OPEN ACCESS

Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) | ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Corrosion Rate Optimization and Prediction for Enhanced Strength and Structural Integrity of Pipeline Weldments Using RSM and ANN

Uwoghiren F. O[1*], Mabiaku T. A[2]

[1]Department of Production Engineering, University of Benin, Benin City, +234, Nigeria Email: frank.uwoghiren@uniben.edu
[2]Department of Production Engineering, University of Benin, Benin City, +234, Nigeria Email: timothy.mabiaku@gmail.com

DOI: https://doi.org/10.36348/sjet.2024.v09i09.005 | **Received:** 21.08.2024 | **Accepted:** 26.09.2024 | **Published:** 30.09.2024

***Corresponding author:** Uwoghiren F. O
Department of Production Engineering, University of Benin, Benin City, +234, Nigeria

Abstract

This study investigates the optimization and prediction of non-elastic performance factors required to augment the pipeline weldments' structural integrity and strength. The study's main focus is on the components of the operation, like the welding current, voltage, and gas flow rate to optimize and predict the corrosion rate of the pipeline weldment. Utilizing Design Expert software for experimental design and data analysis, the study employs the Central Composite Design (CCD) methodology to generate a quadratic model that predicts the responses effectively. The research also integrates Artificial Neural Networks (ANN) to further enhance the prediction accuracy. Experimental results indicate that the optimal welding parameters 160 amps current, 21.28 volts voltage, and 14.67 liters/min gas flow rate—yield a corrosion rate of 0.018 mm/yr. The study concludes that both RSM and ANN can be effectively used for optimization and prediction in welding processes, with RSM showing slightly better predictive capabilities.

Keywords: Corrosion Rate, Response Surface Methodology, Artificial Neural Network, Pipeline Weldments.

1. INTRODUCTION

Pipeline weldments' integrity is essential for the dependability and safety of pipelines across various industries. Welding process parameters significantly affect the resistance to corrosion and mechanical qualities of welds. This paper explores recent studies on optimizing welding parameters to enhance weld quality, focusing on methods such as RSM and ANN. Control of welding factors, including gas flow rate, voltage, and current is essential for achieving desirable weld characteristics like hardness and corrosion resistance. Recent studies emphasize the importance of selecting appropriate welding conditions to minimize defects and ensure uniform weld quality (Smith *et al.*, 2019; Kumar & Singh, 2021). RSM is a statistical technique used for process development, improvement, and optimization. Recent applications of RSM in welding include optimizing parameters to improve mechanical properties and reduce defects. For instance, Zhang *et al.*, (2018) used RSM to optimize the friction stir welding process, achieving significant improvements in weld strength and durability. Similarly, Ali *et al.*, (2020) employed RSM to optimize laser welding parameters, enhancing the weld's mechanical properties. ANNs are computational models that mimic the human brain's ability to identify trends and forecast outcomes using data. Recent research demonstrates ANN's effectiveness in predicting weld quality and optimizing welding parameters. According to Lee and Park (2018) utilized ANN to predict the shape of the weld beads in gas tungsten arc welding, achieving high accuracy. Srirangan and Paulraj (2016) used ANN to optimize TIG welding parameters, showing that ANN can effectively model the nonlinear relationships between welding parameters and weld quality. Another study by Patel and Joshi (2020) employed ANN to optimize TIG welding parameters, demonstrating ANN's capability to model complex, nonlinear relationships. Comparative studies between RSM and ANN indicate that both methods have unique strengths. RSM provides a clear understanding of variable interactions, while ANN excels in predicting complex, nonlinear systems. For instance, Wang *et al.*, (2021) compared RSM and ANN for optimizing MIG welding parameters, concluding that ANN offers superior predictive accuracy but RSM provides better insights into variable interactions. This dual approach helps leverage the strengths of both methodologies.

Corrosion resistance is a critical factor in the longevity of weldments. Recent studies investigate the effect of welding factors on corrosion resistance, revealing that optimized welding conditions significantly improve corrosion behavior. For instance, Singh *et al*., (2019) investigated the effect of current and speed during welding on the corrosion resistance of stainless-steel welds, finding that specific parameter combinations reduce corrosion rates. Similarly, Chen *et al*., (2021) demonstrated that optimized gas flow rates enhance the corrosion resistance of aluminum welds. The corrosion rate of pipeline weldments is a critical factor in ensuring the integrity and longevity of pipelines, particularly in the petroleum industry. Internal corrosion in pipeline weldments can be impacted by a number of variables, comprising the presence of impurities, welding defects, and the chemical composition of the transported substances. For instance, impurities in CO2 can significantly accelerate corrosion rates. Vanaei *et al*., (2017) highlight that impurities such as H2S and chlorides increase the corrosive potential of CO2, leading to higher rates of internal corrosion in weldments (Vanaei *et al*., 2017). External factors, such as environmental conditions and protective coatings, play a crucial role in the corrosion of pipeline weldments. According to a study on X80 pipeline steel weldments exposed to marine atmospheric conditions, cyclic salt spray accelerated corrosion testing revealed that environmental exposure significantly impacts corrosion behavior (Springer Open, 2023). The study indicated that proper protective measures are essential in mitigating these effects. Kiefner and Associates (2016) report that Selective seam weld corrosion (SSWC) is influenced by the properties of the seam material and its interaction with corrosion mechanisms. This type of corrosion is exacerbated in the presence of defective pipe seams and ineffective corrosion control measures (Kiefner & Associates, 2016). The height of welding reinforcement can also affect corrosion rates. Research indicates that an increase in weld reinforcement height under dynamic conditions can lead to higher corrosion rates due to increased galvanic corrosion intensity. Effective management of weld reinforcement is therefore critical to reducing the risk of corrosion failure (AIP Publishing, 2023).

2. METHODOLOGY

2.1 Design of Experiment (DOE)

DOE is a powerful statistical technique used to explore the relationships between several independent variables (factors) and one or more dependent variables (responses). The goal of RSM is to optimize the response by identifying the best combination of factors. The Steps in Design of Experiment includes the following:

i. Identify the objective (maximize, minimize, or target a specific value for the response).
ii. Choose the factors (independent variables) to be studied.
iii. Select the response (dependent variable) to be optimized.
iv. Select the Type of Experimental Design: RSM often uses second-order designs like Central Composite Design (CCD) or Box-Behnken Design (BBD) for fitting a quadratic model.

2.2 Central Composite Design (CCD)

CCD is one of the most used RSM designs. It extends a factorial or fractional factorial design by adding center points and ‘star points’ that allow for the estimation of curvature (quadratic terms). It includes:

i. Factorial Points: A full or fractional factorial design with coded levels −1 and +1.
ii. Center Points: Repeated measurements at the midpoint of the factor levels to estimate pure error.
iii. Axial (Star) Points: Points along the axis of each factor to explore curvature.

3. RESULTS

In order to connect two pieces of sheets made of mild steel that measured 60 x 40 x 10 mm, twenty experimental runs were conducted in this study. Every trial that is conducted included the measurement of current, voltage, and gas flow rate. The carbon content, hardness and the percentage dilution were measured respectively as shown in Table 1.

Table 1: Dataset showing Features and Output variable

	Current	Voltage	Gas flow rate	Corrosion rate
	Amp	Volt	Lit/min	mm/yr
1	190	23	15	0.0299
2	149.8	21.5	13.5	0.0168
3	160	20	15	0.0180
4	175	18.9	13.5	0.0098
5	160	23	15	0.0218
6	200.2	21.5	13.5	0.0248
7	175	21.5	13.5	0.0140
8	190	20	12	0.0218
9	190	20	15	0.0219
10	175	24	13.5	0.0140
11	160	23	12	0.0168

	Current	Voltage	Gas flow rate	Corrosion rate
	Amp	Volt	Lit/min	mm/yr
12	175	21.5	13.5	0.0140
13	190	23	12	0.0218
14	175	21.5	16	0.0376
15	175	21.5	13.5	0.0140
16	175	21.5	13.5	0.0140
17	175	21.5	10.9	0.0299
18	175	21.5	13.5	0.0140
19	175	21.5	13.5	0.0140
20	160	20	12	0.0239

3.1 Modelling and Optimization Using RSM

To verify the suitability of the quadratic model for examining the data, the corrosion rate responses were analyzed using the sequential model squares sum, as indicated in Table 2.

Table 2: Sequential Model Squares Sum for Corrosion Rate

Origin	Squares Sum	df	Square Mean	F-value	p-value	
Average vs Total	0.0077	1	0.0077			
Linear vs Average	0.0001	3	0.0000	0.6326	0.6046	
2FI vs Linear	0.0001	3	0.0000	0.4009	0.7548	
Quadratic vs 2FI	**0.0008**	**3**	**0.0003**	**228.27**	**< 0.0001**	**Suggested**
Cubic vs Quadratic	9.654E-06	4	2.413E-06	10.63	0.0069	Aliased
Residual	1.362E-06	6	2.271E-07			
Total	0.0087	20	0.0004			

The cumulative increase in the fit's model as terms are added is displayed in the sequential model sum of squares table. The best fit was determined by selecting the highest-order polynomial in which the additional terms are significant, and the model is free from aliasing based on the sequential model's computed sum of squares. For every response, the lack of fit test was estimated to determine the extent to which the quadratic model could consider the underlying variation related to the experimental data. It is not possible to use a model with a substantial lack of fit for prediction. Table 3 shows the calculated lack of fit results for the corrosion rate.

Table 3: Lack of Fit Test for Corrosion Rate

Origin	Squares Sum	df	Square Mean	F-value	p-value	
Linear	0.0008	11	0.0001	4.65	0.0480	
2FI	0.0008	8	0.0001	2.83	0.1285	
Quadratic	0.0000	5	2.203E-06	**0.4266**	**0.8821**	**Suggested**
Cubic	1.362E-06	1	1.362E-06	0.1377	0.8746	Aliased
Pure Error	0.0000	5	0.0000			

From the results of Tables 3, it was observed that while quadratic polynomial demonstrated a non-significant lack of fit, whereas the cubic polynomial showed a significant lack of fit and was consequently aliased in the model analysis. Table 4 presents the model statistics computed for the corrosion rate response, categorized by the model sources.

Table 4: Summary Statistics for Corrosion Rate Model

Origin	Std. Dev.	R^2	Adjusted R^2	Predicted R^2	PRESS	
Linear	0.0072	0.1060	-0.0616	-0.4842	0.0014	
2FI	0.0077	0.1817	-0.1959	-0.6576	0.0016	
Quadratic	**0.0010**	**0.9882**	**0.9776**	**0.9088**	**0.0001**	**Suggested**
Cubic	0.0005	0.9985	0.9954	0.6790	0.0003	Aliased

The model fit summary provides information on each completed model, including the standard deviation, r-squared, modified r-squared, predicted r-squared, and predicted error sum of square (PRESS) statistic. The ideal criteria for identifying the optimal model source are low PRESS, R-Squared close to one, and low standard deviation. According to the results shown in Tables 4, the quadratic polynomial model was chosen because it was proposed, while the cubic polynomial model was aliased.

To confirm the quadratic model's suitability by evaluating its capacity to reduce the corrosion rate the goodness of fit statistics displayed in Table 5.

Table 5: GOF Statistics for Corrosion Rate

Std. Dev.	0.0010	**R^2**	0.9882
Mean	0.0196	**Adjusted R^2**	0.9776
C.V. %	5.34	**Predicted R^2**	0.9088
		Adeq Precision	34.7526

The difference between the Adjusted R^2 of 0.9776 and the Predicted R^2 of 0.9088 is under 0.2, indicating a satisfactory agreement.

Adequate Precision assesses the signal-to-noise ratio, which should be above 4. With a ratio of 34.753, the signal strength is sufficient, indicating that this model is suitable for exploring the design space.

The estimated standard error quantifies the deviation between the experimental values and their corresponding predicted values. The normal probability plot of the studentized residuals was used to assess the normality of the calculated residuals. The normal probability plot of residuals, which shows how actual values deviate in terms of standard deviations from the predicted values, was used to assess whether the residuals (observed – expected) followed a normal distribution.

The corrosion rate is displayed in Figure 1. To find a value or group of values that the model finds challenging to identify, the projected values are compared to the actual values.

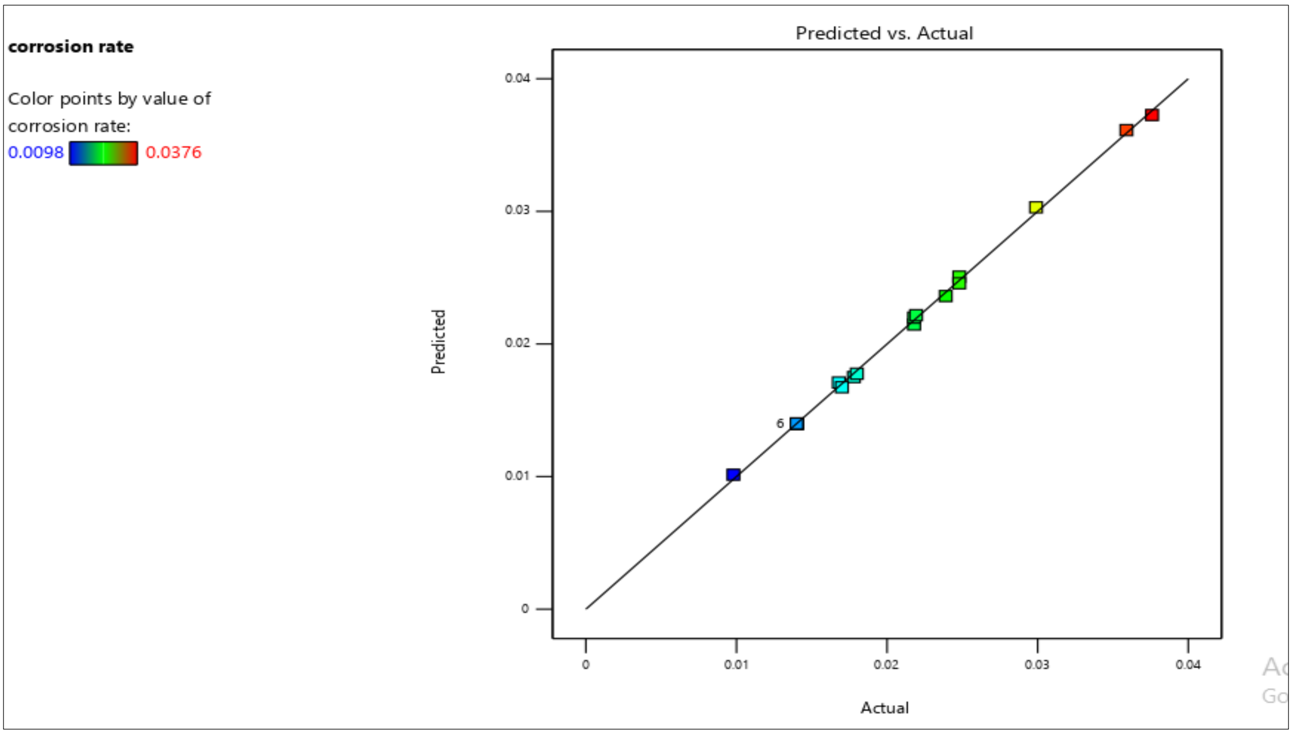

Figure 1: Graph of Predicted versus Actual for Corrosion Rate

The cook's distance indicates the extent to which the regression would be affected if the outlier were taken out of the analysis. Any point that stands out as an anomaly with a significantly high distance value compared to other points should be examined. The calculated Cook's distance for the corrosion rate is shown in Figure 2.

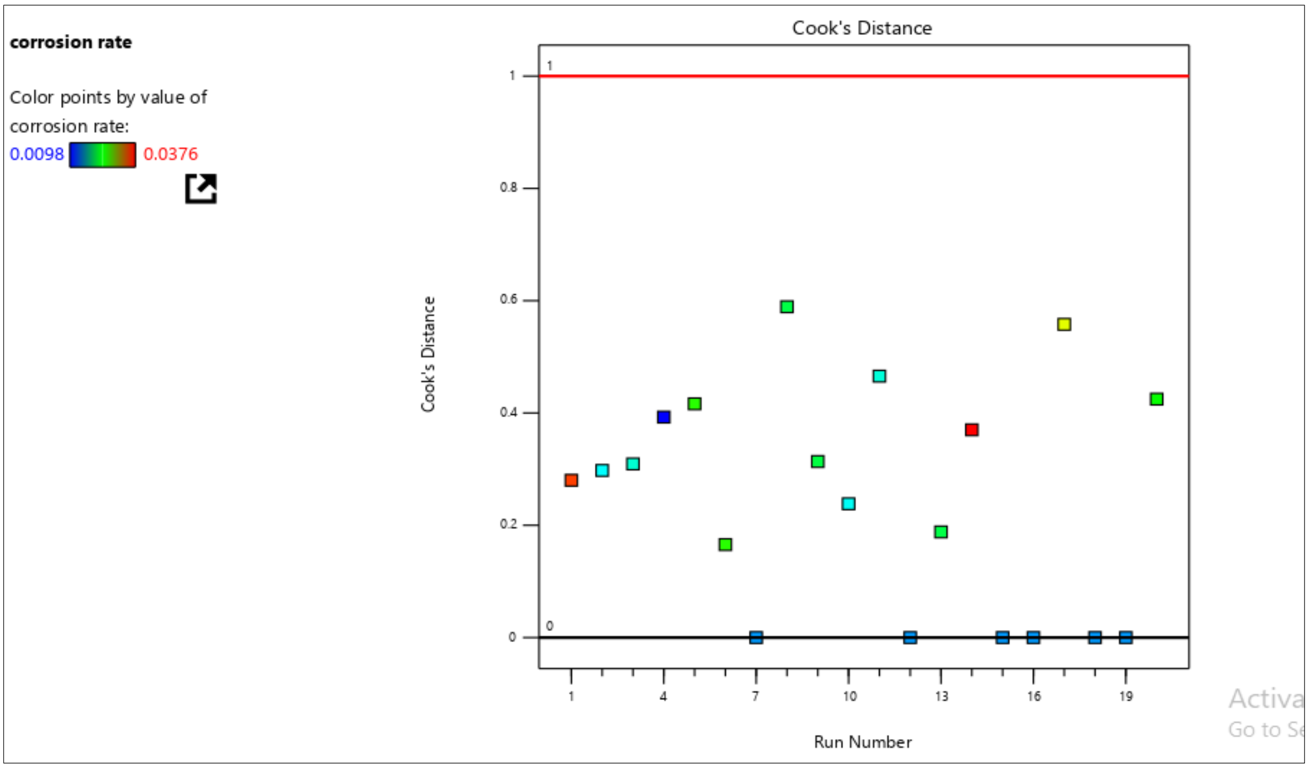

Figure 2: Calculated Cook's Distance for Corrosion Rate

The Cook's distance chart has a maximum limit of 1.00 and a minimum limit of 0.00. Values that substantially differ from these bounds are classified as outliers and require close examination.

The 3D surface plots displayed in Figure 3 were generated using the following ways to investigate the effects of voltage and current rate on the corrosion rate.

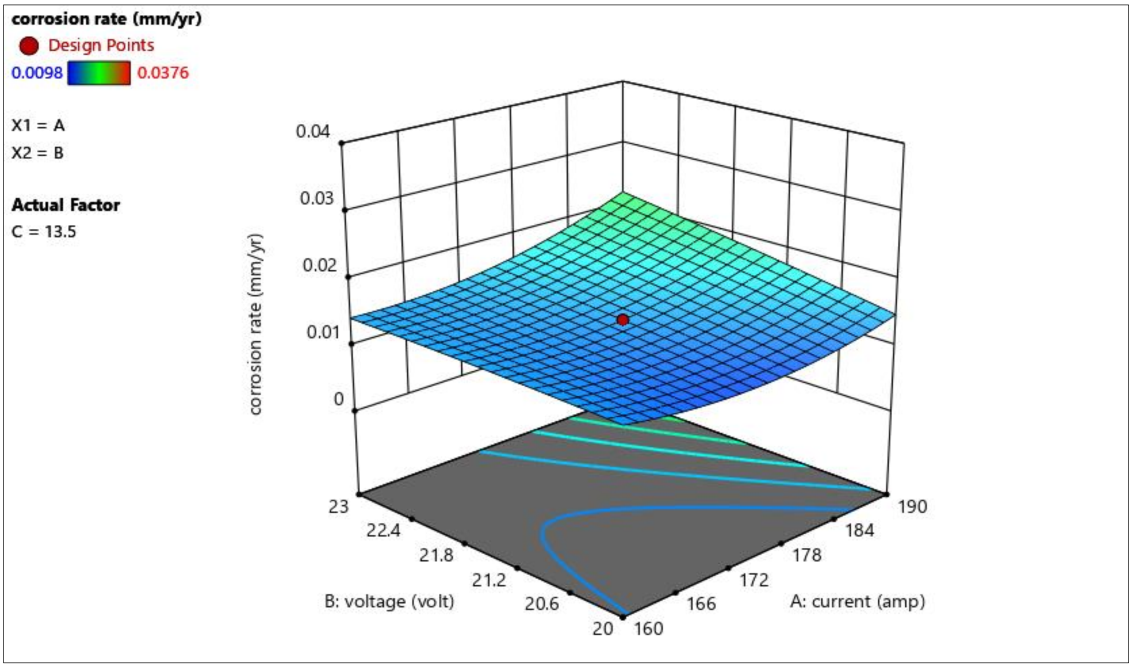

Figure 3: Effect of Current and Voltage on Corrosion Rate

In order to investigate how gas flow rate and current affect corrosion rate, the 3D surface plots are presented in Figure 4.

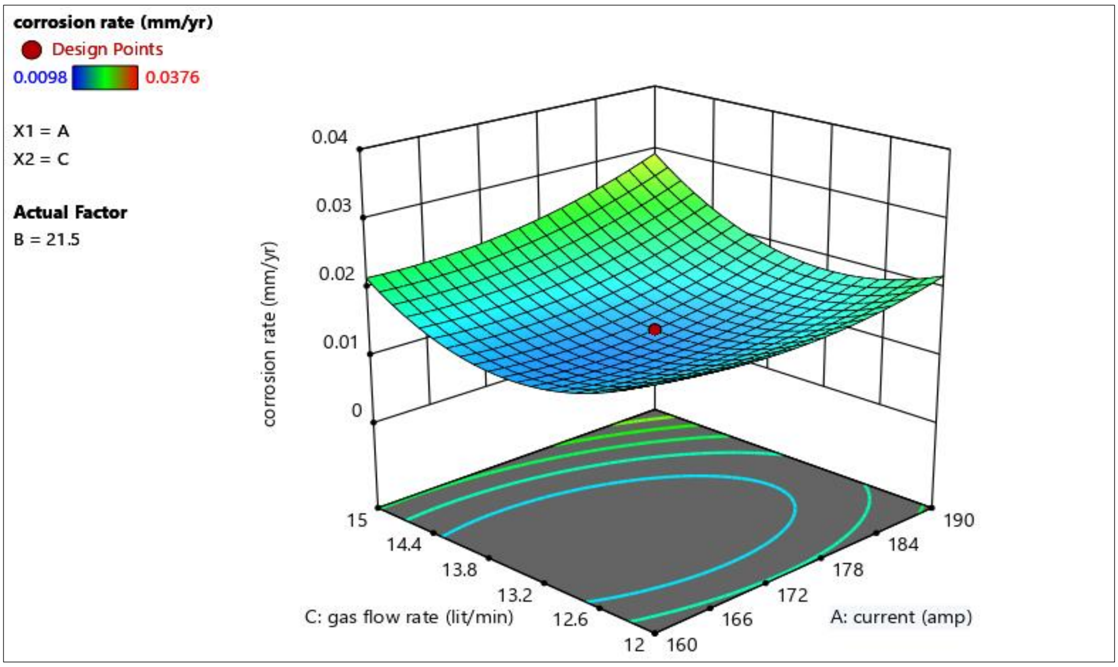

Figure 4: Effect of Current and Gas Flow Rate on Corrosion Rate

The 3D surface plots shown in Figure 5 are shown to investigate the effects of voltage and gas flow rate on corrosion rate.

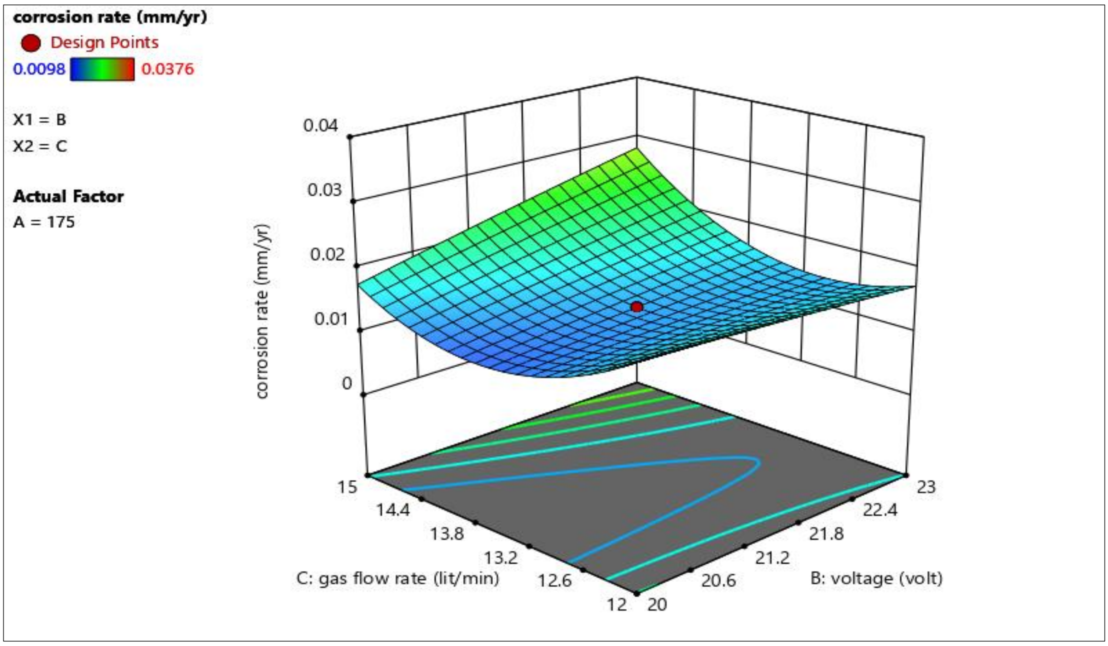

Figure 5: Effect of Gas Flow Rate and Voltage on Corrosion Rate

3.2 Prediction of the Corrosion Rate using ANN

The artificial neural network study is performed using MATLAB R2022a. The Data is saved in the folder of the MATLAB, then normalized by converting to Numeric Matrix form. The network architecture was designed using the enhanced second order gradient method, sometimes referred to as the Levenberg Marquardt Back Propagation Training Algorithm, which was chosen as the optimal learning rule. During network development, the input data was split into training, validation, and testing sets: 70% for training, 15% for validation, and the remaining 15% for testing, with a maximum of 1000 epochs for training. The `trainlm` function, which uses Levenberg-Marquardt optimization for updating weights and biases, was chosen despite its higher memory requirements because it is often the fastest backpropagation algorithm available and is highly recommended as an initial supervised learning method. Figure 6 presents a performance evaluation plot that shows the progress of training, validation, and testing phases.

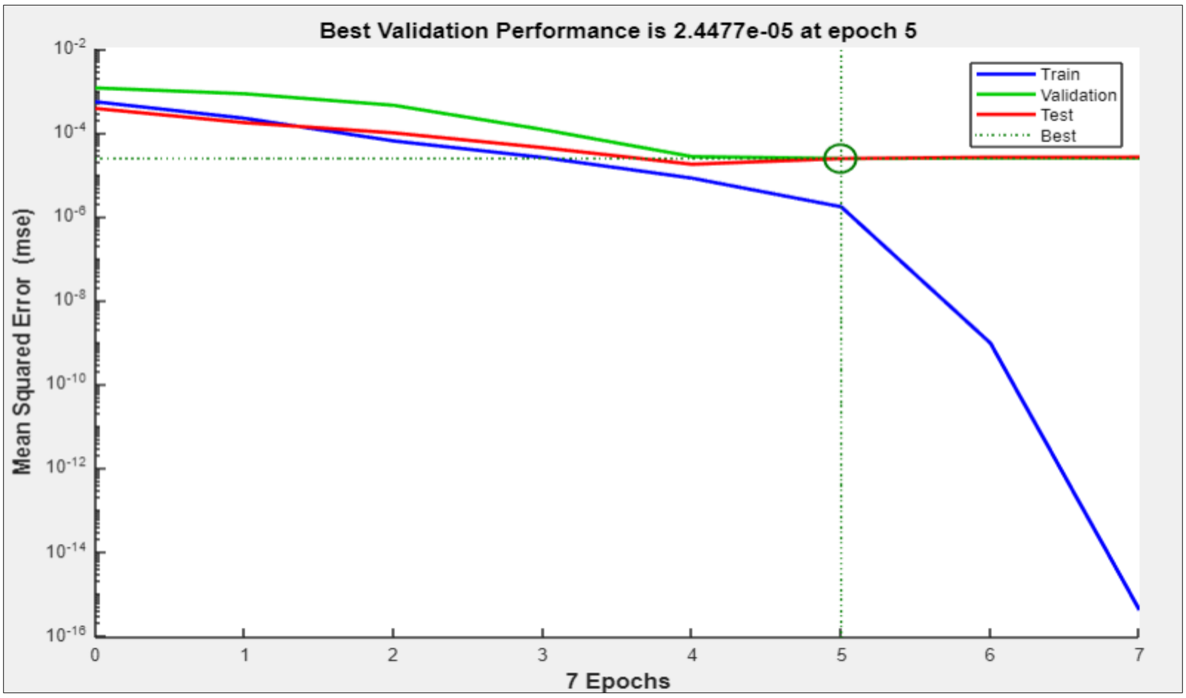

Figure 6: Performance Curve of Trained Network for Predicting Corrosion Rate

The performance plot in Figure 6 did not show any indications of overfitting. An error value of 0.000024477 at epoch 5 indicates that the network has a high ability to forecast the rate of corrosion. Figure 7 displays the training status, including the gradient function, training gain (Mu), and validation check.

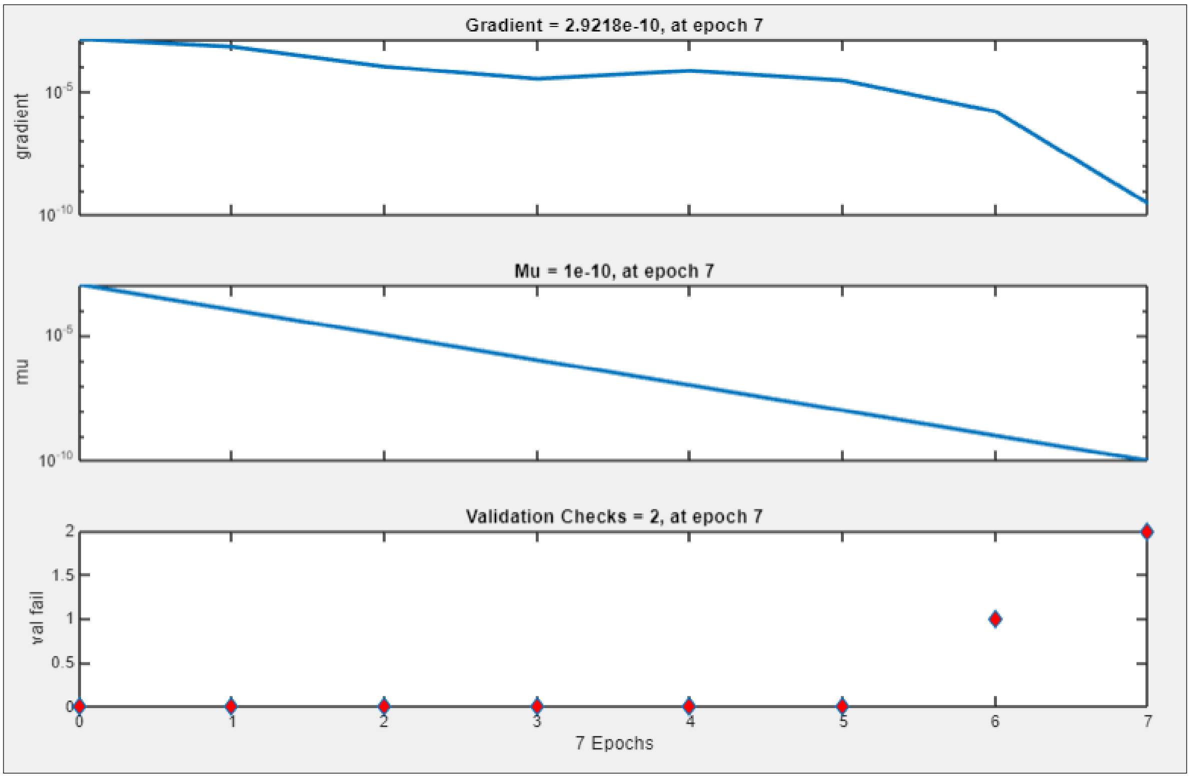

Figure 7: Neural network training state for predicting corrosion rate

Backpropagation is a method employed in artificial neural networks to determine the error contribution of each neuron following a batch of training data. The calculated gradient value of 2.9218 x 10^{-10}, as shown in Figure 7, shows how little each chosen neuron's error contribution is. The control parameter for the neural network training procedure is called momentum gain, or Mu. Its value must be less than unity because it is the training gains. A network with robust capability to forecast the rate of corrosion is demonstrated by momentum gains of 1 x10^{-10}. Figure 8 displays the regression figure, which illustrates the relationship between the training, validation, and testing processes along with the input variables (current, voltage, and gas flow rate) and the target variable (corrosion rate).

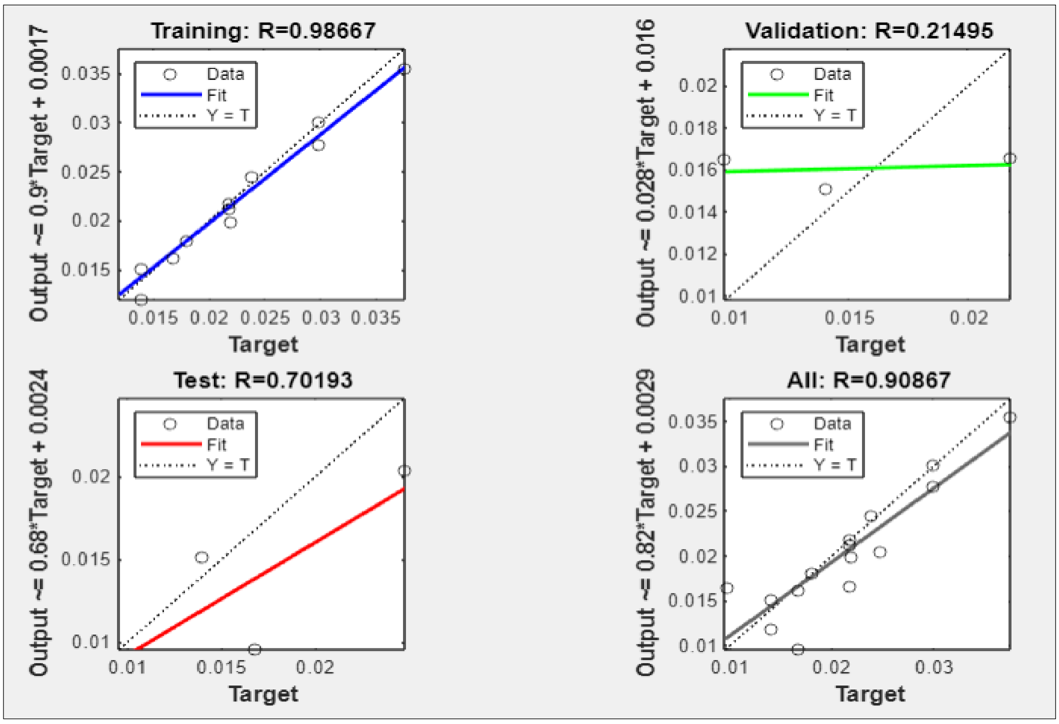

Figure 8: Regression plot illustrating the Advancement of Training, Validation, and Testing

4. CONCLUSION

The useful service duration of a fabricated engineering framework is impacted by its hardness, resistance to shock and corrosion. In this study, the development of numerical models using RSM and ANN to optimize and predict the corrosion rate, considering Current, Voltage and Gas flow rate as input factors. The experimental design adopted was the CCD, which was generated using the design expert software (version 13.0) the RSM analysis produced optimal solutions with current of 160.000 amps, voltage of 21.280 Volt, Gas flow rate of 14.667lit/min to produce a welded joint with corrosion rate of 0.018 and this was obtained at a desirability value of 0.918. To predict the output parameters, the ANN model was also used and contrasted with the RSM. Due to its greater coefficient of determination, the RSM is chosen from the results as the superior predictive model over the ANN.

REFERENCES

- AIP Publishing. (2023). Corrosion of welding reinforcement height under dynamic conditions. *AIP Publishing*.
- Ali, M., Ahmad, Z., & Ullah, S. (2020). Optimization of laser welding parameters using response surface methodology. *Materials Research Express, 7*(8), 086510.
- Chen, J., Liu, Y., & Li, X. (2021). Effect of gas flow rate on corrosion resistance of aluminum welds. *Journal of Materials Science & Technology, 47*, 140-147.
- Kiefner, J. (2016). Selective Seam Weld Corrosion – How big is the Problem. *Kiefner and Associates Inc.*
- Kumar, A., & Singh, P. (2021). Influence of welding parameters on the mechanical properties of weldments. *Journal of Manufacturing Processes, 64*, 10-17.
- Lee, D., & Park, S. (2018). Prediction of weld bead geometry in gas tungsten arc welding using artificial neural networks. *Journal of Welding and Joining, 36*(3), 77-84.
- Patel, R., & Joshi, S. (2020). Optimization of TIG welding parameters using artificial neural networks. *Journal of Manufacturing Processes, 48*, 224-233.
- Singh, R., Gupta, A., & Yadav, M. (2019). Effect of welding speed and current on the corrosion resistance of stainless steel welds. *Corrosion Science, 152*, 123-130.
- Smith, T., Jones, M., & Williams, H. (2019). Control of welding parameters for improved weld quality. *International Journal of Advanced Manufacturing Technology, 102*, 3451-3462.
- SpringerOpen. (2023). Technical Note: Study on Accelerated Corrosion Behavior and Mechanism. *SpringerOpen*.
- Srirangan, A. K., & Paulraj, S. (2016). Multiresponse optimization of process parameters

for TIG welding of Incoloy 800HT by Taguchi grey relational analysis. *Engineering Science and Technology, an International Journal*, *19*(1), 811-817.

- Vanaei, H., Eslami, A., & Egbewande, A. (2017). A review on pipeline corrosion, in-line inspection (ILI), and corrosion growth rate models. *International Journal of Pressure Vessels and Piping*, 149, 43-54.
- Wang, Y., Zhang, H., & Li, Q. (2021). Comparative analysis of RSM and ANN in optimizing MIG welding parameters. *Journal of Materials Processing Technology, 291*, 117015.
- Zhang, X., Wang, L., & Chen, H. (2018). Optimization of friction stir welding parameters using response surface methodology. *Materials Today Communications, 16*, 364-372.