

Modeling and Parametric Optimization of Gas Metal Arc Welding for Inconel 625 and UNS S31603 Using RSM and ANN

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Abstract - Wire Arc Additive Manufacturing (WAAM) is an advanced metal deposition process that requires precise process parameter control to achieve desirable bead geometry, structural integrity, and dimensional accuracy. In this study, Inconel 625 was used as the filler material on a UNS S31603 austenitic stainless steel substrate. Single-bead deposition experiments were designed using a Box-Behnken Design (BBD) L27 orthogonal array. The key input parameters investigated were Voltage (V), Wire Feed Rate (WFR), Gas Flow Rate (GFR), and Travel Speed (TS). The output responses analyzed were Bead Width (BW), Bead Height (BH), and Depth of Penetration (DOP). Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) were employed to develop predictive models. RSM achieved R^2 values of 95.14% for DOP, 98.78% for BW, and 95.40% for BH, while the ANN model attained R^2 values of 0.8454, 0.9316, and 0.7359 for DOP, BW, and BH respectively. ANOVA results confirmed that two-way interaction effects are the dominant contributors to bead geometry variation. The ANN model demonstrated superior capability in capturing nonlinear relationships, while both models proved reliable for WAAM process prediction and optimization.

Key Words: GMAW; Inconel 625; UNS S 31603; RSM; ANN; Bead Geometry; Box-Behnken Design.

1. INTRODUCTION

Additive Manufacturing (AM) represents a paradigm shift from conventional subtractive processes by building components layer by layer, thereby reducing material wastage and enabling complex geometries. In contrast to traditional methods where excess material is removed to achieve the desired shape, AM focuses on adding material only where it is needed, which enhances efficiency and sustainability. This approach not only minimizes waste but also allows for the creation of intricate designs that are difficult or impossible to produce using conventional manufacturing techniques. Furthermore, AM enables greater design flexibility, reduced tooling requirements, and shorter production cycles, making it highly suitable for advanced engineering applications.

Among AM techniques, Wire Arc Additive Manufacturing (WAAM) has emerged as a highly promising method for large-scale metallic component

fabrication, owing to its high deposition rate, cost-effectiveness, and compatibility with standard welding infrastructure [1]. WAAM utilizes an electric arc as a heat source and metal wire as feedstock, similar to traditional arc welding processes, which allows it to leverage existing welding equipment and expertise. Its ability to produce large components efficiently makes it particularly attractive for industries such as aerospace, shipbuilding, and heavy engineering. Additionally, WAAM offers advantages such as high material utilization and flexibility in material selection, although challenges related to surface finish and residual stresses still need to be addressed.

Gas Metal Arc Welding (GMAW), also known as MIG/MAG welding, serves as the deposition source in WAAM. The process uses a continuously fed consumable wire electrode and a shielding gas to protect the molten weld pool from atmospheric contamination. GMAW is widely adopted in WAAM due to its high deposition efficiency, ease of automation, and compatibility with a broad range of materials including stainless steels and nickel-based superalloys [2].

2. LITERATURE REVIEW

Dinovitzer et al. [1] investigated WAAM process parameters for Hastelloy X and demonstrated that travel speed and current significantly influence bead geometry and microstructure, with strong interlayer bonding confirming the importance of controlled heat input. Yu et al. [2] developed a vision-based neural network model for GMA additive manufacturing, achieving a mean absolute error below 0.11 mm for weld reinforcement prediction.

Ghosh et al. [3] applied ANN to predict bead geometry and distortion in WAAM, incorporating thermal history effects to improve multi-layer deposition accuracy. Vora et al. [4] confirmed that GMAW-based WAAM of UNS S31630 produces uniform mechanical properties comparable to conventionally manufactured materials. The same group [5] utilized Box-Behnken Design with the Teaching-Learning-Based Optimization (TLBO) algorithm to produce defect-free components with improved dimensional accuracy.

Le et al. [6] used the Taguchi L16 array combined with ANOVA, GRA, and TOPSIS for multi-response WAAM optimization, achieving R^2 values above 90%. Bhaskar et al. [7] compared SVM, ANN, and ANFIS models, ANFIS showing the lowest RMSE. Yan et al. [8] developed a deep

neural network for WAAM bead geometry prediction that outperformed traditional regression models.

A key research gap identified is the limited use of hybrid RSM-ANN approaches for multi-material WAAM systems. Most studies focus on a single material, with few comparing dissimilar combinations such as Inconel 625 on stainless steel substrates. This work addresses this gap directly.

3. MATERIALS AND METHODS

3.1 Materials

The filler material selected was Inconel 625 wire (ERNiCrMo-3), a nickel-based superalloy composed primarily of Ni (60–65%), Cr (20–23%), and Mo, with additions of Nb (3.15–4.15%) and Fe ($\leq 5\%$). It offers high strength, excellent corrosion and oxidation resistance up to $\sim 980^\circ\text{C}$, and good weldability without post-weld heat treatment. The substrate material was UNS S31603, a low-carbon ($\text{C} \leq 0.03\%$) austenitic stainless steel from the 316 family. Its low carbon content prevents sensitization during welding, and its excellent ductility and toughness make it an ideal substrate for WAAM.

Table-1: Chemical Composition of Inconel 625 (wt%)

Element	Ni	Cr	Mo	Nb	Fe	C
Wt%	60–65	20–23	8–10	3.15–4.15	≤ 5	≤ 0.1



Fig-1: Inconel 625 Filler Wire

Fig-2: UNS S31603 Substrate



Experiments were conducted using a KUKA KR10 R1420 HP 6-axis robotic MIG welding system with position repeatability of ± 0.05 mm and path repeatability < 0.05 mm. Single-bead depositions were made on UNS S31603 plates under controlled conditions. After deposition, specimens were sectioned, polished, and etched with a Nital solution (2–5% nitric acid in methanol, 5–15 seconds) to reveal weld geometry. Bead Width (BW), Bead Height (BH), and Depth of



Penetration (DOP) were measured using a profile projector, providing a magnified and precise cross-sectional view.

Fig-3 KUKA KR10 R120 HP Welding Robot

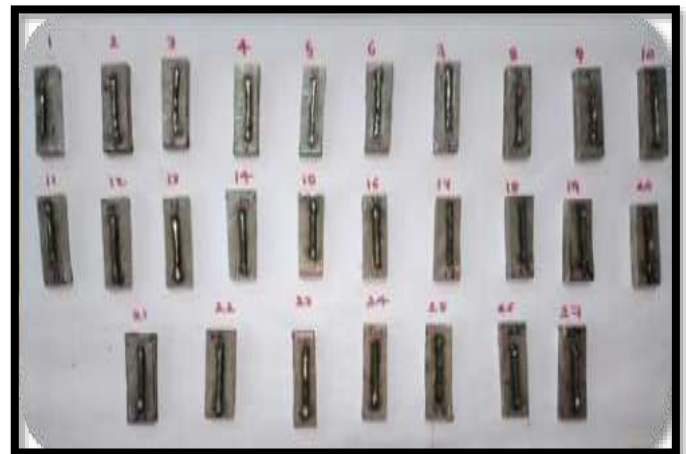


Fig-4: Deposited Weld Beads on UNS S31603 Plate

Design of Experiments

A Box–Behnken Design (BBD) with four factors and three levels was employed to design 27 experimental runs. BBD was selected for its efficiency, avoidance of extreme parameter

Table-2: Process Parameters and Levels

Parameter	Symbol	Low (-1)	Mid (0)	High (+1)
Voltage (V)	V	20	24	28
Wire Feed Rate (m/min)	WFR	4.5	5.5	6.5
Gas Flow Rate (L/min)	GFR	10	14	18
Travel Speed (mm/min)	TS	240	340	440

combinations, and suitability for developing quadratic response surface models.

Modeling Approaches

RSM was applied using Minitab to develop second-order polynomial regression models. ANOVA was performed to evaluate statistical significance of model terms using F-values and P-values. Model adequacy was verified using R^2 , adjusted R^2 , and predicted R^2 . An ANN was implemented in MATLAB (Neural Network Toolbox) with a feedforward 4-10-3 architecture. The Levenberg–Marquardt algorithm was used for training with 70% training / 15% validation / 15% testing split. The model converged after 13 epochs with MSE reducing from 0.798 to 0.000294.

4. EXPERIMENTAL RESULTS

The 27 experiments were conducted varying Voltage (20–28 V), WFR (4.5–6.5 m/min), GFR (10–18 L/min), and Travel Speed (240–440 mm/min). The depth of penetration ranged from 1.18 mm to 2.47 mm, bead width from 2.88 mm to 4.91 mm, and bead height from 2.43 mm to 3.97 mm, demonstrating significant sensitivity of bead geometry to parameter variations.

Table-3: Experimental Results (Selected Runs)

Run	V	WFR	GFR	TS	DOP	BW	BH
1	20	6.5	14	340	1.26	3.30	2.95
4	24	6.5	14	240	1.81	4.35	3.33
7	24	4.5	14	240	1.40	4.85	3.82
10	24	4.5	10	340	1.41	4.31	3.97
13	24	5.5	14	340	1.75	4.14	3.22
16	24	4.5	18	340	2.47	4.91	3.73
19	24	5.5	18	440	2.06	3.23	2.86
22	28	4.5	14	340	2.44	3.20	2.84
26	24	5.5	18	240	1.98	3.91	3.10
27	28	5.5	14	440	1.24	4.33	3.27

RSM MODELING AND ANOVA

Depth of Penetration (DOP)

The RSM model for DOP achieved $R^2 = 95.14\%$, adjusted $R^2 = 89.46\%$, and predicted $R^2 = 74.87\%$, with standard error $S = 0.1248$ mm. ANOVA results revealed that two-way interaction effects dominate, contributing 76.56% of total variation. The most significant interactions were WFR $\times$ Voltage (21.79%), Voltage $\times$ TS (21.08%), WFR $\times$ GFR (18.80%), and WFR $\times$ TS (14.45%). Among linear terms, Gas Flow Rate (6.12%) had the highest individual contribution. The lack-of-fit was not significant ($P = 0.605$), confirming good model fit.

Table-4: RSM Model Summary

Response	S	R ² (%)	R ² Adj(%)	R ² Pred(%)
DOP	0.1248	95.14	89.46	74.87
BW	0.0677	98.78	97.36	93.23
BH	0.1288	95.40	90.04	76.06

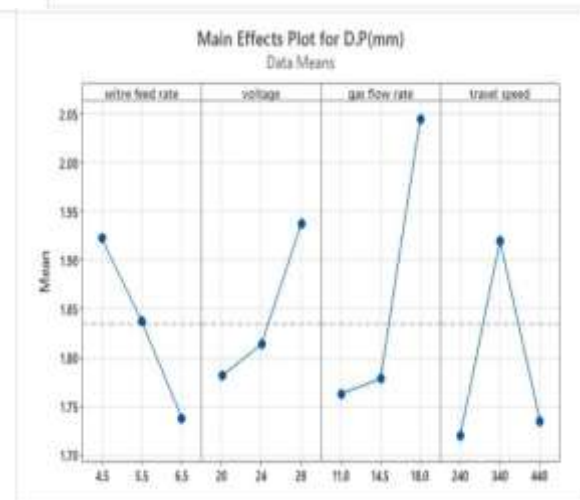
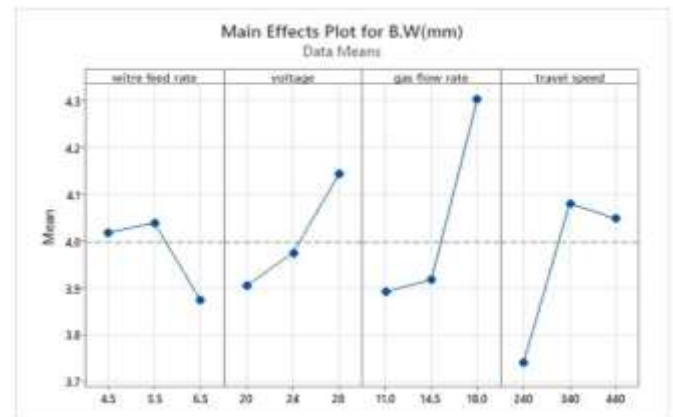


Fig-5: Main Effects Plot for Depth of Penetration

From the slope magnitudes in the main effects plot, gas flow rate has the strongest influence on depth of penetration, followed by wire feed rate and travel speed, while voltage has a comparatively moderate effect. Optimal penetration appears to occur at low wire feed rate, high voltage, high gas flow rate, and moderate travel speed.

The response surface analysis confirms that voltage is the most dominant factor enhancing depth of penetration, while wire feed rate negatively affects penetration. Optimal welding performance, in terms of maximum D.P., is obtained at high voltage and low wire feed rate. Therefore, careful control and balancing of these parameters are essential to achieve the desired weld quality and penetration characteristics as shown in Fig.6.

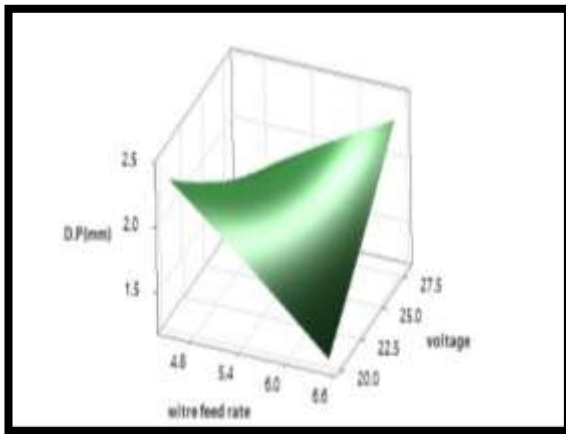


Fig-6: Surface Plot of DOP vs Voltage & Wire Feed Rate

Bead Width (BW)

The Bead width model showed the highest predictive accuracy, with $R^2 = 98.78\%$, adjusted $R^2 = 97.36\%$, and predicted $R^2 = 93.23\%$. Two-way interaction terms contributed 66.61% of variation, with $WFR \times GFR$ (38.06%) being most dominant, followed by $WFR \times Voltage$ (14.19%) and $Voltage \times TS$ (7.46%). Gas Flow Rate (11.09%) and Travel Speed (6.26%) were most influential linear terms. The insignificant lack-of-fit ($P = 0.264$) confirms excellent model adequacy.

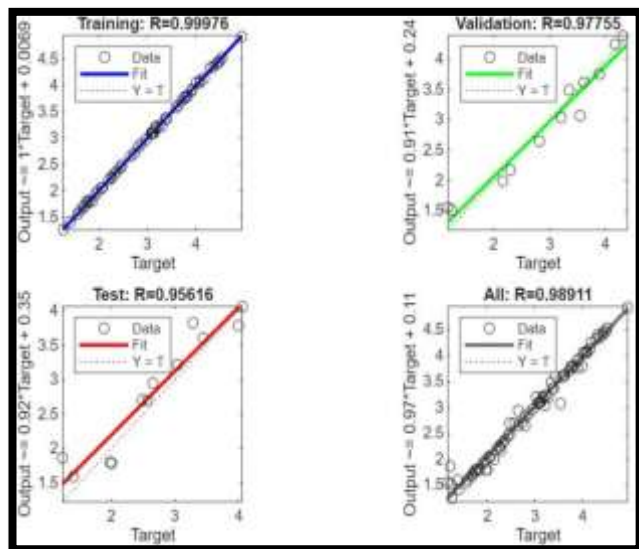


Fig-7: Main Effects Plot for Bead Width

Bead Height (BH)

The BH model achieved $R^2 = 95.40\%$ with adjusted $R^2 = 90.04\%$. Travel Speed was the most dominant linear factor (29.73%), governing heat input per unit length, followed by Gas Flow Rate (5.50%). Interaction effects contributed 47.10% of variation, with $WFR \times GFR$ (32.44%) and $GFR \times TS$ (11.32%) being most significant. Quadratic terms contributed 11.56%. The lack-of-fit was insignificant ($P = 0.575$).

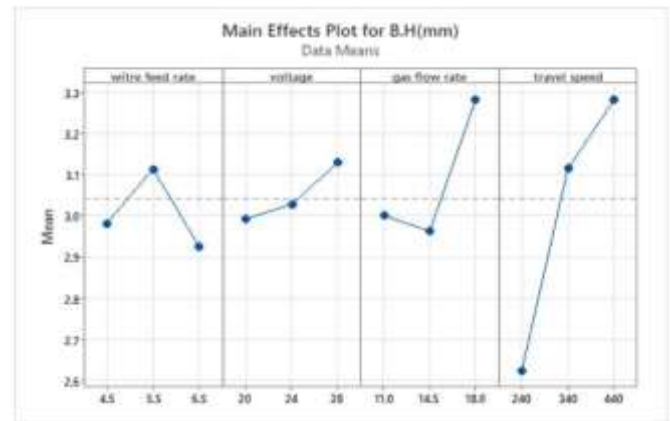


Fig-8: Main Effects Plot for Bead Height

ANN MODELING

Network Architecture and Training

A feedforward ANN with architecture 4-10-3 (input-hidden-output) was trained using the Levenberg-Marquardt algorithm in MATLAB. The network mapped the four process parameters (V, WFR, GFR, TS) to three bead geometry outputs (DOP, BW, BH). Training halted after 13 epochs due to early stopping based on validation performance, preventing overfitting. The MSE improved from 0.798 to 0.000294, demonstrating rapid convergence. The overall regression coefficient was $R = 0.98911$, with training $R = 0.99976$ and validation $R = 0.97755$.

Fig-9: ANN Regression of Backward Model

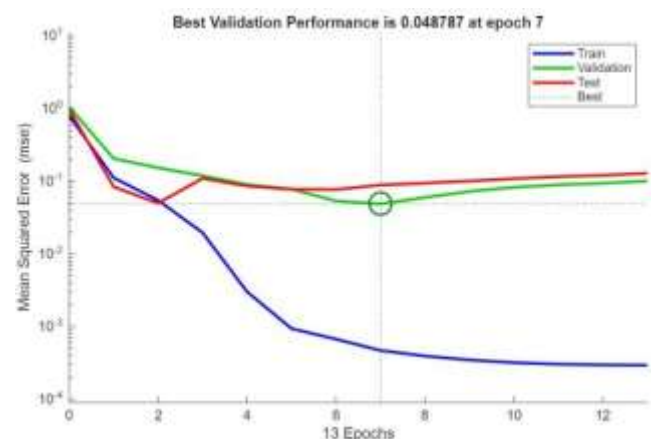


Fig-10: ANN Training Performance

ANN Prediction Performance

The ANN model achieved R^2 of 0.9316 for Bead Width, 0.8454 for Depth of Penetration, and 0.7359 for Bead Height. Prediction errors for DOP were mostly within ± 0.30 mm, bead height errors within ± 0.25 mm, and bead width exhibited the lowest prediction error.

Table-5: ANN Predicted vs. Experimental Values

Run	DOP Exp	DOP Pred	BW Exp	BW Pred	BH Exp	BH Pred
1	1.26	1.29	3.30	3.51	2.95	2.77
7	1.40	1.45	4.85	4.89	3.82	3.90
9	1.97	2.00	3.80	3.90	3.07	3.12
13	1.75	1.81	4.14	4.01	3.22	3.07
16	2.47	2.47	4.91	4.95	3.73	3.76

4. DISCUSSION

4.1 RSM vs. ANN Performance

Both RSM and ANN models demonstrated reliable predictive capability for WAAM bead geometry. The RSM models achieved high R^2 values ($>95\%$) for all three responses. The ANN model showed superior performance for Bead Width ($R^2 = 0.9316$) due to its ability to capture complex nonlinear interactions. The ANN's lower R^2 for BH (0.7359) suggests BH exhibits smoother, polynomial-like behavior that RSM captures more effectively. The combination of both methods provides a more complete process understanding.

4.2 Influence of Process Parameters

Voltage and Wire Feed Rate exert the most significant combined influence on DOP (21.79%), reflecting joint control of heat input and filler deposition. Gas Flow Rate emerged as a strong factor for BW (11.09%) and BH (5.50%) due to its effect on arc stability. Travel Speed is the primary linear driver of BH (29.73%), governing heat input per unit length. The dominance of two-way interactions (76.56%, 66.61%, 47.10% for DOP, BW, BH) reinforces the need for multivariate modeling.

4.3 Model Validation

RSM predicted R^2 values of 74.87%, 93.23%, and 76.06% for DOP, BW, BH confirmed adequate generalization. The ANN test set regression ($R = 0.95616$) further corroborated its generalization capability. Residual plots showed no systematic patterns, confirming model assumptions were satisfied.

5. CONCLUSION

- RSM models achieved high predictive accuracy with R^2 of 95.14% (DOP), 98.78% (BW), and 95.40% (BH), confirming strong statistical relationships

between WAAM process parameters and bead geometry.

- ANOVA identified two-way interaction effects as dominant contributors. WFR $\times$ GFR was most influential for BW (38.06%), Voltage $\times$ TS most affected DOP (21.08%), and Travel Speed was the primary linear factor for BH (29.73%).
- The ANN model (4-10-3 feedforward, Levenberg–Marquardt) achieved overall $R = 0.989$ and showed superior prediction accuracy for Bead Width due to its ability to capture complex nonlinear parameter interactions.
- Both RSM and ANN proved effective as complementary modeling tools. RSM provides interpretable statistical insight while ANN excels at nonlinear relationships. Hybrid use of both is recommended for WAAM process optimization.

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