Optimization of the Tungsten Inert Gas Process Parameters using Response Surface Methodology

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ABSTRACT

Optimization is a very important techniques applied in the manufacturing industry that utilizes mathematical and artificial intelligence methods. The complexity associated with most optimization techniques have resulted to search for new ones. This search has led to the emergence of response surface methodology (RSM). The paper aims to optimize tungsten inert gas process parameters required to eliminate post-weld crack formation and stabilize heat input in mild steel weldment using RSM. The main input variables considered are voltage, current and speed whereas the response parameter is Brinell hardness number (BHN). The statistical design of experiment was done using the central composite design technique. The experiment was implemented 20 times with 5 specimens per experiment. The responses were measured, recorded and optimized using RSM. From the results, it was observed that a voltage of 21.95 V, current of 190.0 A, and welding speed of 5.00 mm/s produced a weld material with the following optimal properties; BHN (200.959 HAZ), heat input (1.69076 kJ/mm), cooling rate (72.07 °C/s), preheat temperature (150.68 °C) and amount of diffusible hydrogen (12.36 mL/100g). The optimal solution was selected by design expert with a desirability value of 95.40 %.

1. Introduction

Poor weld strength coupled with poor quality of raw materials are some of the critical factors responsible for most of the structural failures happening today [1-2]. In addition, welding failures are mostly influenced by improper combination of the welding process factors such as voltage, current, welding speed and gas flow rate [3-4]. One of the fundamental issues facing engineers in the manufacturing sector is the problem of choosing the most suitable combinations of input process parameters to achieve the required optimum weld bead quality. Since the quality and strength of a weld is described by the reduction and elimination of weld defects such as cracks, undercut, deformation and porosity, it is important to employ standard methods for the selection of input variables that can influence the quality and strength of the welded material [5-6]. To achieve this task, response surface methodology can be employed.

Response surface methodology (RSM) is an advance numerical technique, which involves the incorporation of the second-order effects of non-linear relationships [7]. It is a common optimization method employed in most process industries to determine the best possible combination of variables needed to optimize a specific response. It explores the correlation between multi-explanatory variables and either a single or multiple response parameters [8]. The goal is to utilize a sequence of experimental designs to deduce an optimum response. The

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optimization technique comprises an experimental design to determine an estimate model between the input and output parameters, the numerical model as well as the optimization responses [9]. In [10], the response surface model was employed for yielding better weldments and estimation of the deposition rate of a low carbon steel. A response surface model was developed and presented in [11] to examine the effect of process parameters of weld bonding on tensile shear strength. Usage of the model suggest that a significant and controllable process parameters of the weld bonding such as curing time, surface roughness, welding current and time as well as electrode pressure were optimized. An empirical relationship was developed and presented in [12] to estimate the tensile strength of pulsed current gas tungsten arc welded AZ31B magnesium alloy joints. The study considered different process variables (base current, peak current, pulse frequency and pulse on time). Result showed that these variables affect the tensile strength to a high degree.

It is very valuable to understand the correlation between multiple predictor variables with either one or several predictands. In this study, a second-order numerical relationship between three input variables (voltage, current, welding speed) and five response variables (Brinell hardness number, cooling rate, heat input, preheat temperature and amount of diffusible hydrogen) was developed using the RSM technique. The goal was to utilize a sequence of experimental designs to deduce an optimum response of the tungsten inert gas process variables.

2. Methods

The Design Expert Statistical Software (Version 7.01), was used in the analysis to determine the parametric effects and statistical parameters of the fitted models. The behavior of the system utilized to assess the relationship between the response variables and the independent variables was explained using the empirical second-order polynomial relation of equation (1) proposed by [13].

$$Y = \beta_0 + \sum_{i=1}^q \beta_i x_i + \sum_{i=1}^q \beta_{ii} x_i^2 + \sum_{i=1, i < j}^{q-1} \sum_{j=2}^q \beta_{ij} x_i x_j + \varepsilon \quad (1)$$

Where, Y is the response variable, $x_1, x_2, \dots, x_k$ are input variables, $\beta_0, \beta_i, \beta_{ii}$, and β_{ij} are the known parameters and ε is the random error.

The input (independent) variables considered are welding voltage, current, and speed whereas the response parameters comprise Brinell hardness number (BHN), cooling rate (CR), heat input (HI), preheat temperature (PT) and amount of diffusible hydrogen (H_{IIW}). The methodology for samples preparation, welding and testing as well as the range and level of the independent variables utilized for the experimental design, are described in [14]. These parameters were implemented using central composite design technique; twenty experiments were performed with 5 samples per experiment. Table 1 shows the design of experiment.

Table 1 Design of Experiment.

Run	Type	Welding Voltage (V)	Welding Current (A)	Welding Speed (mm/s)	BHN (HAZ)	HI (kJ/mm)	CR (°C/s)	H_{IIW} (mL/110g)
1	Center	23	180	3.5	200	1.667	93.45	13.56
2	Center	23	180	3.5	196	1.667	94.55	14.05
3	Center	23	180	3.5	200	1.665	91.75	13.21
4	Center	23	180	3.5	200	1.667	94.5	14.45
5	Center	23	180	3.5	200	1.667	95.6	13.55
6	Center	23	180	3.5	200	1.768	92.55	13.44
7	Axial	23	163.1820717	3.5	172	0.755	63.85	12.93
8	Axial	23	196.8179283	3.5	188	1.12	97.88	13.02
9	Axial	19.63641434	180	3.5	198	0.88	75.66	10.07
10	Axial	26.36358566	180	3.5	182	1.173	85.66	14.33
11	Axial	23	180	0.977310754	187	1.258	68.05	17.08
12	Axial	23	180	6.022689246	180	1.775	75.67	10.98
13	Fact	21	170	2	190	1.203	94.33	13.09
14	Fact	21	190	2	184	0.944	68.34	12.23
15	Fact	25	170	2	190	1.012	45.18	13.76
16	Fact	25	190	2	180	0.806	55.76	12.87
17	Fact	21	170	5	175	0.756	90.36	10.58
18	Fact	21	190	5	202	1.412	97.4	9.57
19	Fact	25	170	5	160	1.203	101.23	15.23
20	Fact	25	190	5	184	2.009	85.67	16.77

To verify the correctness of the developed quadratic model in evaluating the experimental data, the sequential model sum of squares was computed for each response variable. Based on the computed value, the highest-order polynomial where the additional terms are significant and the model is not aliased was chosen as the best fit. In addition, the lack-of-fit test and the model summary statistics were used to justify the use of quadratic polynomial in assessing the suitability of the quadratic model. In evaluating the strength of the quadratic model towards maximizing BHN and HI while also minimizing CR, PT and H_{IIW} , one-way analysis of variance (ANOVA) table was generated for each response variable.

Furthermore, numerical optimization was carried out to establish the suitability of the overall model. The optimization objective was to maximize the Brinell hardness number and heat input while also minimizing cooling rate, preheat temperature and amount of diffusible hydrogen. The relative importance was set at the optimum value of 5.0 whereas the lower and upper boundary conditions set at 0.1 and 1.0 for maximization, respectively. For minimization, boundary conditions were set at 1.0 and 0.1. An upper limit of 1.0 constrains the optimization tool to maximize the response variable while a lower limit of 1.0 constrains the tool to minimize the response variable.

3. Results and Discussion

Results of the analysis (ANOVA), which was employed to established that the model developed is significant is presented in Table 2. For response 1, the calculated F-value of 163.54 shows that the model is significant. The significant model terms for response 1 as observed from Table 2 includes; A, B, C, AC, BC, A^2 , B^2 , and C^2 . In addition, the calculated lack-of-fit value for response 1 is 0.26, which is good since a non-significant lack-of-fit implies that the model developed is significant.

Table 2 Validation of Model Significance Towards Maximizing BHN, HI, CR, PT, and H_{IIW} .

ANOVA for Response Surface Quadratic Model [Partial Sum of Squares-Type III]						
Source		Sum of square	Df	Mean square	F value	p-value Prob>F
<i>Response 1: Brinell Hardness Number</i>						
Model		2473.99	9	274.89	163.54	<0.0001
A-current		280.64	9	280.64	166.96	<0.0001
B-voltage		299.07	9	299.07	177.92	<0.0001
C-welding speed		88.54	9	88.54	52.67	<0.0001
AB		6.12	9	6.12	3.64	0.0854
AC		561.13	9	561.13	333.83	<0.0001
BC		105.12	9	105.12	62.54	<0.0001
A^2		693.23	9	090.23	412.42	<0.0001
B^2		166.61	9	166.61	99.12	<0.0001
C^2		467.93	9	467.93	278.38	<0.0001
Residual		16.81	10	1.66		<0.0001
	Lack-of-Fit	3.48	5	0.70	0.26	0.9166
	Pure Error	13.33	5	2.67		
C or Total		2490.80	19			
<i>Response 2: Heat Input</i>						
Model		2.00	9	0.3	181.67	0
A-current		0.19	7	0.19	108.86	<0.0001
B-voltage		0.11	1	0.11	61.25	<0.0001
C-welding speed		0.38	7	0.38	219.14	<0.0001
AB	5,151E	003	7	5.151E 003	2.95	<0.0001
AC		0.48	7	0.46	266.78	<0.0001
BC		0.24	1	0.24	155.13	0.1164
A^2		0.94	7	0.94	530.95	<0.001
B^2		0.72	7	0.72	414.32	<0.001
C^2		0.037	7	0.037	21.21	<0.001
Residual		0.017	10	1744F-003		0.0010
	Lack-of-Fit	8.867E-003	5	1.773E-003	1.03	0.4056
	Pure Error	8.571E-003	5	1.714E-003		
C or Total		2.92	19			

Table 2 Validation of Model Significance ... (Continuation).

ANOVA for Response Surface Quadratic Model [Partial Sum of Squares-Type III]						
Source		Sum of square	Df	Mean square	F value	p-value Prob>F
<i>Response 3: Cooling Rate</i>						
Model		1698.06	9	522.01	119.96	<0.001
A-current		130.25	7	130.26	31.77	0.0002
B-voltage		67.58	7	67.58	15.53	0.0028
C-welding speed		134.31	7	134.31	30.87	0.0002
AB	5,151E	415.30	7	115.30	95.44	<0.0001
AC		400.72	7	400.72	111.00	<0.0001
BC		46.85	7	46.85	10.77	0.0083
A ²		3344.72	7	3344.72	768.87	<0.0001
B ²		0.18	7	0.18	0.012	0.8409
C ²		0.022	7	0.022	4.903E-003	0.9451
Residual		43.51	10	4.35		
	Lack-of-Fit	33.36	5	8.67	3.29	0.1088
	Pure Error	10.15	5	2.03		
C or Total		4741.50	19			
<i>Response 4: Preheat Temperature</i>						
Source		Sum of square	Df	Mean square	F value	p-value Prob>F
Model		5402.46	9	600.27	184.76	<0.0001
A-current		517.22	7	517.22	158.20	<0.0001
B-voltage		292.72	7	292.72	90.10	<0.0001
c-welding speed		292.72	7	292.72	90.10	<0.0001
AB	5,151E	0.50	7	0.50	0.15	<0.0001
AC		840.50	7	840.50	258.70	<0.0001
BC		840.50	7	840.50	258.70	<0.0001
A ²		106.10	7	106.10	32.66	0.0002
B ²		1379.00	7	1379.00	424.65	<0.0001
C ²		897.88	7	897.88	276.36	<0.0001
Residual		32.49	10	3.25		
	Lack-of-Fit	19.18	5	3.83	1.44	
	Pure Error	13.33	5	2.67		
C or Total		5434.05	10			
<i>Response 5: Amount of Diffusible Hydrogen</i>						
Model		70.56	9	7.84	54.15	<0.0001
A-current		1.23	1	1.23	8.33	0.0153
B-voltage		2.63	1	2.63	18.11	0.0017
c-welding speed		2.37	1	2.37	15.97	0.0025
AB	5,151E	11.07	1	11.07	76.44	<0.0001
AC		15.99	1	15.99	110.43	<0.0001
BC		0.18	1	0.18	1.22	0.2948
A ²		0.10	1	0.10	2.77	0.1271
B ²		24.82	1	24.82	171.40	<0.0001
C ²		0.02	1	0.02	66.54	<0.0001
Residual		1.45	10	0.14		
	Lack-of-Fit	0.47	5	0.083	0.40	0.8313
	Pure Error	1.03	5	0.27		
C or Total		72.02	19			

For response 2, the calculated F-value of 184.67 shows that the model is significant. The significant model terms for response 2 as observed (Table 2) includes; A, B, C, AC, BC, A², B², and C². Also, the calculated lack-of-fit value for response 2 is 1.03, which is good since a non-significant lack-of-fit implies that the model developed is significant. For response 3, the calculated F-value of 119.96 shows that the model is significant. The significant model terms for response 3 as observed (Table 2) includes; A, B, C, AB, AC, BC, and A². Moreover, the calculated lack-of-fit value for response 3 is 3.29, which is good since a non-significant lack-of-fit implies that the model developed is significant. For response 4, the calculated F-value of 184.76 shows that the model is significant. The significant model terms for response 4 as observed from the results of Table 2 includes; A, B, C, AC, BC A², B², and C². Also, the calculated lack-of-fit value for response 4 is 1.44, which is good since a non-significant lack-of-fit implies that the model developed is significant. For response 5, the calculated F-value of 54.15 shows that the model is significant. The significant model terms for response 5 as observed from the results of Table 2 includes; A, B, C, AB, AC, B², and C². In addition, the calculated lack-of-fit value for response 4 is 0.40, which is good since a non-significant lack-of-fit implies that the model developed is significant.

To validate the model and further reiterate its ability to optimize the selected input variables, selected goodness of fit statistics presented in Table 3 were employed. It was seen that the "Predicted R-squared" value calculated for all the response variables are in reasonable agreement with the "Adjusted R-squared" value. Also, adequate precision, which measures the signal-to-noise ratio were also calculated and a ratio greater than 4 is desirable. Since the calculated adequate-precision-ratios presented in Table 3 are greater than 4, it was concluded that the model is highly significant. Based on the Goodness of Fit statistics, the optimized mathematical model, which shows the relationship between the input and output variables were generated and presented as equations (2) – (6).

Table 3 Computed Goodness of Fit Statistics for Validating Model Significance.

Index	BHN	HI	CR	PT	H _{IHW}
R-Square	0.9933	0.9940	0.9908	0.9940	0.9799
Adjusted R-Square	0.9872	0.9886	0.9826	0.9886	0.9618
Predicted R-Square	0.9816	0.9721	0.9397	0.9696	0.9325
Adequacy Precision	46.278	41.917	37.152	51.448	28.40
CV (%)	0.69	3.160	2.500	1.10	2.87
PRESS	0.75	0.081	2.07	5.38	4.85

$$BHN = -2476.97511 + 24.47372 X_1 + 48.86565 X_2 - 56.67801 X_3 - 0.043750 X_1 X_2 + 0.55833 X_1 X_3 - 1.20833 X_2 X_3 - 0.069356 X_1^2 - 0.85003 X_2^2 - 2.53254 X_3^2 \quad (2)$$

$$HI = -94.50168 + 0.84575 X_1 + 2.19053 X_2 - 3.93715 X_3 + 0.00126875 X_1 X_2 + 0.016058 X_1 X_3 + 0.057208 X_2 X_3 - 0.00256372 X_1^2 - 0.055977 X_2^2 - 0.022518 X_3^2 \quad (3)$$

$$CR = -6657.12941 + 65.26818 X_1 + 61.83169 X_2 + 73.07664 X_3 - 0.36025 X_1 X_2 - 0.52000 X_1 X_3 + 0.80667 X_2 X_3 - 0.15235 X_1^2 + 0.028309 X_2^2 - 0.017240 X_3^2 \quad (4)$$

$$PT = 1908.41615 - 6.47345 X_1 - 119.91417 X_2 + 72.05994 X_3 - 0.012500 X_1 X_2 - 0.68333 X_1 X_3 + 3.41667 X_2 X_3 + 0.027133 X_1^2 + 2.44610 X_2^2 - 3.50812 X_3^2 \quad (5)$$

$$H_{IHW} = -20.00473 - 0.45246 X_1 + 4.45946 X_2 + 15.94529 X_3 + 0.058813 X_1 X_2 - 0.094250 X_1 X_3 - 0.049583 X_2 X_3 - 0.00166784 X_1^2 - 0.32807 X_2^2 - 0.34778 X_3^2 \quad (6)$$

Using the optimal equations (2) – (6), the response variables (BHN, HI, CR, PT and H_{IHW}) were predicted and a reliability plot of observed versus estimated values of each of the response variable was obtained and shown in Fig. 1. The high R²-values (0.9933, 0.9940, 0.9908, 0.9940 and 0.9799) observed in Fig. 1 (a)-(e), indicate the suitability of response surface methodology in maximizing Brinell hardness number and heat input while also minimizing cooling rate, preheat temperature and amount of diffusible hydrogen.

Fig. 1 Reliability Plots of RSM Predicted Versus Observed Values of (a) Brinell Hardness Number, (b) Heat Input, (c) Cooling Rate, (d) Preheat Temperature, and (e) Amount of Diffusible Hydrogen.

Table 4 shows optimum solutions of the numerical optimization performed. From the results, it was noted that a current of 190.0 A, voltage of 21.95 V and welding speed of 5.0 mm/s will produce a weld material with the following properties: Brinell hardness number (200.959 HAZ); heat input (1.69076 kJ/mm); cooling rate (72.0727 °C/s); preheat temperature (150.677 °C); amount of diffusible hydrogen (12.3562 mL/100g); and the optimal solution was selected by design expert with a desirability value of 95.40 %.

Table 4 Optimal Solutions of Numerical Optimization.

Number	Current (A)	Voltage (V)	Welding Speed (mm/s)	BHN (HAZ)	HI (kJ/mm)	CR (°C/s)	PT (°C)	H _{ITW} (mL/100g)	Desirability	
1	190.00	21.95	5.00	200.959	189076	70.0727	150.677	12.3582	0.954	Selected
2	189.99	21.93	5.00	201.01	1.68603	72.1133	150.636	12.3383	0.954	
3	190.00	21.98	5.00	200.885	1.69761	72.0463	150.759	12.3822	0.954	
4	190.00	22.05	5.00	200.684	1.71503	71.9447	150.906	12.4468	0.954	
5	190.00	21.78	5.00	201.42	1.64389	72.3076	150.375	12.1757	0.954	
6	189.79	21.89	4.99	201.146	1.67386	72.2494	150.776	12.2933	0.954	
7	189.72	22.04	5.00	200.707	1.71709	72.5994	150.864	12.4963	0.954	
8	190.00	22.14	5.00	200.394	1.74348	72.704	151.153	12.6062	0.963	
9	190.00	22.78	5.00	196.042	1.86833	70.9786	154.175	12.9467	0.963	
10	188.86	22.15	4.88	200.645	1.72186	72.7981	153.308	12.4971	0.963	
11	190.00	22.42	5.00	199.435	1.81586	74.9173	152.134	13.0105	0.960	
12	170.00	22.46	4.66	200.005	1.74949	74.0488	157.624	12.6864	0.959	
13	170.00	23.03	2.00	193.099	1.33013	70.7123	134.014	12.7828	0.956	
14	170.00	23.00	2.00	193.104	1.33181	70.6133	134.093	12.8047	0.956	
15	170.00	23.05	2.00	193.097	1.32927	70.7665	133.989	12.7716	0.956	
16	170.00	23.09	2.00	193.09	1.32681	70.9074	133.885	12.7404	0.956	
17	170.00	23.16	2.00	193.065	1.32138	71.1856	133.718	12.6757	0.956	
18	170.00	22.96	2.00	193.155	1.336	70.6538	134.269	12.8437	0.956	
19	170.00	23.10	2.01	193.087	1.32539	71.0106	134.083	12.7277	0.956	
20	170.00	22.77	2.02	193.088	1.34154	69.8452	135.224	12.9622	0.956	
21	170.00	22.60	2.00	193.005	1.34457	69.222	135.546	13.0446	0.956	

4. Conclusion

But for a few literatures of welding and fabrication, only conventional methods of experimentation (varying one variable and fixing the others) have been employed to study the effects of variables governing the welding process. These methods of experimentation commonly give rise to large experimental runs; hence, limiting the establishment of the multiple interacting effects of the selected variables. Also, determining the optimal conditions is almost beyond the scope of the conventional methods. These limitations of the traditional process of experimentation can be eradicated by optimizing all the controlling variables collectively using statistical design of experiment, since it permits a large number of parameters to be screened simultaneously. In this study, response surface methodology has been successfully employed to optimize selected welding parameters (welding voltage, current and speed).

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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