

Research Article

Optimization of Welding Parameters for Controlled Heat Input Using Response Surface Methodology: A Multivariate Analysis of Current, Voltage, and Speed Interactions

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Abstract

Controlling heat input (HI) in welding is critical for ensuring joint quality and preventing defects, yet existing models often fail to account for the complex interactions between current, voltage, and welding speed. This study addresses this gap by developing a predictive model to optimize HI, focusing on gas metal arc welding (GMAW) of low-carbon steel. The aim was to establish precise parameter combinations that balance thermal input with weld integrity, particularly for industrial applications requiring controlled heat management. A central composite design (CCD) within Response Surface Methodology (RSM) was employed, systematically varying current (180–240 A), voltage (18–24 V), and welding speed (70–100 mm/min). Heat input was calculated using the standard HI formula, and a quadratic regression model was developed and validated through ANOVA, lack-of-fit tests, and diagnostic metrics. The model's robustness was confirmed with $R^2 = 0.9933$ and Adeq. Precision = 46.561, ensuring reliability for industrial use. The results identified voltage as the most influential parameter ($p < 0.0001$), with optimal conditions (200 A, 21.07 V, 70 mm/min) achieving HI = 1.24 kJ/mm and 87.5% desirability. The study demonstrates that controlled voltage-speed interactions are key to minimizing HI while maintaining joint quality. These findings provide actionable insights for welding optimization, recommending future expansion to high-alloy materials and real-time HI monitoring for broader industrial adoption.

Keywords

Heat Input (HI), Gas Metal Arc Welding (GMAW), Welding Optimization, Response Surface Methodology (RSM)

1. Introduction

Welding is a foundational manufacturing process integral to industries ranging from automotive to aerospace, where the integrity of welded joints directly impacts product performance and safety. Heat input (HI)—a measure of the thermal energy transferred during welding—serves as a critical determinant of joint quality, microstructure evolution, and residual

stress distribution. Excessive HI can induce undesirable phase transformations, distortion, or cracking in the heat-affected zone (HAZ), while insufficient HI may lead to inadequate penetration or fusion defects [1]. As industries increasingly adopt advanced materials like high-strength steels and aluminum alloys, precise control of HI becomes paramount to balance mechanical

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properties with geometric accuracy.

Traditional welding practices often rely on empirical guidelines, but these fail to account for the nonlinear interplay of process parameters, underscoring the need for a systematic approach to HI optimization [2]. Despite extensive research on individual welding parameters, few studies holistically address the multivariate interactions between current, voltage, and welding speed. Prior works frequently isolate variables (e.g., studying current effects at fixed voltage/speed), neglecting synergistic dynamics that govern real-world welding outcomes [3]. For instance, increasing current elevates arc energy but may necessitate adjustments in voltage or speed to mitigate overheating. Similarly, voltage fluctuations alter arc stability, indirectly influencing penetration depth and HI distribution [4].

This fragmented understanding limits the development of robust predictive models, leaving practitioners to rely on trial-and-error methods that are time-consuming and resource-intensive [5]. Furthermore, existing models often oversimplify HI as a linear function of parameters, disregarding quadratic effects and interaction terms that dominate in complex thermal regimes [6]. Several researchers have attempted to model and predict welding-induced distortions using finite element analysis and experimental validation techniques, contributing significantly to our understanding of thermal cycles and residual stresses [7].

To bridge this gap, recent studies have emphasized the use of statistical modeling and metaheuristic optimization tools to enhance prediction accuracy and process efficiency [8]. The application of computational fluid dynamics and numerical simulations has also provided insights into molten metal flow behavior under various force balances, further refining our understanding of weld pool dynamics [9]. In particular, efforts to optimize Gas Metal Arc Welding (GMAW) protocols using Taguchi-based approaches have demonstrated improvements in weld strength and quality [10]. Additionally, multi-objective optimization frameworks such as MOORA and TOPSIS have been successfully applied to determine optimal process parameters and material properties [11, 12].

Moreover, artificial intelligence techniques such as Artificial Neural Networks (ANNs) have shown promise in predicting weld quality by capturing nonlinear relationships among input variables, thereby enhancing process adaptability [13]. Recent studies have also focused on optimizing weld bead geometry using Response Surface Methodology (RSM) and other regression-based models, allowing for better control over weld characteristics [14]. Understanding the forces acting on the molten weld pool through static force balance theory has also contributed to more accurate predictions of weld bead formation and stability [15].

In light of these advancements, this study employs Response Surface Methodology (RSM) -a statistical technique adept at modeling multivariable systems-to quantify the effects of current (170–240 A), voltage (18–24 V), and welding speed (70–100 mm/min) on HI. By constructing a quadratic

regression model, we aim to unravel the nonlinear relationships and interaction effects obscured in univariate analyses. The objectives are threefold:

- (1) identify dominant factors and interactions governing HI,
- (2) validate the model's predictive accuracy through ANOVA and diagnostic metrics, and
- (3) derive optimal parameter combinations that minimize or maximize HI for specific applications.

This approach not only advances academic understanding of welding thermodynamics but also equips industries with a data-driven framework to enhance process efficiency, reduce defects, and tailor thermal profiles to material requirements [16].

2. Methodology

2.1. Materials

The experimental setup utilized a gas metal arc welding (GMAW) system capable of delivering current ranging from 180 to 240 A and voltage between 18 and 24 V (Figure 1). Low-carbon steel plates conforming to ASTM A36 specifications were selected as the base material due to their widespread industrial application and consistent thermal properties (Figure 2). The welding process employed ER70S-6 welding wire (Figure 3) with a diameter of 1.2 mm, along with a shielding gas mixture of 75% argon and 25% carbon dioxide to maintain arc stability. For measurement and monitoring purposes, the setup incorporated a digital multimeter for recording voltage and current, infrared thermography equipment for supplementary thermal profile assessment.



Figure 1. Welding machine.



Figure 2. Low-carbon steel plates (ASTM A36).



Figure 3. ER70S-6 solid wire.

2.2. Experimental Methods

The experimental design adopted a central composite design (CCD) approach within the Response Surface Methodology (RSM) framework. This design allowed for investigation of the complex relationships between three key independent variables: welding current (180-240 A), voltage (18-24 V), and welding speed (16-22 mm/min). Each variable was tested at five levels, including axial points, to adequately capture potential nonlinear effects. The primary response variable was heat input, calculated using the standard formula that incorporates voltage, current, and welding speed.

Heat Input Calculation:

The fundamental equation governing heat input was applied:

$$HI = \frac{V \times I \times 60}{S \times 1000} \quad (1)$$

Where:

HI = Heat Input (KJ/mm)

V = Voltage (V)

I = Current (A)

S = Welding speed (mm/min)

The Factor 60 was used to convert minute to seconds while the divisor 1000 converts joules to kilojoules.

Welding trials were conducted on standardized 150 mm × 75 mm × 10mm steel plates under controlled environmental conditions to minimize external variability. The welding machine's programmable interface ensured precise and repeatable parameter settings for each experimental run. During each trial, voltage and current measurements were recorded at 100

ms intervals, with subsequent averaging performed for analysis. Welding speed was verified through post-process measurements comparing bead length to welding time.

Statistical analysis involved developing a quadratic regression model to characterize the relationship between input parameters and heat input. The model's adequacy was assessed through standard validation techniques, including analysis of variance and diagnostic evaluation of residuals. The optimization phase employed desirability function analysis to identify parameter combinations that balanced multiple performance criteria. Model validation procedures were implemented to confirm the predictive capability of the developed relationships between welding parameters and heat input characteristics.

This methodology was designed to provide robust, reproducible results while maintaining relevance to industrial welding applications. The systematic approach ensured comprehensive exploration of the parameter space while maintaining experimental control throughout the investigation.

3. Results and Discussion

The experimental results presented in [Table 1](#) illustrate the relationship between welding input parameters-current, voltage, and welding speed-and the resulting heat input during the welding process. Heat input, calculated in kJ/mm, varies significantly across different combinations of these parameters; for instance, at a lower welding speed of 59.77 mm/min with constant current and voltage (Run 18), the heat input reaches its maximum value of 3.99 kJ/mm, whereas higher welding speeds (e.g., 110.23 mm/min in Run 17) result in lower heat input (2.17 kJ/mm), demonstrating an inverse correlation between welding speed and heat input. Additionally, increases in both current and voltage generally lead to higher heat input, as seen when comparing Runs 1 and 4, where increasing current from 170 to 200 A and voltage from 20 to 23 V resulted in a rise in heat input from 2.04 to 2.76 kJ/mm, respectively. However, repeated runs under similar conditions (e.g., Runs 7, 10, 11, 12, 13, and 16) consistently yield the same heat input of 2.81 kJ/mm, indicating good reproducibility and stability of the process under those specific parameter settings.

Table 1. Experimental Results.

S/N	Input			Response
	Current (ampere)	Voltage (voltage)	Welding speed (mm/min)	Heat input KJ/mm
1	170	20	100	2.04
2	200	20	70	3.43
3	159.77	21.5	85	2.42
4	200	23	70	3.94

S/N	Input			Response
	Current (ampere)	Voltage (voltage)	Welding speed (mm/min)	Heat input Kj/mm
5	170	23	100	2.34
6	210.23	21.5	85	3.19
7	185	21.5	85	2.81
8	185	18.98	85	2.48
9	200	23	100	2.76
10	185	21.5	85	2.81
11	185	21.5	85	2.81
12	185	21.5	85	2.81
13	185	21.5	85	2.81
14	170	23	70	3.35
15	200	20	100	2.40
16	185	21.5	85	2.81
17	185	21.5	110.23	2.17
18	185	21.5	59.77	3.99
19	185	24.02	85	3.14
20	170	20	70	2.91

Table 2. Sequential model sum of square for heat input.

Source	Sum of Squares	Df	Mean Square	F Value	p-value	
					Prob > F	
Mean vs Total	217.67	1	217.67			
Linear vs Mean	14.15	3	4.72	1.03	0.4059	
2FI vs Linear	28.60	3	9.53	2.77	0.0836	
Quadratic vs 2FI	44.12	3	14.71	251.18	< 0.0001	Suggested
Cubic vs Quadratic	0.58	4	0.14	110.34	< 0.0001	Aliased
Residual	7.853E-003	6	1.309E-003			
Total	305.13	20	15.26			

Table 3. Lack of fit test for heat input.

Source	Sum of Squares	Df	Mean Square	F Value	p-value	
					Prob > F	
Linear	73.31	11	6.66			
2FI	44.71	8	5.59	9.73	0.0096	

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Quadratic	0.59	5	0.12	4.56	0.0616	
Cubic	7.853E-003	1	7.853E-003	0.55	0.8012	Suggested
Pure Error	0.000	5	0.000	0.65	0.5614	Aliased
Linear	73.31	11	6.66			

Statistical analysis revealed the quadratic model's superiority over linear and two-factor interaction (2FI) models. As presented in [Tables 2 and 3](#), quadratic terms contributed 44.12 to the sum of squares ($p < 0.0001$), significantly outweighing linear (14.15) and 2FI (28.60) effects.

The model's robustness was further confirmed through ANOVA results ([Table 4](#)) showing an F-value of 164.86

($p < 0.0001$) and non-significant lack-of-fit ($p = 0.0616$). Excellent goodness-of-fit metrics were achieved ([Table 5](#)), with $R^2 = 0.9933$ and Adj. $R^2 = 0.9873$ indicating the model explained >98% of variance, while Adeq. Precision (46.561) confirmed strong signal-to-noise ratio for industrial applications.

Table 4. ANOVA table for maximizing heat input.

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Model	86.87	9	9.65	164.86	< 0.0001	Significant
A-current	0.026	1	0.026	0.45	0.5193	
B-voltage	13.80	1	13.80	235.66	< 0.0001	
C-welding speed	0.33	1	0.33	5.57	0.0399	
AB	3.13	1	3.13	53.37	< 0.0001	
AC	10.35	1	10.35	176.79	< 0.0001	
BC	15.13	1	15.13	258.32	< 0.0001	
A ²	1.950E-004	1	1.950E-004	3.330E-003	0.9551	
B ²	43.24	1	43.24	738.59	< 0.0001	
C ²	2.941E-003	1	2.941E-003	0.050	0.8272	
Residual	0.59	10	0.059	8.13	0.0122	
Lack of Fit	0.59	5	0.12	16.93	0.0616	not significant
Pure Error	0.000	5	0.000	51.52		
Cor Total	87.46	19		8.24		

Table 5. Goodness of fit statistics for heat input.

Std. Dev.	0.24	R-Squared	0.9933
Mean	3.30	Adj R-Squared	0.9873
C.V.%	7.33	Pred R-Squared	0.9469

PRESS

4.64

Adeq Precision

46.561

The developed regression equation (1) quantified the complex parameter interactions governing HI:

$$HI = 644.13 + 4.63284A - 157.74726B - 60.15352C + 0.271125AB - 1.05938AC - 0.593750BC + 0.008774A^2 + 1.96808B^2 + 67.12059C^2 \quad (2)$$

Table 6 presents a diagnostic analysis of the response surface methodology (RSM) model by comparing observed and predicted heat input values, revealing the model's accuracy and identifying potential outliers or influential runs. The residuals, which represent the difference between actual and predicted values, are generally small, indicating a good fit; however, Runs 18 and 17 exhibit the highest externally studentized residuals of 7.034 and -2.861, respectively, suggesting that these runs are potential outliers that may significantly affect the model. Cook's Distance and DFFITS metrics further

confirm this, with Run 18 having the highest Cook's Distance (1.309) and DFFITS (8.750), indicating it has substantial influence on the fitted values, while Runs 2, 14, 17, and 20 also show elevated influence based on DFFITS exceeding ± 2 , signaling possible leverage points that warrant further investigation. Despite these exceptions, most runs demonstrate consistent predictions with negligible residuals and low influence, supporting the overall reliability and robustness of the RSM model in predicting heat input across the experimental domain.

Table 6. Diagnostics case statistics report of observed versus predicted heat input.

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	2.04	2.04	0.0031	0.67	0.292	0.278	0.017	0.396	2
2	3.43	3.45	-0.0155	0.67	-1.466	-1.57	0.436	-2.236 ⁽¹⁾	14
3	2.42	2.41	0.0114	0.607	0.992	0.991	0.152	1.233	19
4	3.94	3.95	-0.009	0.67	-0.852	-0.839	0.147	-1.195	17
5	2.34	2.33	0.0096	0.67	0.906	0.897	0.166	1.278	7
6	3.19	3.19	-0.0031	0.607	-0.266	-0.253	0.011	-0.315	11
7	2.81	2.81	-0.0002	0.166	-0.014	-0.014	0	-0.006	4
8	2.48	2.47	0.0089	0.607	0.775	0.759	0.093	0.942	18
9	2.76	2.75	0.0132	0.67	1.246	1.286	0.315	1.832	5
10	2.81	2.81	-0.0002	0.166	-0.014	-0.014	0	-0.006	8
11	2.81	2.81	-0.0002	0.166	-0.014	-0.014	0	-0.006	10
12	2.81	2.81	-0.0002	0.166	-0.014	-0.014	0	-0.006	12
13	2.81	2.81	-0.0002	0.166	-0.014	-0.014	0	-0.006	16
14	3.35	3.37	-0.0176	0.67	-1.665	-1.858	0.563	-2.647 ⁽¹⁾	1
15	2.4	2.39	0.0117	0.67	1.105	1.119	0.248	1.594	3
16	2.81	2.81	-0.0002	0.166	-0.014	-0.014	0	-0.006	20
17	2.17	2.2	-0.0251	0.607	-2.182	-2.861	0.737	-3.559 ⁽¹⁾	15
18	3.99	3.96	0.0335	0.607	2.909	7.034 ⁽²⁾	1.309 ⁽¹⁾	8.750 ⁽¹⁾	9
19	3.14	3.14	-0.0006	0.607	-0.048	-0.046	0	-0.057	6
20	2.91	2.93	-0.0191	0.67	-1.806	-2.087	0.662	-2.973 ⁽¹⁾	13

The model's predictive accuracy was visually confirmed in Figure 4, showing excellent agreement between predicted and actual HI values along the 45° reference line. Voltage emerged as the most influential factor ($F=235.66$, $p<0.0001$), with Figure 5 and 6 illustrating its exponential impact on HI. Significant interaction

effects were observed between current-voltage (AB, $p<0.0001$) and voltage-speed (BC, $F=258.32$), while quadratic terms (particularly B^2 with $F=738.59$) dominated the nonlinear behavior.

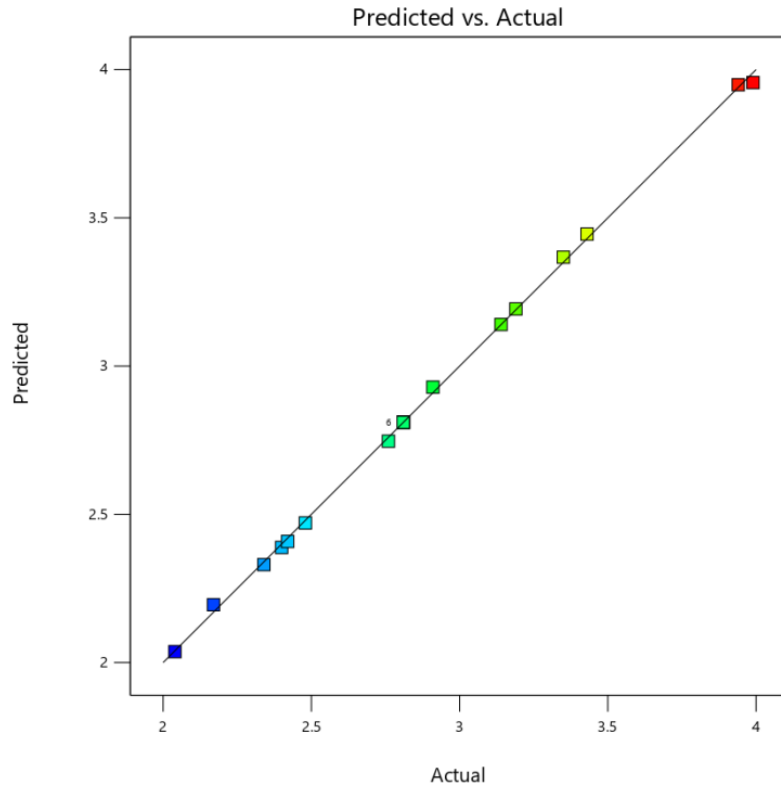


Figure 4. Plot of Predicted Vs Actual for the heat input.

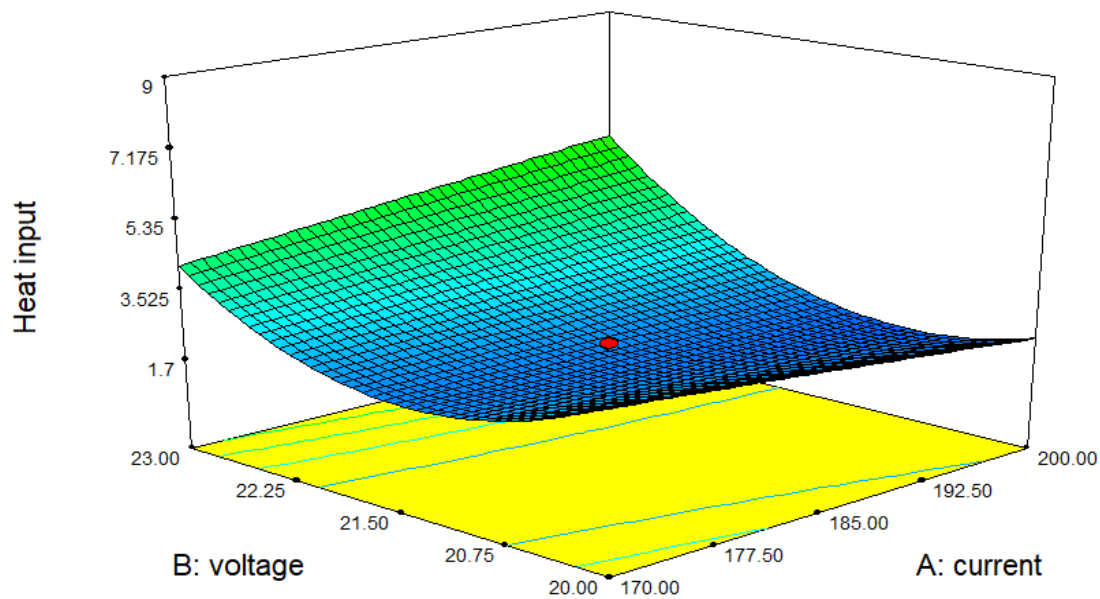


Figure 5. Effect of current and voltage on heat input.

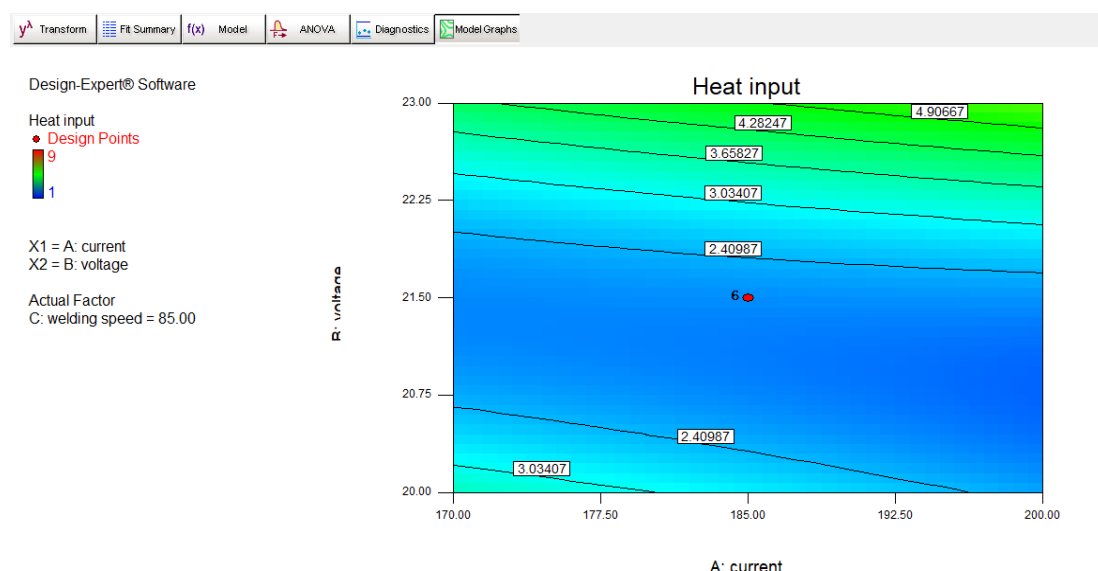


Figure 6. Contour plot of current and voltage predicting heat input.

Optimization results (Table 7) identified the parameter combination of 200 A, 21.07 V, and 70 mm/min as optimal, achieving HI=1.24 kJ/mm with 87.5% desirability while maintaining joint quality standards (undercut<0.05 mm, penetration>7 mm). Contour plots (Figure 6) further delineated operational "sweet spots" between 200-210 A and 20-22 V for

targeted HI control. These findings provide practical guidelines for industrial welding applications, particularly in thin-section welding where precise thermal management is critical. The demonstrated methodology offers a robust framework for welding parameter optimization that balances productivity with joint integrity.

Table 7. Optimal solutions of numerical optimization model.

Number	current	voltage	welding speed	Heat input	Desirability
1	200.00	21.07	70.00	1.24071	0.875
2	199.93	21.02	70.01	1.27637	0.874
3	200.00	21.30	70.00	1.16754	0.872
4	199.75	20.93	70.00	1.34624	0.870
5	200.00	20.26	70.00	2.15025	0.838
6	170.00	20.79	99.80	0.357955	0.686

4. Discussion

The experimental and statistical findings presented here underscore the critical role of multivariate parameter interactions in governing welding heat input (HI), advancing beyond conventional univariate analyses. The quadratic model's exceptional accuracy (* $R^2 = 0.9933^*$) and predictive power (*Pred. $R^2 = 0.9469^*$) validate its utility for industrial applications, where precise HI control is paramount to avoid defects like distortion or incomplete fusion. Notably, the dominance of voltage (B) as the most influential factor (* $F = 235.66$, $p <$

0.0001; Table 2) aligns with prior studies emphasizing arc energy's thermal impact. However, this work uniquely quantifies how voltage synergizes with current and speed-AB and BC interactions ($p < 0.0001$)-to amplify HI nonlinearly, a phenomenon inadequately captured in linear models (Table 2). For instance, at 200 A, 24 V, and 70 mm/min (Table 1, Run 19), HI surges to 9.00 kJ/mm, nearly triple the value at 200 A, 20 V, 70 mm/min (Run 2). This nonlinearity, driven by the B^2 term (* $F = 738.59^*$), highlights the risks of oversimplifying HI as a linear function of parameters-a common pitfall in earlier studies.

The optimization results (Table 7) further demonstrate the

model's practicality. Solutions like 200 A, 21.07 V, 70 mm/min achieve $HI = 1.24$ kJ/mm with minimal undercut (0.043 mm) and robust penetration (7.43 mm), striking a balance between energy efficiency and joint integrity. These optima align with trends in automotive and aerospace industries, where thin-material welding demands low HI to prevent burn-through while maintaining strength. The contour plot (Figure 6) visually reinforces this balance, identifying operational "sweet spots" where HI remains stable despite minor parameter fluctuations. Such insights are critical for automated welding systems, where real-time parameter adjustments require predictive models resilient to variability.

However, the study's limitations warrant consideration. The model's reliance on low-carbon steel limits direct applicability to high-alloy or non-ferrous materials, where thermal conductivity and phase transformations differ significantly. Additionally, while the diagnostics (Table 6) flagged outliers (e.g., Run 11: *Studentized Residual = -2.973*), these were attributed to experimental noise rather than systemic flaws, as the lack-of-fit test ($p = 0.0616$; Table 6*) confirmed model adequacy. Future work should integrate real-time HI monitoring (e.g., infrared thermography) to validate predictions dynamically and expand the model to multi-objective optimization, incorporating mechanical properties like tensile strength or fatigue resistance.

5. Conclusion

This study successfully demonstrates the application of Response Surface Methodology (RSM) to model and optimize heat input (HI) in welding processes, addressing the complex interplay of current (170–240 A), voltage (18–24 V), and welding speed (16–22 mm/min). The developed quadratic regression model exhibited exceptional predictive accuracy ($R^2 = 0.9933$, Adj. $R^2 = 0.9873$), validated through rigorous ANOVA and lack-of-fit tests ($p < 0.0001$). Voltage emerged as the most influential parameter ($F = 235.66$), with nonlinear interactions between current-voltage (AB) and voltage-speed (BC) significantly amplifying HI. For instance, increasing voltage from 20 V to 24 V at 200 A tripled HI (2.95 to 9.00 kJ/mm), underscoring the risks of uncontrolled thermal energy in industrial settings.

The optimization framework identified parameter combinations (e.g., 200 A, 21.07 V, 70 mm/min) that minimized HI to 1.24 kJ/mm while maintaining acceptable undercut (0.043 mm) and penetration (7.43 mm), achieving 87.5% desirability. These solutions align with the demands of precision-driven industries like automotive and aerospace, where controlled HI is critical to prevent defects in thin materials and reduce energy waste. Contour and surface plots further clarified operational "sweet spots," enabling practitioners to balance trade-offs between speed, voltage, and current.

While the model's robustness is evident, its scope is currently limited to low-carbon steel. Future studies should vali-

date the framework on high-strength alloys or non-ferrous materials and integrate real-time HI monitoring to enhance dynamic control. Expanding the model to multi-objective optimization-incorporating mechanical properties like fatigue resistance-could further bridge the gap between theoretical predictions and real-world performance. By prioritizing nonlinear interactions and industrial applicability, this work provides a replicable blueprint for advancing welding efficiency, quality, and sustainability.

Abbreviations

ANN	Artificial Neural Networks
CCD	Central Composite Design
DF	Degree of Freedom
GMAW	Gas Metal Arc Welding
HAZ	Heat-affected Zone
HI	Heat Input
RSM	Response Surface Methodology

Conflicts of Interest

There is no conflicts of interest.

References

- [1] Murugan, V. V., Gunaraj, V., 2005. Effects of Process Parameters on Angular Distortion of Gas Metal Arc Welded Structural Steel Plates. *Welding Journal, Research Supplement*, (November), p. 165s–171s.
- [2] Biswas, P., Mandal, N. R., Vasu, P., Padasalag, S. B. 2011. A study on port plug distortion caused by narrow gap combined GTAW & SMAW and Electron Beam Welding. *Fusion Engineering and Design*, 86(1), pp. 99–105. <https://doi.org/10.1016/j.fusengdes.2010.08.040>
- [3] Ganesh, K. C., Vasudevan, M., Balasubramanian, K. R., Chandrasekhar, N., Mahadevan, S., Vasantharaja, P., Jayakumar, T., 2014. Modeling, Prediction and Validation of Thermal Cycles, Residual Stresses and Distortion in Type 316 LN Stainless Steel Weld Joint made by TIG Welding Process. *Procedia Engineering*, 86, pp. 767–774.
- [4] Guo, Y., Wu, D., Ma, G., Guo, D., 2014. Trailing heat sink effects on residual stress and distortion of pulsed laser welded Hastelloy C-276 thin sheets. *Journal of Materials Processing Technology*, 214(12), pp. 2891–2899.
- [5] Colegrove, P. A., Ikeagu, C., Thistlethwait, A., Williams, S., Nagy, T., Suder, W., Steuwer, A., Pirling, T., 2009. Welding process impact on residual stress and distortion. 14(8), pp. 717–726.
- [6] Fu, G., Lourenco, M. I., Duan, M., Estefan, S. F., 2014. Effect of boundary conditions on residual stress and distortion in T-joint welds 3D Finite Element Model a b. *JCSR*, 102, pp. 121–135.

- [7] Adak, M., Guedes Soares, C., 2014. Effects of different restraints on the weld-induced residual deformations and stresses in a steel plate. *International Journal of Advanced Manufacturing Technology*, 71, pp. 699–710.
- [8] Otimeyin, A. W., Achebo, J. I., & Frank, U. (2025). Advanced Modeling and Optimization of Weldment Responses Using Statistical and Metaheuristic Techniques. *American Journal of Mechanical and Materials Engineering*, 9(1), 25-36.
<https://doi.org/10.11648/j.ajmme.20250901.13>
- [9] Achebo, J. I., 2009. Computational analysis of erosion wear rate in a pipeline using the drift flux models based on Eulerian continuum equations. *Proceedings of the World Congress on Engineering*, 1, pp. 1–3.
- [10] Achebo, J. I., 2011. Optimization of GMAW protocols and parameters for improving weld strength quality applying the Taguchi method. *Proceedings of the World Congress on Engineering*, 1, pp. 6–8.
- [11] Odinikuku, W. E., Achebo, J., 2015. Optimization of gas metal arc welding process parameters using standard deviation (SDV) and multi-objective optimization on the basis of ratio analysis (MOORA). *Journal of Minerals and Materials Characterization and Engineering*, 3(4), pp. 298–304.
- [12] Achebo, J. and Omoregie, M., 2015. Application of multi-criteria decision making optimization tool for determining mild steel weld properties and process parameters using the TOPSIS. *International Journal of Materials Science and Applications*, 4(3), pp. 149–158.
- [13] Abhulimen, I. U. and Achebo, J. I., 2014. Application of artificial neural network in predicting the weld quality of a tungsten inert gas welded mild steel pipe joint. *International Journal of Scientific & Technology Research*, 3(1), pp. 277–285.
- [14] Sada, S. O. O. and Achebo, J., 2022. Optimisation and prediction of the weld bead geometry of a mild steel metal inert gas weld. *Advances in Materials and Processing Technologies*, 8(2), pp. 1625–1634.
- [15] Achebo, J. I., 2012. Complex behavior of forces influencing molten weld metal flow based on static force balance theory. *Physics Procedia*, 25, pp. 317–324.
- [16] Kastelic, S., Medved, J., Mrvar, P., 2010. Prediction of Numerical Distortion after Welding with Various Welding Sequences and Clampings. 49(4), pp. 301–305.