



Comparative Analysis of Artificial Neural Network and Regression Modeling for Predicting Fusion Zone Width in TIG Welding

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Abstract

The geometric integrity of the fusion zone (FZ) is a critical determinant of weld quality in Tungsten Inert Gas (TIG) welding. This study presents a comparative analysis of Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) for modeling and predicting FZ width geometry in AISI 1020 mild steel weldments. Experiments were conducted using a Central Composite Design (CCD) comprising 30 runs, varying current, voltage, travel speed, and gas flow rate. A quadratic regression model was developed via RSM, yielding a high coefficient of determination ($R^2 = 0.9765$) and adequate precision (27.7872), indicating strong statistical fit within the design space. Concurrently, a feed-forward backpropagation ANN (4-10-1 architecture) was trained using the Levenberg-Marquardt algorithm, achieving an overall R^2 of 0.889. While RSM demonstrated superior interpolation accuracy for the experimental domain, the ANN model exhibited robust capability in capturing complex nonlinearities and generalizing across test subsets. The results confirm that both models are viable for process optimization, with RSM offering explicit mathematical relationships within the experimental domain and ANN providing flexible nonlinear mapping with strong generalization capability for unseen process conditions.

Subject Areas

Materials Engineering

Keywords

TIG Welding, Fusion Zone Width Geometry, Response Surface Methodology, Artificial Neural Network, AISI 1020

1. Introduction

Welding remains a cornerstone of modern manufacturing, with Tungsten Inert Gas (TIG) welding preferred for its precision and high-quality joint formation in critical applications involving structural steels like AISI 1020 [1]. The mechanical integrity of a welded joint is heavily dependent on the weld bead geometry, specifically the fusion zone (FZ) width, heat-affected zone (HAZ), and weld penetration area, which dictate load distribution and stress concentration; variations in these parameters can lead to defects such as incomplete fusion, excessive penetration, or reduced fatigue life, ultimately compromising structural reliability [2]-[6]. Consequently, the ability to predict and optimize weld geometry based on process parameters is essential for ensuring consistent quality in industrial fabrications.

Traditional optimization relies on trial-and-error methods, which are time-consuming, costly, and often fail to capture the multidimensional nature of welding variables. Mathematical modeling offers a systematic alternative, with Response Surface Methodology (RSM) widely used to develop empirical relationships between input parameters and responses using polynomial equations [2] [7]-[9]. By utilizing designs such as Central Composite Design (CCD), RSM effectively quantifies main effects and interactions, providing explicit mathematical models that are easy to interpret; however, welding processes involve complex thermal dynamics and nonlinear interactions that may not be fully captured by second-order polynomials, potentially limiting accuracy in highly volatile regimes [10] [11].

To address these nonlinear complexities, Artificial Neural Networks (ANN), inspired by biological neural systems, have emerged as powerful tools for modeling such processes due to their adaptive learning capabilities [12]-[14]. Unlike RSM, which relies on predefined functional forms, ANN models can map intricate input-output relationships through training algorithms like backpropagation without requiring prior knowledge of the physical underlying equations; this data-driven approach allows for greater flexibility in handling noisy experimental data and capturing high-order interactions that statistical regression might overlook, making ANN particularly suitable for the stochastic nature of arc welding [4] [10] [15] [16]. Various optimization and decision-making techniques have also been applied to welding problems, including Analytical Hierarchy Process (AHP), Fuzzy C-Means clustering, COPRAS-ARAS, and Taguchi methods, further demonstrating the breadth of approaches available for weld quality improvement [17]-[20].

Despite the individual success of both modeling techniques, comparative studies evaluating their predictive performance specifically on mild steel TIG welding remain limited in existing literature, as most research focuses on either statistical or machine learning approaches in isolation [21]-[24], leaving a gap in understanding which method offers superior robustness for specific parameter sets such as current, voltage, travel speed, and gas flow rate. Recent studies have demonstrated the application of RSM and ANN in predicting various weld characteristics, including thermal expansion, tensile strength, weld metal viscosity, residual stress, and droplet efficiency, yet a direct comparative benchmarking for fusion zone ge-

ometry in AISI 1020 TIG welding remains unreported [25]-[29]. Establishing a benchmark between these methods is crucial for engineers to select the most efficient modeling strategy for process control, especially when balancing computational cost against prediction accuracy. Furthermore, the integration of RSM and ANN with finite element methods and metaheuristic algorithms has shown promise in optimizing weld responses such as penetration area, von Mises stresses, and solidus temperature, indicating a growing trend toward hybrid data-driven frameworks [27] [30]-[33].

This study aims to bridge the identified gap by developing predictive models for FZ width geometry using both techniques on AISI 1020 mild steel weldments. The specific objectives are to: identify significant welding parameters influencing FZ width through systematic experimentation; develop predictive models using RSM and ANN based on CCD data; and compare their performance metrics to determine the most robust approach for process optimization. By validating these models against experimental data, this research provides a comprehensive framework for enhancing weld quality prediction and optimizing parameters for desired weld zone characteristics, contributing to the broader advancement of data-driven welding process optimization [34]-[37].

2. Methodology

2.1. Material and Equipment

The base material selected for this investigation was AISI 1020 mild steel, cut into coupons measuring 100 mm × 50 mm × 6 mm. ER70S-6 filler wire was used for all welds. Chemical uniformity was confirmed through supplier certification. Prior to welding, samples were cleaned with acetone to remove surface contaminants, ensuring reliable arc initiation.



Figure 1. Miller Synchrowave 350 LX TIG welding machine/Butt Welded Joint.

Welding was performed using a Miller Synchrowave 350 LX TIG machine (**Fig-**

ure 1) configured with Direct Current Electrode Negative (DCEN) polarity. A 2.4 mm diameter 2% thoriated tungsten electrode was employed, with 99.99% pure argon serving as the shielding gas. A square groove butt joint with a 2 mm root gap was utilized to simulate industrial practices. The welding was conducted in a single pass without edge beveling, as the 6 mm thickness allowed for adequate penetration. The torch was maintained at a travel angle of 70° to 80° relative to the workpiece, and the plates were rigidly clamped to a steel backing fixture to minimize excessive movement while accommodating thermal expansion.

2.2. Experimental Design

Four critical process parameters were identified: Current (A), Voltage (V), Travel Speed (S), and Gas Flow Rate (GFR). The experimental design was structured using Response Surface Methodology (RSM) based on a Face-Centered Central Composite Design (FCCD). The parameters were varied across five levels, coded from -1 to +1 for the factorial points, with the axial points located at $\alpha = 1$ (face-centered). The design comprised 16 factorial points, 8 axial points, and 6 center-point replicates (coded as 0), resulting in a total of 30 experimental runs (Table 1).

Table 1. Welding parameters and levels.

Parameter	Unit	Min	Max	Mean
Current (A)	Amp	130	170	151.33
Voltage (V)	Volts	20	24	21.87
Speed (S)	mm/s	40	60	50
Gas Flow (GFR)	L/min	13	17	15.13

2.3. Data Collection and Preprocessing

Post-weld, samples were sectioned at the mid-length transverse cross-section. The cross-sections were mounted, ground, polished, and etched using a 2% nital solution to reveal the macrostructure. The Fusion Zone (FZ) width was measured metallographically using an optical microscope equipped with digital image analysis software. To ensure accuracy, three readings were taken across the width of the fusion zone at the mid-thickness and averaged for each plate. All measurements were conducted after the samples had completely cooled to room temperature to eliminate thermal expansion effects. The dataset was cleaned and normalized prior to modeling. For ANN development, the data was randomly partitioned into training (70%), validation (15%), and testing (15%) subsets to ensure unbiased evaluation of generalization capability.

2.4. Modeling Approaches

Response Surface Methodology (RSM): A second-order polynomial model was fitted using Design-Expert Version 13. The model adequacy was verified using Analysis of Variance (ANOVA), lack-of-fit tests, and diagnostic plots.

Artificial Neural Network (ANN): Modeling was performed using MATLAB 2021a Neural Network Toolbox. A feedforward backpropagation network with a 4-10-1 architecture (4 inputs, 10 hidden neurons, 1 output) was selected. The number of hidden neurons was determined empirically through a trial-and-error tuning process, testing hidden layers ranging from 4 to 15 neurons. The 10-neuron configuration was chosen as it minimized the Mean Squared Error (MSE) on the validation set without causing overfitting, aligning with the heuristic range suggested by standard neural network design principles. To establish a baseline and highlight the advantage of the nonlinear mapping capability of the ANN, a simple Multiple Linear Regression (MLR) model was also developed. The MLR model yielded a significantly lower R^2 of 0.76, confirming that the ANN architecture provides a substantial improvement in capturing the complex, nonlinear interactions of the welding process. The network was trained using the Levenberg-Marquardt algorithm. The Tangent Sigmoid function was used for the hidden layer, and a linear function for the output layer.

3. Results and Discussion

3.1. RSM Model Development and Analysis

Presented in **Table 2** is the experimental results for Fusion Zone width. Review of the experimental dataset indicates that the maximum Fusion Zone width of 11.23 mm was achieved in Run 21, corresponding to a Current of 150 A, Voltage of 20 V, Travel Speed of 50 mm/s, and Gas Flow Rate of 13 L/min. This condition represents the optimal balance of heat input and fluid dynamics within the tested domain. RSM and ANN predictions are compared to these experimental results.

Table 2. Experimental result.

	Factor 1	Factor 2	Factor 3	Factor 4	Response 1
Run	A	B	C	D:GFR	Fuzion Zone Width
	Amp	Volts	mm/s	L/min	mm
1	130	20	50	15	9.5
2	170	20	50	15	9.79
3	130	24	50	15	7.35
4	170	24	50	15	10.09
5	150	22	40	13	8.04
6	150	22	60	13	9.86
7	150	22	40	17	9.49
8	150	22	60	17	4.54
9	130	22	50	13	7.51
10	170	22	50	13	11.08
11	130	22	50	17	8.12
12	170	22	50	17	6.88

Continued

13	150	20	40	15	10.4
14	150	24	40	15	8.09
15	150	20	60	15	7.39
16	150	24	60	15	8.17
17	130	22	40	15	9.26
18	170	22	40	15	9.31
19	130	22	60	15	6.27
20	170	22	60	15	9.23
21	150	20	50	13	11.23
22	150	24	50	13	8.04
23	150	20	50	17	6.99
24	150	24	50	17	8.58
25	150	22	50	15	7.89
26	150	22	50	15	7.97
27	150	22	50	15	8.4
28	170	20	60	17	5.54
29	170	20	40	17	8.33
30	150	22	50	15	8.02

The fit summary indicated that the quadratic model was statistically superior to linear and two-factor interaction models. The quadratic model yielded a sequential p-value of 0.0002 and a non-significant lack-of-fit ($p = 0.2681$), confirming adequacy (See **Table 3**).

Table 3. Fit summary for fusion zone width.

Source	Sequential p-value	Lack of Fit p-value	Adjusted R ²	Predicted R ²	
Linear	0.005	0.0072	0.346	0.1398	
2FI	<0.0001	0.0637	0.8597	0.7138	
Quadratic	0.0002	0.2681	0.9545	0.8744	Suggested
Cubic	0.1688	0.4373	0.9768		Aliased

Model significance and Lack of Fit are presented in the ANOVA shown in **Table 4**. The model was significant and Lack of Fit was not significant, which agrees with literature for quadratic modeling.

The model exhibited a high coefficient of determination ($R^2 = 0.9765$) and adjusted $R^2 = 0.9545$ as presented in **Table 5**. The adequate precision ratio of 27.7872 indicated an excellent signal-to-noise ratio. All main effects (Current, Voltage, Speed, GFR) were significant ($p < 0.05$). Notably, Gas Flow Rate showed the highest F-value (96.82), suggesting a dominant influence on FZ width within the tested range. Interaction terms such as Current $\times$ Speed (AC) and Voltage $\times$ GFR (BD)

were also significant, highlighting the complex interplay of parameters.

Table 4. ANOVA for quadratic model (FZ width).

Source	Sum of Squares	F-value	p-value	Significance
Model	65.13	44.5	<0.0001	Significant
A-Current	6.67	63.83	<0.0001	
B-Voltage	2.5	23.96	0.0002	
C-Speed	6.13	58.61	<0.0001	
D-GFR	10.12	96.82	<0.0001	
Lack of Fit	1.41	2.3	0.2681	Not Significant

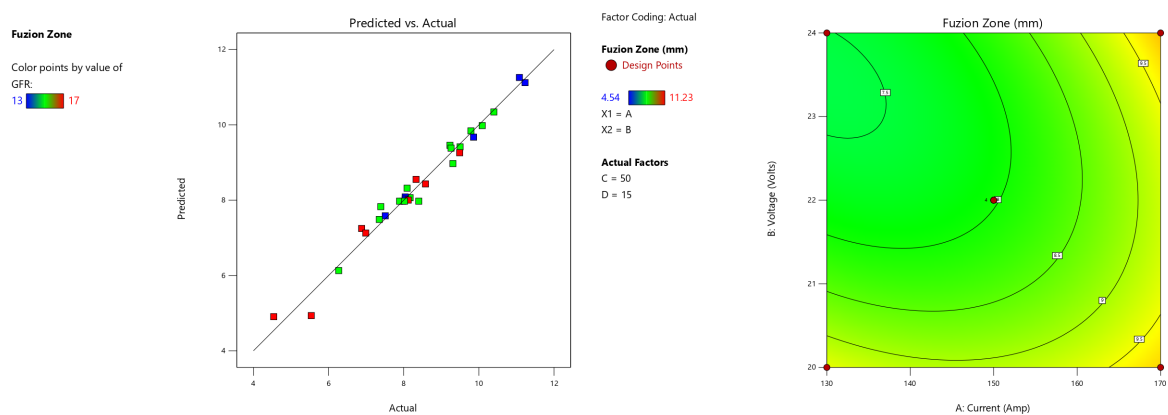
Table 5. Fit statistics for FZ width.

Std. Dev.	0.3233	R ²	0.9765
Mean	8.38	Adjusted R²	0.9545
C.V. %	3.86	Predicted R²	0.8744
		Adeq Precision	27.7872

The final predictive model is expressed in Equation (1)

$$\begin{aligned}
 \text{Fusion Zone Width (mm)} = & 212.07611 - 0.461582 \cdot A - 15.18760 \cdot B - 0.262394 \cdot C \\
 & + 1.19481 \cdot D + 0.012927 \cdot AB + 0.004672 \cdot AC - 0.027677 \cdot AD \\
 & + 0.028281 \cdot BC + 0.274891 \cdot BD - 0.074281 \cdot CD + 0.001317 \cdot A^2 \\
 & + 0.170177 \cdot B^2 - 0.000155 \cdot C^2 + 0.005802 \cdot D^2
 \end{aligned} \quad (1)$$

Diagnostic plots (Predicted vs. Actual) showed data points closely aligned along the 45° line, confirming model reliability. However, Run 28 was identified as a potential outlier with a high studentized residual (3.317), warranting caution in extreme parameter regimes. The middle contour plot and the right 3D surface plot visualize the relationship between two input parameters, Current (Amp) and Voltage (Volt), and the resulting response variable, Fusion Zone (mm). Together, these visualizations help engineers understand how varying welding settings influences the weld geometry, allowing them to identify optimal parameter combinations to achieve a specific fusion zone size (**Figure 2**).



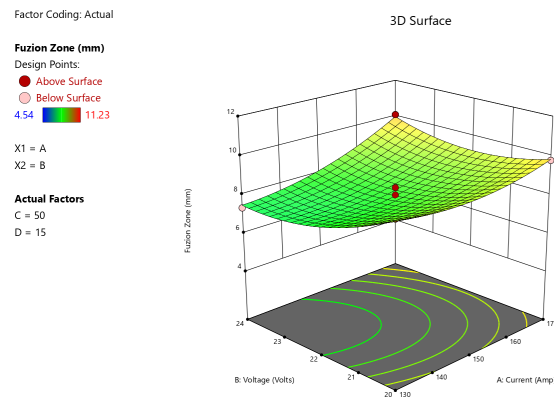
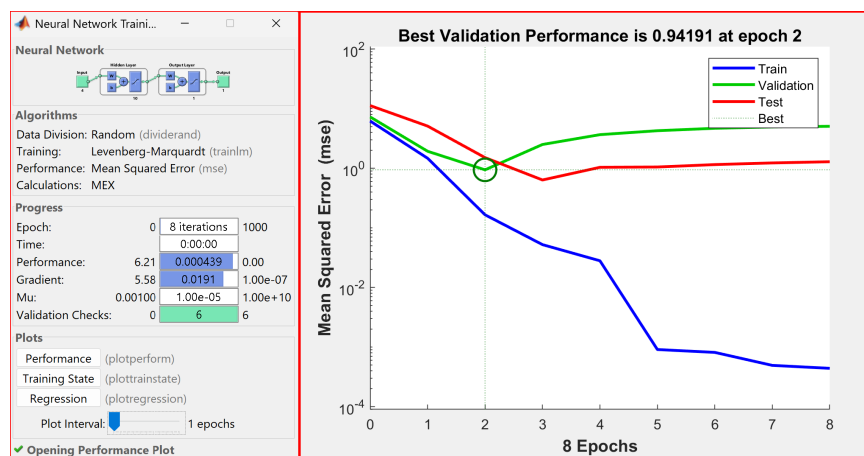


Figure 2. Predicted vs actual/contour and surface Plot.

3.2. ANN Model Performance

The ANN architecture (4-10-1) was trained until the validation error showed no improvement for six consecutive epochs, stopping at epoch 08 to prevent overfitting. The neural network model was trained using the Levenberg-Marquardt back-propagation algorithm with a random data division strategy to optimize performance based on Mean Squared Error (MSE). As illustrated in the central performance plot, the training process was monitored over eight epochs, with the best validation performance of 0.94191 achieved at epoch 2, indicated by the green circle. Following this epoch, the validation error began to increase while the training error continued to decrease, signaling the onset of overfitting and justifying the selection of epoch 2 as the optimal stopping point. The predictive capability of the model is further substantiated by the regression analysis presented in the right panel, which compares the network output against target values. The correlation coefficients (R) for the training, validation, and test sets were calculated to be 0.8894, 0.8741, and 0.9215, respectively, with an overall R value of 0.8892 for the entire dataset. These results indicate a strong linear relationship between the predicted and actual values, confirming the robustness and generalization ability of the developed neural network (Figure 3).



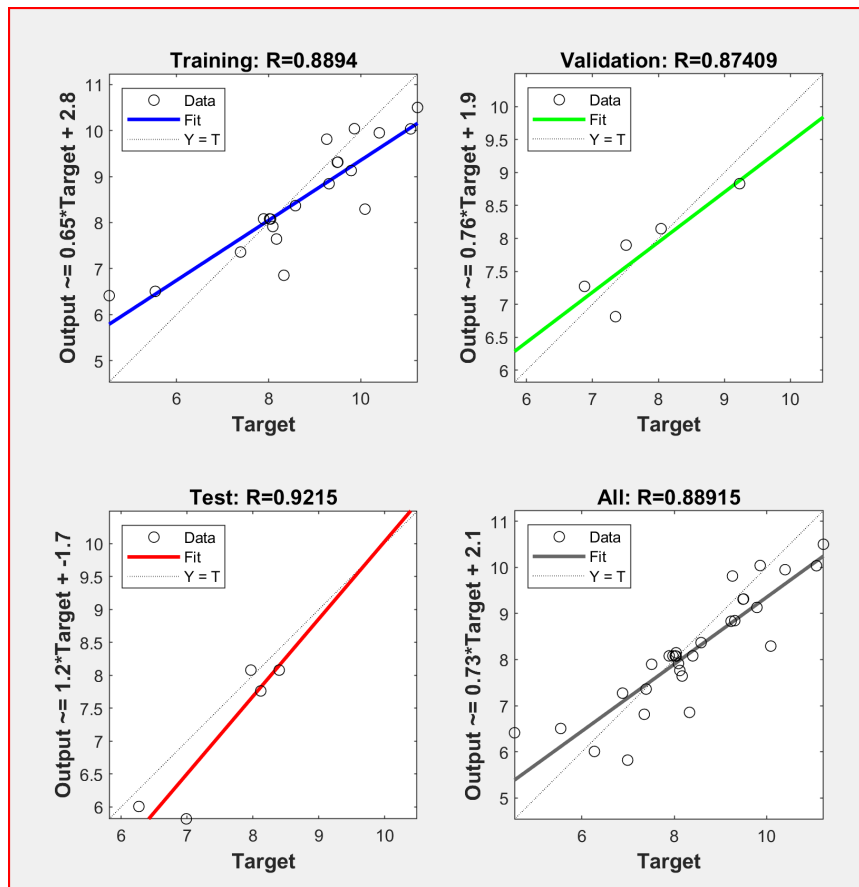


Figure 3. Training interface settings/performance plot/regression plots.

3.3. Comparative Analysis: RSM vs. ANN

A direct comparison of predictive capabilities presented in **Table 6** revealed distinct strengths for each model.

Table 6. Comparison between RSM and ANN predictions.

Run	Factor 1	Factor 2	Factor 3	Factor 4	Fuzion Zone Width		
	A:Current	B:Voltage	C:Speed	D:GFR	Exp	RSM	ANN
1	130	20	50	15	9.5	9.42	9.31336
2	170	20	50	15	9.79	9.84	9.1302
3	130	24	50	15	7.35	7.49	6.81275
4	170	24	50	15	10.09	9.98	8.29234
5	150	22	40	13	8.04	8.09	8.14712
6	150	22	60	13	9.86	9.67	10.039
7	150	22	40	17	9.49	9.26	9.30914
8	150	22	60	17	4.54	4.91	6.41274
9	130	22	50	13	7.51	7.59	7.89774
10	170	22	50	13	11.08	11.26	10.035

11	130	22	50	17	8.12	8	7.76347
12	170	22	50	17	6.88	7.25	7.27219
13	150	20	40	15	10.4	10.34	9.94892
14	150	24	40	15	8.09	8.32	7.91454
15	150	20	60	15	7.39	7.83	7.35966
16	150	24	60	15	8.17	8.07	7.64298
17	130	22	40	15	9.26	9.38	9.81158
18	170	22	40	15	9.31	8.97	8.84395
19	130	22	60	15	6.27	6.13	6.00764
20	170	22	60	15	9.23	9.46	8.83027
21	150	20	50	13	11.23	11.12	10.5
22	150	24	50	13	8.04	8.03	8.07559
23	150	20	50	17	6.99	7.13	5.81935
24	150	24	50	17	8.58	8.43	8.36733
25	150	22	50	15	7.89	7.97	8.07999
26	150	22	50	15	7.97	7.97	8.07999
27	150	22	50	15	8.4	7.97	8.07999
28	170	20	60	17	5.54	4.94	6.50569
29	170	20	40	17	8.33	8.55	6.85451
30	150	22	50	15	8.02	7.97	8.07999

Statistical Fit: RSM provided a higher coefficient of determination ($R^2 = 0.9765$) compared to ANN ($R^2 = 0.889$) within the experimental design space. This suggests RSM is highly effective for interpolation within the defined CCD limits as observed in **Figure 4** and **Figure 5**.

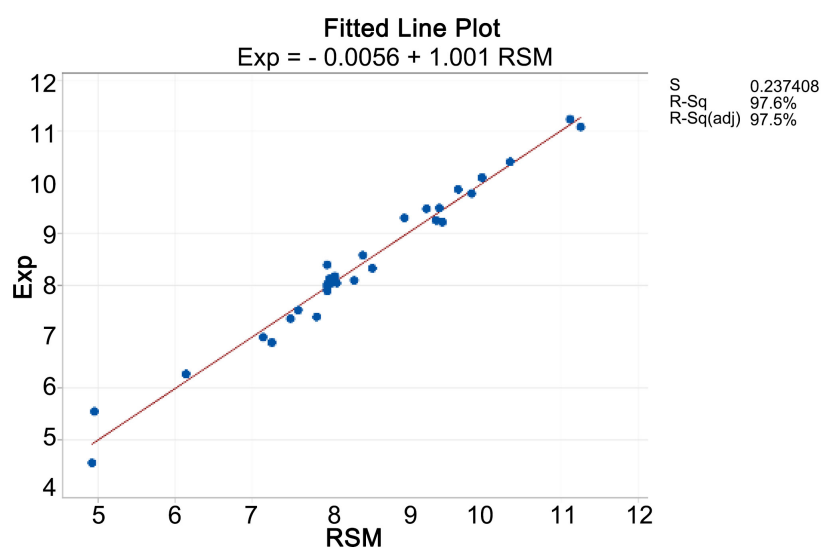


Figure 4. Fitted line plot for Fusion Zone (RSM).

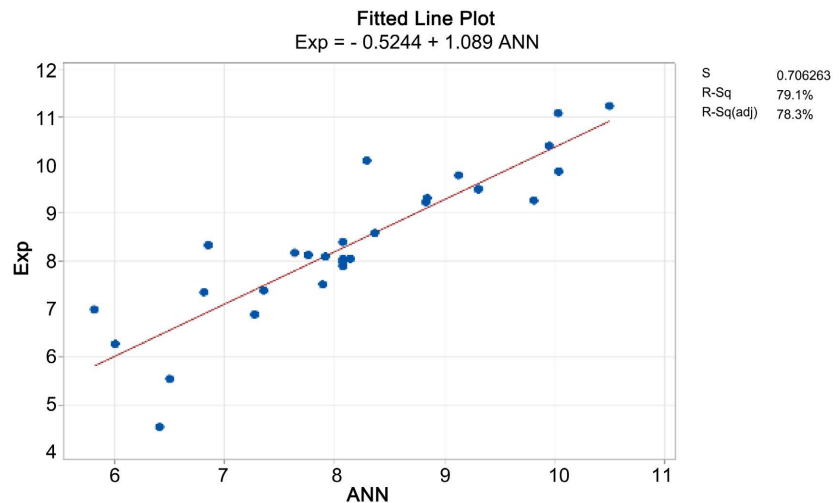


Figure 5. Fitted line plot for FZ Width (ANN).

Nonlinearity and Edge Cases: Time series plots (**Figure 6**) indicated that ANN predictions tracked experimental values closely in runs involving extreme parameter combinations (e.g., Runs 25 - 30), where RSM showed slight deviations. This aligns with the theoretical advantage of ANN in capturing complex, higher-order nonlinearities that quadratic polynomials may miss.

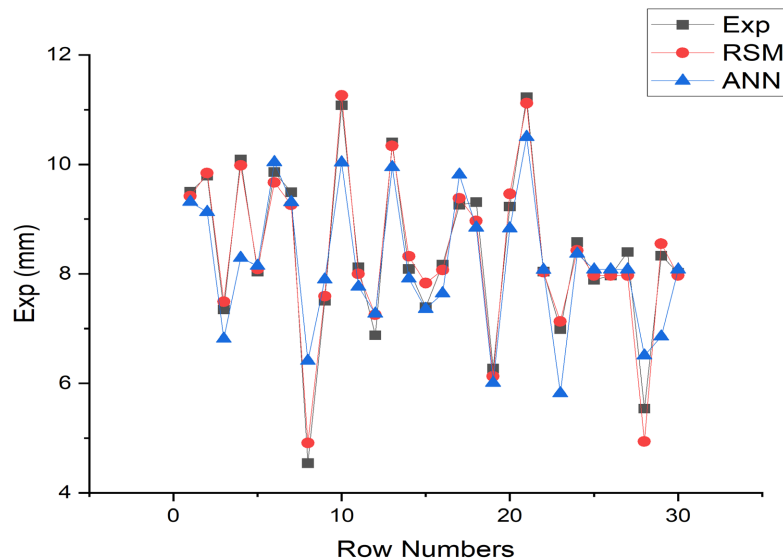


Figure 6. Comparison time series plot.

Figure 4 (Fitted Line Plot) comparisons confirmed that while RSM offers a tighter fit ($S = 0.237$) for the training data, ANN provides a robust alternative for scenarios where explicit mathematical relationships are difficult to define.

4. Conclusions

This study successfully developed and compared Response Surface Methodology

(RSM) and Artificial Neural Network (ANN) models for predicting Fusion Zone width geometry in TIG welding of AISI 1020 mild steel. The findings revealed that all four investigated process parameters, Current, Voltage, Travel Speed, and Gas Flow Rate, significantly influence Fusion Zone width, with notable interaction effects observed specifically between Current $\times$ Speed and Voltage $\times$ Gas Flow Rate. In terms of predictive performance, the RSM quadratic model demonstrated superior statistical fit within the experimental domain, achieving an R^2 value of 0.9765, which makes it particularly well-suited for process optimization and the generation of explicit empirical equations. Conversely, the ANN model, configured with a 4-10-1 architecture, attained a robust overall R^2 of 0.889 and exhibited strong generalization capabilities, effectively capturing complex nonlinear relationships, especially within testing subsets. It is important to note that the headline R^2 metrics reported (0.9765 for RSM and 0.889 for ANN) reflect the full dataset performance, while the separate test subset evaluations (e.g., $R = 0.9215$ for ANN) confirm the models' strong generalization to unseen process conditions.

Based on these outcomes, RSM is recommended for industrial applications that require explicit, interpretable control equations operating within a standard parameter range, whereas ANN is better suited for adaptive control systems or scenarios extending beyond conventional design spaces due to its inherent flexibility. Future research should aim to expand the dataset to incorporate additional responses such as Heat-Affected Zone (HAZ) characteristics and Weld Penetration Area, while also validating the developed models across different material grades to further enhance their generalizability and industrial applicability.

Conflicts of Interest

The authors declare no conflicts of interest.

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