A-Current	0.025	1	0.025	22.55	0.0008	
B-Voltage	0.25	1	0.25	230.30	< 0.0001	
C-Welding Speed	0.023	1	0.023	20.49	0.0011	
AB	0.035	1	0.035	32.14	0.0002	
AC	1.755E-003	1	1.755E-003	1.60	0.2352	
BC	0.059	1	0.059	54.07	< 0.0001	
A²	0.071	1	0.071	64.70	< 0.0001	
B²	0.13	1	0.13	114.31	< 0.0001	
C²	0.18	1	0.18	164.67	< 0.0001	
Residual	0.011	10	1.100E-003			
Lack of Fit	9.154E-003	5	1.831E-003	4.95	0.0519	not significant
Pure Error	1.849E-003	5	3.698E-004			
Cor Total	0.73	19				

Figure 5: ANOVA table for validating the model significance towards minimizing the heat input

Std. Dev.	0.033	R-Squared	0.9849
Mean	0.51	Adj R-Squared	0.9713
C.V. %	6.50	Pred R-Squared	0.8998
PRESS	0.073	Adeq Precision	24.638

The "Pred R-Squared" of 0.8998 is in reasonable agreement with the "Adj R-Squared" of 0.9713.

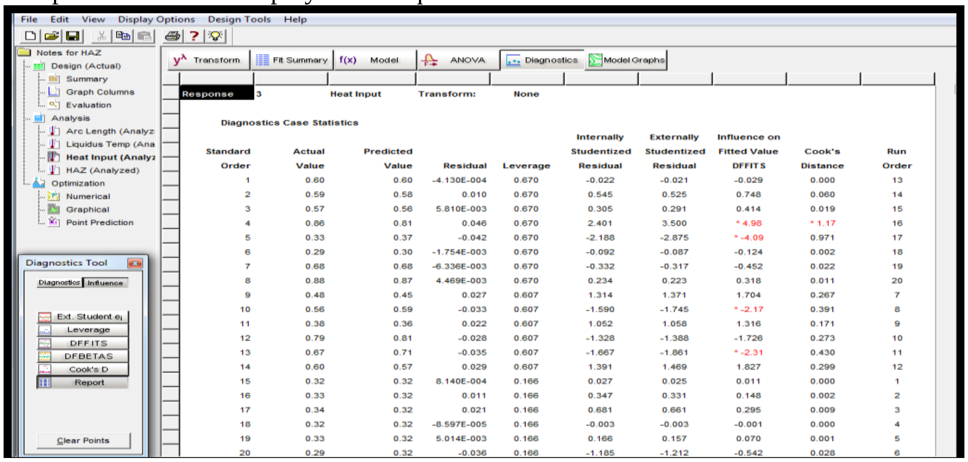
Figure 6: GOF statistics for validating model significance towards minimizing heat input

From the result of Figure 6, it was observed that the "Predicted R-Squared" value of 0.8998 is in reasonable agreement with the "Adj R-Squared" value of 0.9713. Adequate precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The computaed ratio of 24.638observed in Figure 6 indicates an adequate signal. This model can be used to navigate the design space and adequately minimize the heat input

The optimal equation which shows the individual effects and combine interactions of the selected input variables (current (Amp), voltage (V) and welding speed (m/min)) against the mesured response(heat input) is presented below.

Heatinput = $0.32+0.034A+0.14B-0.041C+0.066A*B0.015A*C+0.086B*C+0.07A^2+0.093B^2+0.11C^2$…Equation 2

The diagnostics case statistics which shows the observed values of each response variable(heat input) against their predicted values is presented in Figure 7.The diagnostic case statistics actually give insight into the model strength and the adequacy of the optimal second order polynomial equation.



Response 3 Heat Input Transform: None

Diagnostics Case Statistics

Standard Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residual	Externally Studentized Residual	Influence on Fitted Value DFFITS	Cook's Distance	Run Order
1	0.60	0.60	-4.130E-004	0.670	-0.022	-0.021	-0.029	0.000	13
2	0.59	0.58	0.010	0.670	0.545	0.525	0.748	0.060	14
3	0.57	0.56	5.810E-003	0.670	0.305	0.291	0.414	0.019	15
4	0.86	0.81	0.046	0.670	2.401	3.500	* 4.98	* 1.17	16
5	0.33	0.37	-0.042	0.670	-2.188	-2.875	* -4.09	0.971	17
6	0.29	0.30	-1.754E-003	0.670	-0.092	-0.087	-0.124	0.002	18
7	0.68	0.68	-6.336E-003	0.670	-0.332	-0.317	-0.452	0.022	19
8	0.88	0.87	4.469E-003	0.670	0.234	0.223	0.318	0.011	20
9	0.48	0.45	0.027	0.607	1.314	1.371	1.704	0.267	7
10	0.56	0.59	-0.033	0.607	-1.590	-1.745	* -2.17	0.391	8
11	0.38	0.36	0.022	0.607	1.052	1.058	1.316	0.171	9
12	0.79	0.81	-0.028	0.607	-1.328	-1.388	-1.726	0.273	10
13	0.67	0.71	-0.035	0.607	-1.667	-1.861	* -2.31	0.430	11
14	0.60	0.57	0.029	0.607	1.391	1.469	1.827	0.299	12
15	0.32	0.32	8.140E-004	0.166	0.027	0.025	0.011	0.000	1
16	0.33	0.32	0.011	0.166	0.347	0.331	0.148	0.002	2
17	0.34	0.32	0.021	0.166	0.681	0.661	0.295	0.009	3
18	0.32	0.32	-8.597E-005	0.166	-0.003	-0.003	-0.001	0.000	4
19	0.33	0.32	5.014E-003	0.166	0.166	0.157	0.070	0.001	5
20	0.29	0.32	-0.036	0.166	-1.185	-1.212	-0.542	0.028	6

Figure 7: Diagnostics case statistics report of observed and predicted heat input

To study the effects of combine input variables on the response variable(heat input), the 3D surface plot presented in Figure 8 was developed.

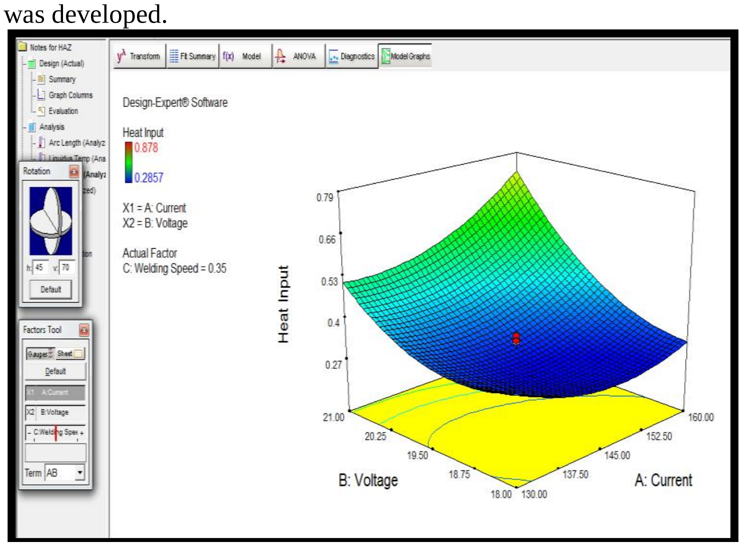


Figure 8: Effect of current and voltage on the heat input

Conclusion

The quality and integrity of welded joints is highly influenced by the optimal combination of the welding input parameters. This study developed a model using Response Surface Methodology to predict weld heat input from input parameter such as current, voltage and welding speed. The results from the study shows that the voltage has a very strong influence on the heat input that is an increase in voltage will result in a corresponding increase in the heat input.

References

[1] Kundan K, Somnath C, Avadhesh Y, 2012, *Surface response methodology for predicting the output responses of tig welding process.*, Asian Journal of Engineering Research ISSN--2319–2100, Asian J Eng Res/Vol. I/Issue I/

[2] Pawan Kumar, Kishor Purushottamrao Kolhe, Sashikant Janardan Morey, " Process Parameters Optimization of an Aluminium Alloy with Pulsed Gas Tungsten Arc Welding (GTAW) Using Gas Mixtures", (2011), 2, 215-2257.

[3] Nagesh D.S, Datta G.L., Genetic Algorithm for Optimization of Welding Variables for Height to Width Ratio and Application of ANN for Prediction of Bead Geometry for TIG

[4] Kiaee,N. and Aghaie-Khafri,M. (2014) "Optimization of gas tungsten arc welding process by response surface methodology", Materials and Design 54, 2014, pp. 25–31.

[5] Kumar,A. and Sundar rajan S. (2009): "Optimization of pulsed TIG welding process parameters on mechanical properties of AA 5456 Aluminum alloy weldments" Materials and Design 30 (2009) 1288–1297