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Original Research Article

Advanced Optimization of Pipeline Weldments: Predicting HCl Immersion Durability with RSM and ANN Techniques

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Abstract

The current research is centered on the optimization and prediction of non-elastic performance factors crucial for improving the structural integrity and strength of pipeline weldments, with a specific emphasis on the period of immersion in an HCl solution. The research investigates the results of welding factors on immersion period. Utilizing Design Expert software, the study employs Central Composite Design (CCD) methodology to generate an experimental matrix and develop models. Additionally, Response Surface Methodology (RSM) and Artificial Neural Networks (ANN) are utilized for the predicting and optimizing these parameters. The research concludes that optimal welding parameters, 160 amps current, 21.28 volts voltage, and 14.67 liters/min gas flow rate, which results in an immersion period of 18.067 days in the HCl solution. The study shows that both the RSM and ANN are effective for optimization and prediction, with RSM demonstrating slightly superior predictive capabilities.

Keywords: Pipeline Weldments, Artificial Neural Network, Response Surface Methodology, Period of Immersion.

1. INTRODUCTION

Pipeline weldments are critical components in various industries, especially in the oil and gas sector, where they ensure the integrity and reliability of pipelines. The period of immersion of these weldments in different environments, such as seawater, has significant implications for their corrosion resistance, mechanical properties, and overall lifespan. Recent studies underscore the importance of optimizing welding parameters to enhance mechanical properties and reduce defects in weldments. Several studies have investigated the impact of immersion time on the corrosion behavior of pipeline weldments. Zhang *et al.*, (2021) examined resistance of corrosion of X70 welded steel pipeline in seawater over varying immersion periods. The study found that longer immersion times resulted in increased corrosion rates due to the prolonged exposure to aggressive chloride ions (Zhang, Li, & Wang, 2021). The period of immersion in corrosive environments such as HCl solutions is crucial in assessing the corrosion resistance of weldments. Studies have shown that welding parameters significantly impact the corrosion behavior of welded joints. For instance, the optimal welding parameters can enhance the corrosion resistance and prolong the period of immersion before significant degradation occurs. Lee *et al.*, (2020) showed that optimized current and voltage settings can extend the immersion period, thereby improving the corrosion resistance and overall integrity of the welds. Further, Giasin *et al.*, (2023) reviewed the optimization techniques for friction stir welding and their impact on the immersion period, highlighting the role of process parameters in enhancing corrosion resistance. Chen *et al.*, (2021) studied the impact of gas flow rate in correspondence with the resistance presented by the aluminum welds, concluding that specific gas flow rates bring about a more standardized and smaller surface areas, enhancing corrosion resistance and extending the immersion period. Similarly, Kumar and Singh (2021) highlighted welding current with its corresponding voltage effects on the resistance to corrosion of various alloys, emphasizing the need for precise control of these parameters to enhance the durability of welds.

The influence of environmental factors, such as temperature and salinity, on the corrosion behavior of pipeline weldments has also been extensively studied. Liu *et al.*, (2020) reported that higher temperatures accelerated the corrosion process in X80 steel weldments immersed in seawater. Additionally, increased salinity was found to exacerbate pitting corrosion, leading to a higher rate of material degradation (Liu, Chen, & Zhang, 2020). The mechanical properties of pipeline weldments, including tensile strength and fatigue life, are significantly affected by the period of immersion. According to a study by Wang *et al.*, (2022), the tensile strength of X65 steel weldments decreased after prolonged immersion in a simulated seawater environment. The reduction in tensile strength was attributed to the formation of corrosion pits and the weakening of the weld metal (Wang, Zhao, & Li, 2022). Impact toughness is another critical property influenced by immersion. A study by Kim *et al*., (2021) evaluated the impact toughness of pipeline weldments immersed in seawater for different periods. The results indicated a significant decline in impact toughness with increasing immersion time, primarily due to hydrogen embrittlement and the accumulation of microstructural defects (Kim, Lee, & Park, 2021). The use of corrosion inhibitors has been investigated as a measure to enhance the corrosion resistance of pipeline weldments during immersion. An experimental study by Martinez *et al*., (2020) demonstrated that adding a specific inhibitor to seawater reduced the corrosion rate of X70 steel weldments by forming a protective film on the metal surface (Martinez, Gonzalez, & Hernandez, 2020). Protective coatings are widely used to mitigate the effects of immersion on pipeline weldments. Zhang and Liu (2023) reviewed various coating materials and their effectiveness in preventing corrosion in pipeline weldments. The study concluded that epoxy-based coatings provided superior protection against seawater corrosion compared to traditional coatings, extending the lifespan of the weldments (Zhang & Liu, 2023).

Studies comparing ANN and RSM applied in optimizing welding parameters have shown that both techniques have unique strengths. Patel and Joshi (2020) demonstrated ANN's effectiveness in modeling complex nonlinear relationships in TIG welding, achieving high accuracy in predicting the period of immersion under various conditions. Wang *et al*., (2021) compared RSM and ANN for optimizing MIG welding parameters, concluding that while ANN offers superior predictive accuracy, RSM provides better insights into variable interactions. The period of immersion significantly impacts the corrosion behavior and mechanical properties of pipeline weldments. Factors such as immersion time, environmental conditions, and protective measures play crucial roles in determining the durability and performance of these critical components. Future research should focus on developing advanced materials and coatings to enhance the resistance of pipeline weldments to prolonged immersion in aggressive environments.

2. METHODOLOGY

2.1 Design of experiment

Design of Experiments (DoE) is a structured approach used to explore the relationships between multiple explanatory variables (factors) and one or more response variables. The process begins with selecting key factors and determining their levels based on preliminary studies or expert knowledge. This is followed by designing experiments, often using Central Composite Design (CCD) or Box-Behnken Design (BBD), which are efficient in fitting quadratic models that capture both linear and quadratic effects. The experiments are then conducted according to the design matrix, ensuring all necessary combinations of factor levels are tested. The data obtained are used to fit a second-order polynomial model, which includes linear, interaction, and squared terms. Statistical analysis, such as Analysis of Variance (ANOVA), is applied to evaluate the significance of the model. The fitted model is then used to generate response surfaces and contour plots, facilitating optimization to identify the optimal factor levels. Finally, validation experiments are conducted to confirm the model's accuracy. This systematic approach allows for a comprehensive understanding of the interactions between factors and responses, enabling precise optimization in research areas that demand high accuracy. Depending on the number of input parameters, the central composite design of experiment was selected the central composite design user interphase is shown in Table 1.

Table 1: Design expert user interphase

Name	Units	Low	High	-Alpha	+Alpha
A		-1	1	-1.68179	1.68179
B		-1	1	-1.68179	1.68179
C		-1	1	-1.68179	1.68179

2.2 Response Surface Methodology (RSM)

RSM is particularly useful when the relationships between the variables and the response are complex and not well understood. The methodology involves the design of experiments to efficiently explore the space of input variables, the development of an empirical model (often a second-order polynomial) to approximate the true response surface, and the use of this model to identify the optimal conditions for the desired response. RSM typically starts with a preliminary study to determine the important factors and their appropriate ranges. A well-planned experimental design, such as Central Composite Design (CCD) or Box-Behnken Design (BBD), is then used to systematically vary the input factors, allowing for the estimation of both linear and interaction effects. The resulting data are used to fit a model, usually a quadratic equation, which represents the response surface. The fitted model is then used to generate response surfaces and contour plots, providing visual insights into the effects of the input variables and helping to identify optimal conditions.

2.3 Artificial Neural Network

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, designed to recognize patterns, make decisions, and predict outcomes based on input data. ANNs consist of interconnected layers of nodes, or "neurons," where each node represents a mathematical function. The structure typically includes an input layer, one or more hidden layers, and an output layer. The input layer receives the data, which is then processed through the hidden layers, where the actual computation occurs using weighted connections between neurons. The output layer provides the final prediction or decision. ANNs learn from data through a process called training, where the network adjusts the weights of the connections between neurons to minimize the difference between the predicted output and the actual outcome. This adjustment is done using algorithms like back propagation, which iteratively updates the weights by calculating gradients and using optimization techniques such as gradient descent. The ability of ANNs to model complex and non-linear relationships makes them particularly powerful in various applications, including image recognition, speech processing, and predictive analytics. ANNs can be designed with different architectures, such as feed forward networks, where data moves in one direction from input to output, or recurrent networks, which allow for feedback loops and are suited for time-series data. The performance of an ANN depends on factors like the number of hidden layers, the number of neurons per layer, the activation functions used, and the quality and quantity of the training data.

3. RESULT AND DISCUSSION

In a bid to connect two plates made of mild steel, measuring 62 x 42 x 12 mm, twenty experimental runs were conducted in this study. Each experimental run included the measurement of current, voltage, and gas flow rate. The period of immersion was measured respectively and is shown in Table 2.

Table 2: Measured period of immersion

	Current	Voltage	Gas flow rate	Period of immersion
	Amp	**Volt**	**Lit/min**	**days**
1	190	23	15	17
2	149.773	21.5	13.5	21
3	160	20	15	18
4	175	18.9773	13.5	17
5	160	23	15	18
6	200.227	21.5	13.5	18
7	175	21.5	13.5	16
8	190	20	12	19
9	190	20	15	18
10	175	24.0227	13.5	14
11	160	23	12	18
12	175	21.5	13.5	16
13	190	23	12	16
14	175	21.5	16.0227	18
15	175	21.5	13.5	16
16	175	21.5	13.5	16
17	175	21.5	10.9773	19
18	175	21.5	13.5	16
19	175	21.5	13.5	16
20	160	20	12	20

3.1 Modelling and Optimization using RSM

Using Response Surface Methodology (RSM), a second-order mathematical relationship is established in this work between a few selected input variables; current (I), voltage (V), and gas flow rate (GFR) and the response variable, which is the period of immersion. Finding the ideal values for each input variable which are current (Amp), voltage (Volt), and gas flow rate (l/min), that would reduce the immersion time was the aim of the optimization procedure. To produce experimental data for the process of optimization:

i. First, the Central Composite Design (CCD) method was used to carry out a statistical design of experiments (DOE). Design Expert 7.01, a statistical tool, was used for the design and optimization.
ii. Secondly, after creating an experimental design matrix, 20 experimental runs were produced, comprising six (6) centre points (k) and six (6) axial points.

Table 3 shows the results of the sequential model sum of squares for the immersion period response.

Table 3: Sequential model sum of square for period of immersion

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Mean vs Total	6020.45	1	6020.45			
Linear vs Mean	15.92	3	5.31	2.32	0.1144	
2FI vs Linear	3.00	3	1.0000	0.3865	0.7646	
Quadratic vs 2FI	**33.04**	**3**	**11.01**	**185.75**	**< 0.0001**	**Suggested**
Cubic vs Quadratic	0.5831	4	0.1458	89.05	< 0.0001	Aliased
Residual	0.0098	6	0.0016			
Total	6073.00	20	303.65			

As terms are added, the sequential model sum of squares table shows the progressive improvement in model fit. The optimal fit was identified by calculating the sequential model sum of squares and applying the highest-order polynomial where additional terms are significant and the model is not aliased. According to the results in Table 3, the cubic polynomial was found to be aliased and therefore unsuitable for fitting the final model. Moreover, the quadratic and 2FI models were suggested to best match the data, endorsing the use of quadratic polynomials in this analysis.

To validate the adequacy of the quadratic model according to its capacity to decrease the period of immersion, the figures for goodness of fit displayed in Table 4.

Table 4: GOF statistics for period of immersion

Std. Dev.	0.2435	**R^2**	0.9887
Mean	17.35	**Adjusted R^2**	0.9786
C.V. %	1.40	**Predicted R^2**	0.9143
		Adeq Precision	37.6009

The difference between the Adjusted R^2 of 0.9786 and the Predicted R^2 of 0.9143 is less than 0.2, suggesting a fairly good correlation. Adequate Precision assesses the signal-to-noise ratio, which should exceed 4. With a ratio of 37601, the signal strength is robust, indicating that this model is suitable for navigating the design space.

Figure 1 depicts the immersion duration, where the predicted and observed values are compared to identify any specific values or sets of values that the model has difficulty accurately predicting.

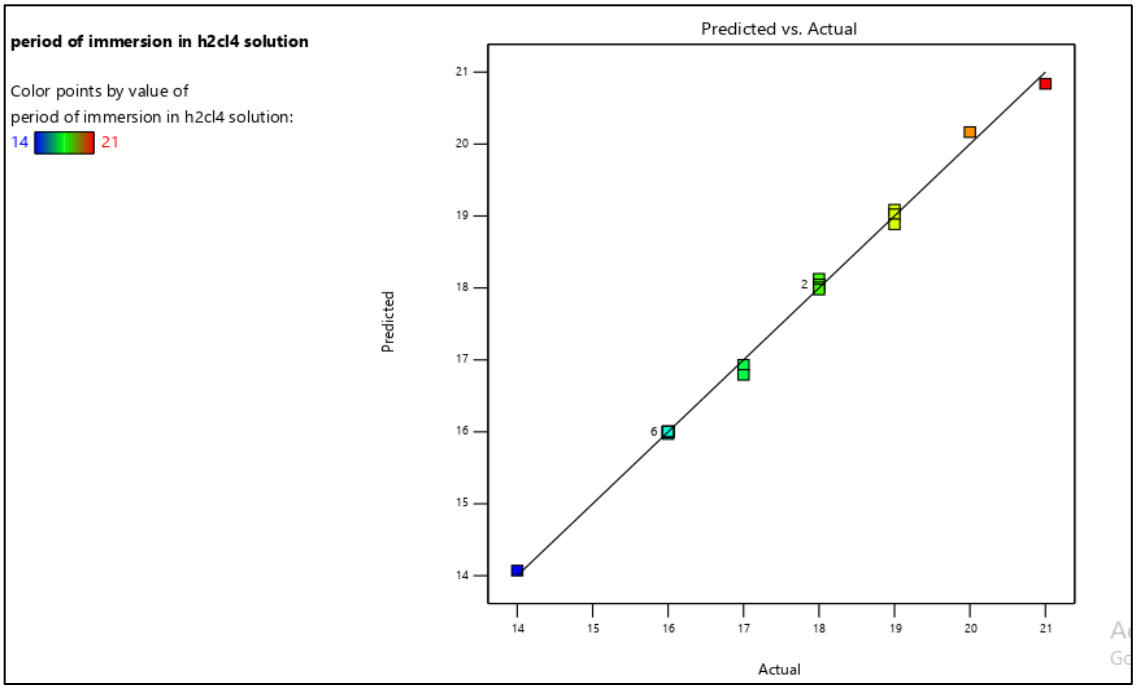

Figure 1: Plot of Predicted Vs Actual for period of immersion

To research the impacts of current and voltage on the period of immersion, Figure 2 displays the resulting 3D surface plots as follows:

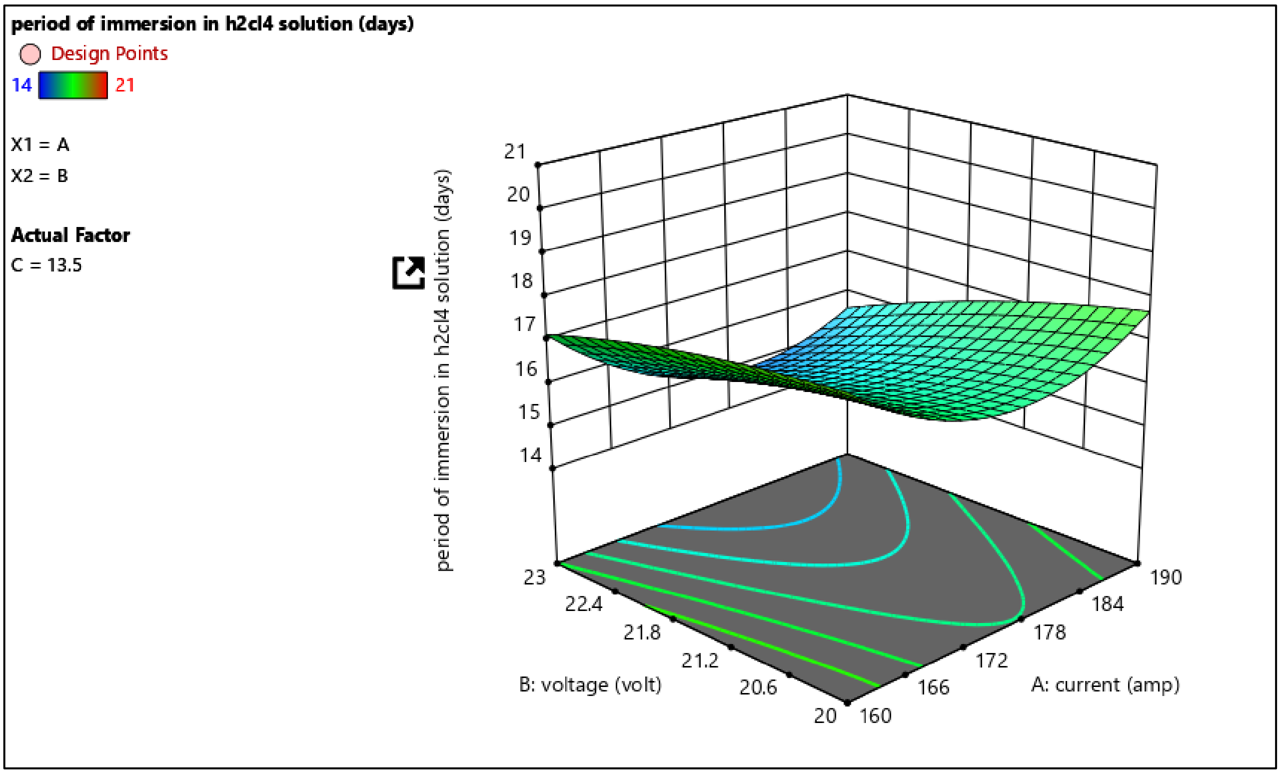

Figure 2: Impact of voltage and current on period of immersion

To research the impacts of current and gas flow rate on the period of immersion, Figure 3 displays the resulting 3D surface plots as follows:

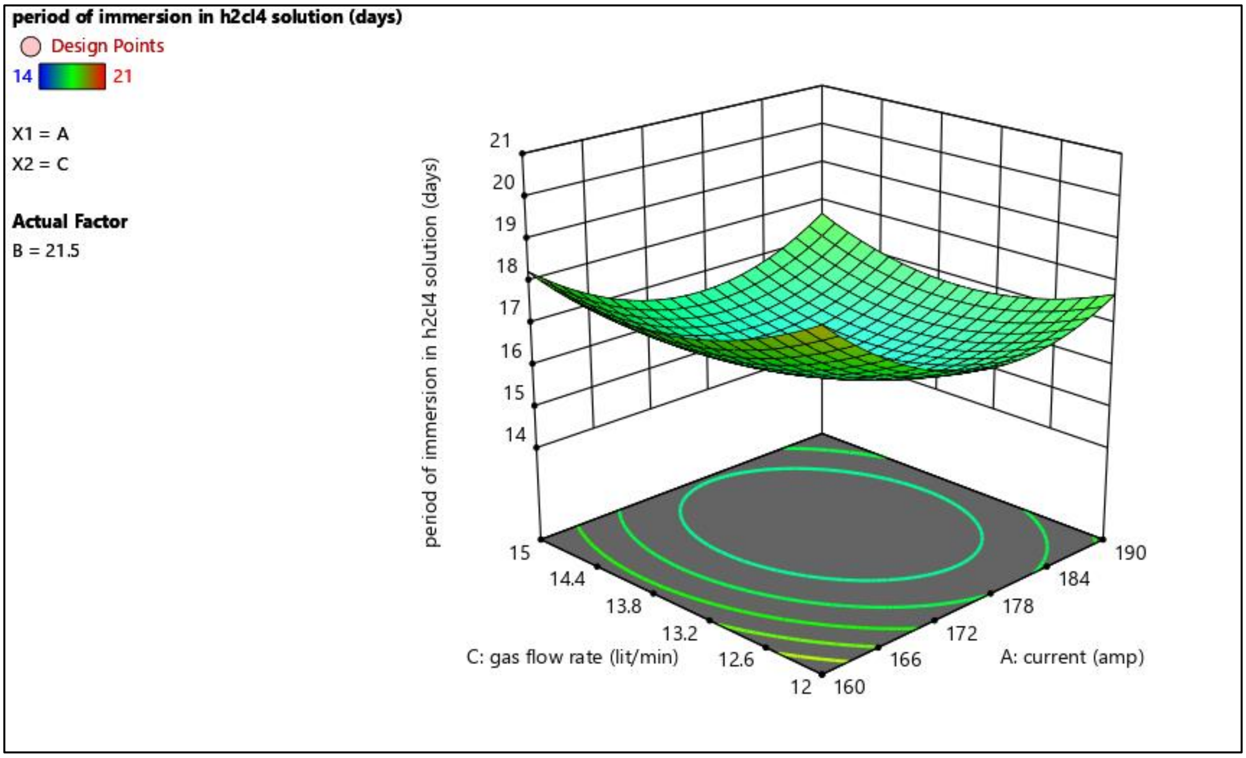

Figure 3: Impact of gas flow rate and current on period of immersion

To research the impacts of voltage and gas flow rate on the period of immersion, Figure 4 displays the resulting 3D surface plots as follows:

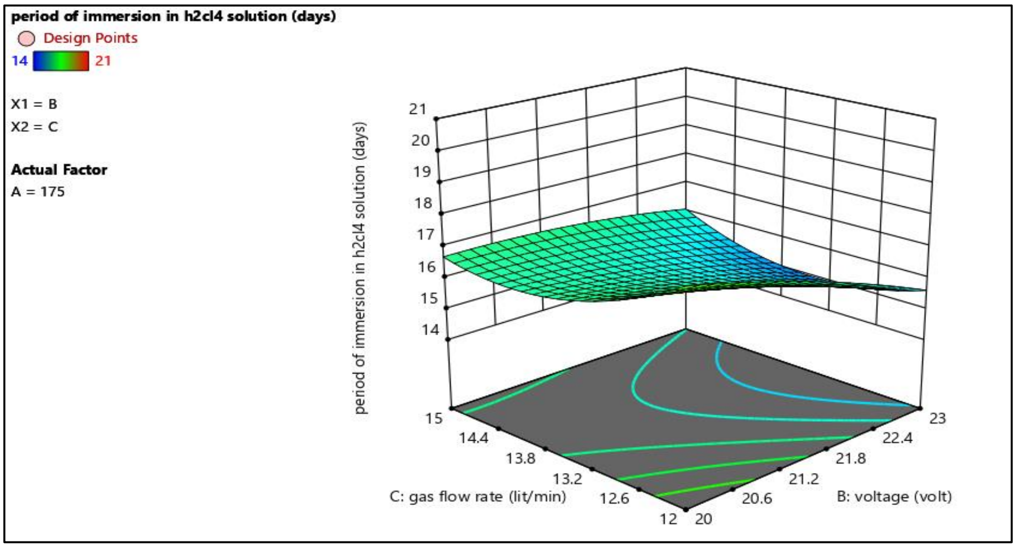

Figure 4: Impact of voltage and gas flow rate on period of immersion

Table 5 presents the approximately fifteen (15) optimal solutions that are produced by numerical optimization.

Table 5: Numerical optimization of optimal solutions

Number	Current	Voltage	Gas Flow Rate	period of immersion in h2cl4 solution	Desirability	
1	**160.000**	**21.280**	**14.667**	**18.067**	**0.918**	**Selected**
2	160.000	21.286	14.676	18.071	0.918	
3	160.000	21.268	14.662	18.066	0.918	
4	160.000	21.303	14.690	18.077	0.918	
5	160.001	21.259	14.650	18.061	0.918	
6	160.000	21.314	14.671	18.067	0.918	
7	160.000	21.301	14.703	18.084	0.918	
8	160.001	21.243	14.629	18.052	0.918	
9	160.000	21.219	14.600	18.041	0.918	
10	160.001	21.367	14.714	18.085	0.918	

3.2 Prediction of the Period of Immersion using ANN

The analysis utilized Matlab R2022a for implementing an Artificial Neural Network. The data was stored in a Matlab folder, then normalized by converting it to a Numeric format. The Levenberg-Marquardt training algorithm, an improved second-order gradient technique chosen as the ideal learning rule, was used to build the network architecture. Using this method, several counts of hidden neurons were tested to create a trained network, enabling researchers to determine the precise number of hidden neurons needed. The findings indicate that a network with three (3) input processing elements (PEs) and one (1) output processing element was trained using two hidden neurons and the Levenberg-Marquardt back propagation training approach. Mean Squared Error (MSE) and coefficient of determination (R^2) were used to track the network's performance, using a hidden neuron count of two per layer. The input layer calculated the layer output from the network input using the hyperbolic tangent (tan-sigmoid) transfer function, but the network's output layer used the linear (purelin) transfer function. Training, validation, and testing sets of input data were created during the network generation process. With a maximum training cycle of 1000 epochs, 70% of the data in the current study were used for training, 15% for validation, and the remaining 15% for testing. The Model summary is described in Table 6.

Table 6: Model summary for predicting period of immersion

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	9	1000
Elapsed Time	-	00:00:03	-
Performance	16.9	0.679	0
Gradient	40.5	0.00243	$1x10^{-7}$
MU	0.001	$1x10^{-5}$	$1x10^{10}$
Validation Checks	0	6	6

As described in Figure 5, a performance curve displays the development of the trained network.

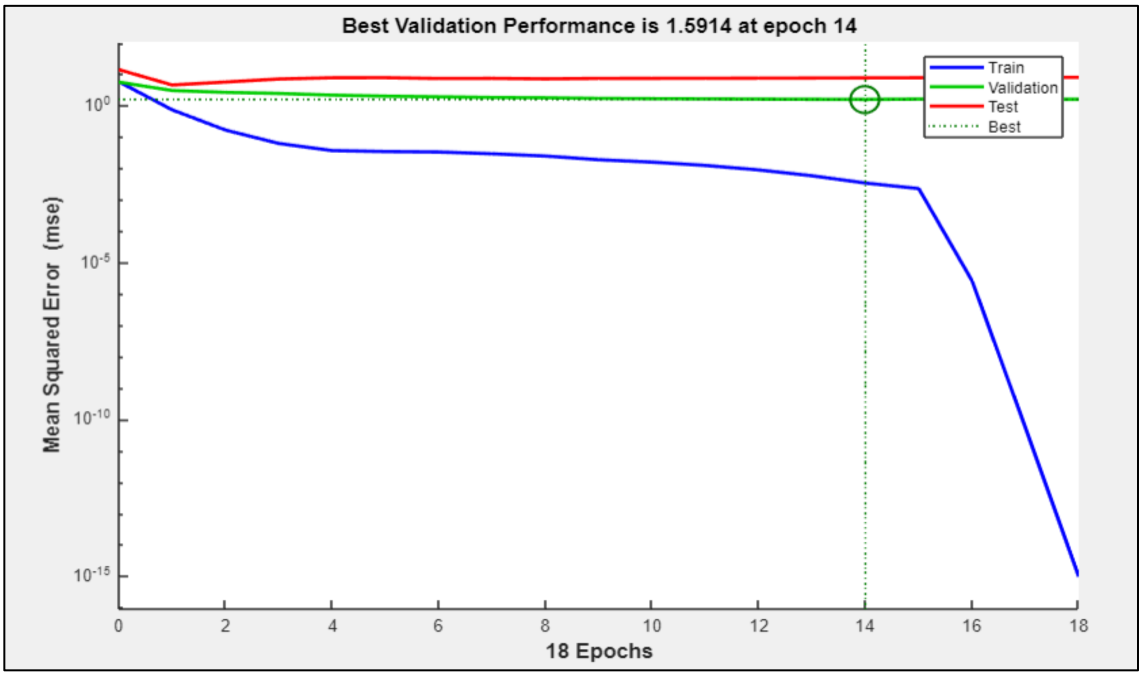

Figure 5: Performance curve of trained network for predicting period of immersion

Figure 5 performance plot did not show any indications of overfitting. However, one basic metric used to assess a network's training accuracy is lower mean square error, used in forecasting the period of immersion, demonstrated by an error value of 1.5914 at epoch 14. Figure 6 displays the training state, which includes the gradient function, training gain (Mu), and validation check.

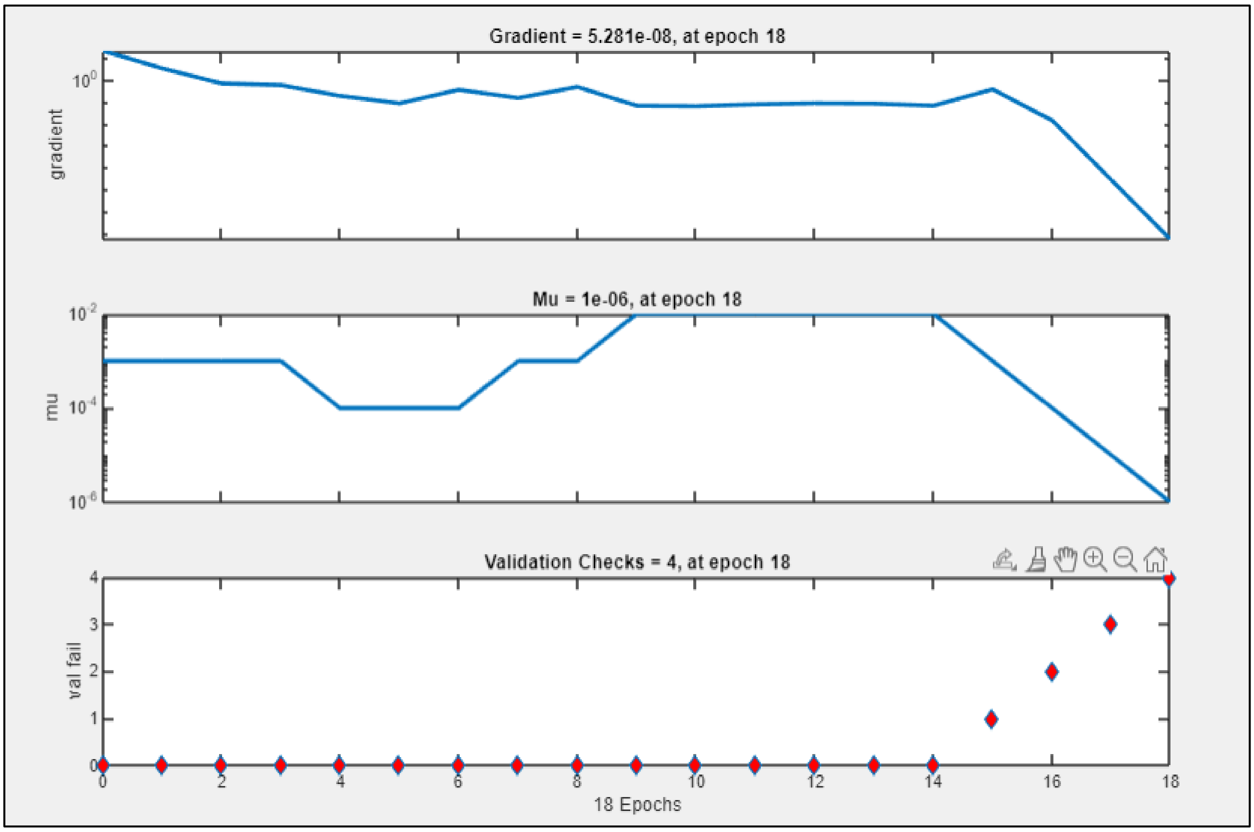

Figure 6: Training state for predicting period of immersion

Each selected neuron's error contribution is explained by the neural network by computing the gradient of the loss function. Gradient value of 0000000528 is computed, showing how little each chosen neuron's error contribution is. The Momentum gain increase of 0.000001 indicates a highly predictive network during the immersion period. Figure 7 displays the regression figure, which illustrates the relationship between the objective (time of immersion) and input variables as well as the development of training, validation, and testing.

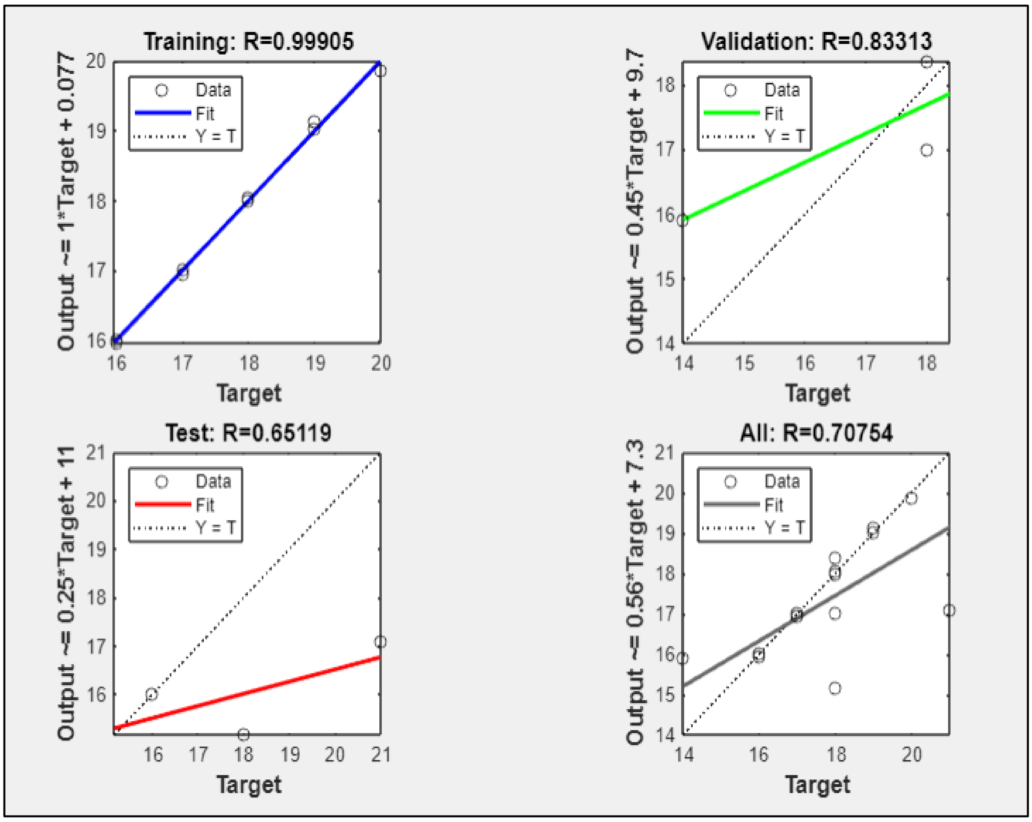

Figure 7: Regression plot illustrating training, validation, and testing progress

The correlation coefficient (R) values, as shown in Figure 7, indicate that the network has been appropriately trained and can be utilized for the prediction of period of immersion.

4. CONCLUSION

The useful service life of a fabricated engineering design is impacted by its hardness, resistance to shock and corrosion. In this paper, the development of numerical models using RSM and ANN in modelling the period of immersion, in correspondence with the current, voltage and gas flow rate.

The matrix of experiment adopted is the CCD. The RSM produced optimized solutions with current value of 162.000A, voltage of 21.290V and flow rate of 15.667lit/min to produce a welded joint with period of immersion 18.067 days and this was obtained at a desirability value of 0.928. The ANN model was utilized to anticipate the responses, as the result obtained were in correspondence with that obtained using the RSM. Due to its greater coefficient of determination, the response surface methodology is chosen from the results as the superior predictive model over the artificial neural network.

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