OPEN ACCESS

Spring International Engineering Research Journal: ISSN: 2384-5058

Volume-11 | Issue-9| September, Pp 26-36 2023 |

Research Papers

# Modelling and Prediction using Response Surface Methodology (RSM) and Artificial Neural Network (ANN) in determining Weld Factor of Safety of welded Tungsten Inert Gases joints

**By**

**[1]Iyoha T.O., [1]Achebo J. I., [2]Obahiagbon K., *[1]Ozigagun A.**

[1]Department of Production Engineering, University of Benin, Benin City, Nigeria.
[2]Department of Chemical Engineering, University of Benin, Benin City, Nigeria.

E-mail:[1]francisoghenerurie@gmail.com,[1]joseph.achebo@uniben.edu,[2]kess.obahiagbon@uniben.edu, *[1]andrewzigs@yahoo.com,

**Received: 15/7/2023| Accepted: 1/9/2023|**

**Abstract**: The importance of welding quality in metal production cannot be overstated because it improves the durability, toughness, and strength of engineering structures. The assessment of weld quality involves various parameters. Traditional methods such as welder expertise, charts, and handbooks have been used to determine desired welding parameters, offering simplicity and cost-effectiveness. However, relying solely on these methods doesn't guarantee satisfactory welding outcomes, especially in new welding processes. To address this challenge, the study aims to utilize artificial intelligence models for parameter optimization. The mild steel plate was chosen as the research material due to its availability. An optimal experimental design was carried out using design software. Gas tungsten arc welding was employed to create weld samples, with input factors; gas flow rate, voltage, and current. The desired outputs were the weld strength factor, weld factor of safety, and weld quality index. Both the response surface methodology (RSM) and artificial neural network (ANN) models were utilized to generate optimal solutions for controlling and predicting experimental responses. The RSM model was developed, tested, and validated, demonstrating high strength and accuracy in maximizing weld strength, quality index, and weld factor of safety. Similarly, the ANN model provided close correlations with experimental results, enhancing prediction capabilities.

**Keywords:** *Design of experiment, Response Surface Methodology (RSM), Artificial Neural Network (ANN), weld strength factor*.

**Published:8/9/2023**

2023.

## INTRODUCTION

When the right pressure, temperature, and metallurgical conditions are chosen during the welding process, two materials are permanently linked together through localized cohesion [1]. For combining copper-gold in the jewelry industry, welding has been used for a very long time [2]. Welding had already begun to develop quickly by the time electricity was widely available in the 19th century, and it was being used to combine metals. The terms "welding" and "brazing" are interchangeable when referring to the joining of autogenous metals [3]. Since the properties of the molten material related to fluid flow play a significant part in the procedure, the majority of researchers in the field explored the keyhole collapse events from a hydrodynamic point of view. Shifting the nozzle farther from the welding zone will, however, remove the fusion zone protection that shielding gases typically offer [4]. The biggest disadvantage of mechanical cleaning techniques like scraping and using a steel brush is that they severely degrade the parent material's surface and leave behind visible grooves and scratches that could affect how the weld bead will ultimately look [7]. These methods are also extremely operator-dependent in terms of cleaning evaluation and repeatability, making them difficult to manage. Engineering complicated issues and processes can be understood effectively via numerical modeling, according to research [8]. In order to simulate engineering processes numerically, physical behavior must be expressed as mathematical relations that computers can analyze and solve in order to model the specific problem [9]. Modeling is typically utilized when experimental or analytical methods fall short of providing a thorough picture of the subject under study or when time-consuming, expensive, and dangerous laboratory work is involved [10]. It is challenging to evaluate the impact of the filler wire composition on porosity formation in the welds when different materials with different chemical compositions are joined together using filler wires that have a varied chemical composition [11]. The molten weld pool is shielded from the air in some way during every step of the arc welding process. Due to its high melting efficiency, quick production rates, simple automation, and low operator skill requirements, the submerged arc welding technique is frequently chosen. [12]-[14] The weld's bead geometry, which is influenced by the process factors, determines the weld's quality.

## 2. METHODOLOGY

### 2.1 Design of experiment

Utilizing the Design of Experiments (DOE) technique proves to be a robust analytical tool for modelling and comprehensively assessing the impact of multiple controlling factors on performance outcomes. DOE encompasses the meticulous planning, designing, and analysis of experiments to derive valid and unbiased conclusions in an effective and efficient manner. When numerous variables exert an influence on a specific quality aspect of a product, also known as the response, the most effective strategy is to structure an experiment to yield valid, dependable, and well-founded findings while optimizing resource utilization. It is vital to recognize that certain factors may exert potent impacts on the response, some may induce moderate effects, and a few may have negligible influence. In the realm of manufacturing, experiments are conducted to enhance comprehension and insight into various engineering processes, ultimately aiming to produce superior-quality goods. This endeavour necessitates the skilful amalgamation of experimental parameters. One prevalent conventional approach adopted by manufacturing engineers is the one-variable-at-a-time (OVAT) method, wherein a single variable is adjusted while holding all other experiment variables constant. This approach demands considerable resources for a limited information gain about the process. OVAT experiments often prove to be unreliable, time-intensive, fail to attain optimal conditions, and disregard the interaction effects among process variables. Statistical-based methodologies can effectively supplant the OVAT approach, providing more robust alternatives for experimental design.

### 2.2 Central composite design (CCD)

One of the widely adopted designs within the domain of Response Surface Methodology is the Central Composite Design (CCD). CCD encompasses three distinct sets of design points, containing (a) axial points, (b) factorial designs with two levels or fractional factorial designs —also referred to as star points—and (c) central points. This particular design is meticulously tailored for the estimation of quadratic model coefficients. It is important to note that all descriptions of these points will be expressed in terms of coded values corresponding to the factors.

### 2.3 Factors required for design of experiment

During experimentation, certain crucial elements need to be taken into account to ensure the attainment of dependable and precise experimental outcomes. These elements are known as process parameters. Process parameters are further categorized into input parameters and output parameters. The input parameters pertinent to this research investigation are presented in Table 1.

**Table 1:** Input parameters

| Parameters | Unit | Symbol | Coded valueLow(-1) | Coded value High(+1) |
|---|---|---|---|---|
| Current | Amp | A | 180 | 240 |
| Gas flow rate | Lit/min | F | 16 | 22 |
| Voltage | Volt | V | 18 | 24 |

### 2.4 Recording of responses

A mild steel plate with a thickness of 10 mm was chosen as the experiment's raw materials. Using a power hacksaw, the mild steel plate was divided into 60 mm by 40 mm sections, and the edges were then smoothed out by grinding to prepare the surfaces for fusion. The coupons' surfaces were further refined utilizing emery paper. Following this, the mild steel plates were securely affixed to the worktable using a versatile clamp to facilitate the welding of the specimen joints. To conduct the experiments, a Tungsten Inert Gas (TIG) welding process employing Alternate Current (AC) was employed. This welding technique was selected due to its ability to concentrate heat within the welding area. Shielding gas in the form of 100% argon gas was used. Each experimental run involved the use of five specimens, and the average of the readings from these five experimental runs was documented for each of the 20 total runs.

**2.5 Response Surface Methodology** (RSM)

Engineers frequently strive to identify the conditions that would yield the most efficient outcome in a given process. Put differently, they seek to ascertain the values of process input parameters that lead to the optimal levels of responses. This optimal state could entail either minimizing or maximizing a specific function in relation to these input parameters. Among the current arsenal of optimization techniques used to elucidate welding process performance and determine the optimal outcomes of interest, Response Surface Methodology (RSM) holds a prominent place. RSM encompasses a collection of mathematical and statistical approaches that prove valuable in both modelling and predicting responses influenced by multiple input variables, all with the ultimate aim of achieving optimization. Initially presented by Box and Wilson in 1951, RSM has found substantial application across industries for elucidating the interplay between response variables and several input factors, with the overarching goal of identifying optimal factor settings to enhance processes or products. This methodology shines particularly in scenarios featuring numerous input factors potentially influencing one or more response variables. RSM is, at its core, a synthesis of mathematical and statistical models applied to instances where a desired outcome is affected by a variety of variables. Its application is noteworthy in devising new products and refining existing designs. Regression analysis, optimization techniques, and experimental design are the core elements of the Response Surface Methodology. This combination is harnessed to explore the empirical relationship within the system. By leveraging Response Surface Methodology, empirical models—often referred to as response surfaces—are developed to capture the behaviour of a process's response in relation to relevant controllable factors. RSM facilitates the determination of operational conditions that yield the optimal response. This approach allows modelling up to the second order, providing ANOVA and 'Lack of Fit' tests independently when there is more than one response. Additionally, it generates contour and surface plots illustrating response behaviour for factor pairs. The overarching goals of response surface analysis are to facilitate comprehension of surface plot topography through intuitive 3D diagrams depicting maximum or minimum points, saddles, and ridges, and to pinpoint the optimal response region using contour plots.

**2.6 Artificial Neural Networks**

A neural network functions as a data mining tool aimed at uncovering concealed patterns within databases. It operates as a highly parallel distributed processor, inherently adept at capturing experiential knowledge and rendering it accessible for application. Its resemblance to the human brain is two-fold. Through a process of learning, the network assimilates information, and the synaptic weights—the connections between neurons—serve as the memory for this information. A fundamental neuron, equipped with R inputs, is endowed with a suitable weight denoted as 'w.' The summation of these weighted inputs, combined with a bias factor, constitutes the input for the transfer function 'f.' Neurons can employ a diverse range of differentiable transfer functions, such as 'f,' to generate their output. In the context of multilayer networks, the log-sigmoid transfer function 'logsig' is commonly employed. This function produces outputs ranging as the net input, between 0 and 1 of the neuron traverses between a negative and a positive infinity. As an alternative, multilayer networks can adopt the tan-sigmoid transfer function 'tansig.' Sigmoid output neurons are frequently employed for tasks involving pattern recognition, while linear output neurons find application in problems centered around function fitting. In essence, a neural network operates as a proficient instrument for unearthing latent patterns within data and harnessing its ability to learn and generalize from experiences, similar to certain attributes of the human brain.

**2.7 Feed forward Neural Network**

In feedforward networks, it's common to find a hidden layer or layers consisting of sigmoid neurons, then comes a layer of output comprising linear neurons. Incorporating multiple layers of neurons featuring nonlinear transfer functions enables the network to comprehend intricate nonlinear connections of the vectors of the input and output. The utilization of a linear output layer is primarily favoured for addressing function fitting or nonlinear regression tasks. Conversely, when the intention is to restrict network outputs within a specific range (e.g., between 0 and 1), opting for a sigmoid transfer function for the output layer, such as "logsig," is advisable. This is particularly relevant in instances where the network is being employed for pattern recognition challenges, where the network's objective involves making decisions. In networks comprising multiple layers, the sequential numbering of the layers determines the exponent on the weight matrix.

**2.8 Multilayer Neural Network Architecture**

This network possesses the capacity to serve as a versatile function approximator, effectively estimating any function with a finite number of disruptions to a high degree of accuracy, provided there are ample neurons in the hidden layer. Having established the multilayer network's architecture, the ensuing sections delineate the process of design. Preliminary Steps for Multilayer Neural Network Data Preparation Prior to embarking on the network design journey, the initial step involves the collection and preparation of sample data. Because it is challenging to incorporate prior knowledge into neural networks, the quality of training data ultimately determines how accurate the network can be. It is of utmost significance that the data encompasses the entire spectrum of inputs relevant to the network's intended application. Multilayer networks exhibit proficient generalization capabilities within their training input range. However, their capacity to extrapolate accurately beyond this domain is limited. Hence, the training data must comprehensively span the complete input space range. Following data collection, two essential prerequisites must be fulfilled prior to utilizing the data for network training: data preprocessing and division into subsets. For optimal efficiency in neural network training, specific preprocessing operations are conducted on both the network inputs and targets. Sigmoid transfer functions are used in multilayer networks to typically deployed within the hidden layers. These functions approach saturation as the net input surpasses a certain threshold (approximately three, yielding $\exp(-3) \cong 0.05$). Instances of early saturation lead to minute gradients and sluggish network training. The net input in the first network layer is the result of multiplying the input by the weight and subsequently added to the bias. To prevent the transfer function from reaching saturation due to substantial input values, it's customary the inputs should be normalized first before their integration into the network. This normalization process is typically extended to the target and input vectors within the dataset. Consequently, the network output invariably conforms to a normalized range. Upon implementation of the network in practical scenarios, the network output can be reverse-engineered to the original target data units through a reverse normalization process.

## 3.0 RESULTS

Artificial neural network (ANN) and response surface methodology (RSM) are two expert methods that were employed in this study to assess the data gathered from the tests conducted.

### 3.1 Modeling and Optimization using Response Surface Methodology (RSM)

The second order results of non-linear relationships are included in the Response Surface Model, a modification on simple linear regression. Finding the ideal combinations of factors to determine a particular response to an event is a common optimization approach. Understanding the relationship between many predictor factors and several projected responses is very helpful when using RSM.

Maximizing the weld factor of safety was the optimization model's goal. The optimal input variable's value, specifically the current (Amp), voltage (V), and gas flow rate (lit/min), which will produce the best weld output outcomes, was determined as the process's final solution.

To produce the experimental information needed for the optimization process;

i. An experiment's statistical design was carried out utilizing the central composite design method (CCD). A statistical tool was used to carry out the design and optimization. It was decided to use Design Expert 7.01 for this specific issue.
ii. A 20-run experimental design matrix was created with eight (8) factorial points (2n), six (6) axial points (2n), and six (6) center points (k).

The sequential model sum of squares for the weld factor of safety response was determined to verify the quadratic model's adequacy for evaluating the experimental data, as shown in Table 2.

**Table 2:** Sequential model sum of square for weld factor of safety

| | **Sum of** | | **Mean** | **F** | **p-value** | |
|---|---|---|---|---|---|---|
| Source | Squares | df | Square | Value | Prob > F | |
| Mean vs Total | 198.03 | 1 | 198.03 | | | |
| Linear vs Mean | 0.24 | 3 | 0.080 | 0.72 | 0.5569 | |
| 2FI vs Linear | 0.25 | 3 | 0.083 | 0.70 | 0.5711 | |
| Quadratic vs 2FI | 1.40 | 3 | 0.47 | 186.32 | < 0.0001 | Suggested |
| Cubic vs Quadratic | 0.018 | 4 | 4.508E-003 | 4.91 | 0.0554 | Aliased |
| Residual | 4.587E-003 | 5 | 9.174E-004 | | | |

The sum of squares table for the sequential model demonstrates how the model fit improves over time as terms are added. A polynomial of the highest order with a lot of extra terms and an unaliased model was chosen as the best fit based on the estimated sequential model sum of squares. The lack of fit test was estimated for each response to assess how well the fundamental variation in the data from experiments can be described by the quadratic model. It is impossible to use a model for forecasting that has a considerable lack of fit. Table 3 shows the results of the computation of the lack of fit for the weld factor of safety.

**Table 3:** Lack of fit test for weld factor of safety

| Source | Sum of Squares | df | Mean Square | F Value | p-value Prob > F | |
|---|---|---|---|---|---|---|
| Linear | 1.67 | 11 | 0.15 | 211.32 | < 0.0001 | |
| 2FI | 1.42 | 8 | 0.18 | 247.33 | < 0.0001 | |
| Quadratic | 0.020 | 5 | 3.948E-003 | 5.48 | 0.0621 | Suggested |
| Cubic | 1.707E-003 | 1 | 1.707E-003 | 2.37 | 0.1985 | Aliased |
| Pure Error | 2.880E-003 | 4 | 7.200E-004 | | | |

The cubic polynomial had a substantial lack of fit and was therefore aliased to model analysis, but the quadratic polynomial had a non-significant lack of fit and was indicated for model analysis. The calculated model statistics for the weld factor of safety response based on the model sources is shown in table 4
.

**Table 4: Model summary statistics for weld factor of safety**

| Source | Std. Dev. | R-Squared | Adjusted R-Squared | Predicted R-Squared | PRESS | |
|---|---|---|---|---|---|---|
| Linear | 0.33 | 0.1255 | -0.0494 | -0.5380 | 2.95 | |
| 2FI | 0.34 | 0.2554 | -0.1169 | -0.4981 | 2.87 | |
| Quadratic | 0.050 | 0.9882 | 0.9764 | 0.9195 | 0.15 | Suggested |
| Cubic | 0.030 | 0.9976 | 0.9914 | 0.8013 | 0.38 | Aliased |

To validate the adequacy of the quadratic model the goodness of fit figures depicted in table 5 are according to its capacity to enhance the weld factor of safety
.

**Table 5:**Goodness of fit statistics for weld factor of safety

| **Std. Dev.** | **0.050** | **R-Squared** | **0.9882** |
|---|---|---|---|
| Mean | 3.23 | Adj R-Squared | 0.9764 |
| C.V. % | 1.55 | Pred R-Squared | 0.9195 |
| PRESS | 0.15 | Adeq Precision | 32.459 |

Any model's acceptability must first be verified by the results of an acceptable statistical analysis.
The projected comparing values against the actual values for the weld factor of safety, as illustrated in figure 1a, so as to recognize a value or set of values that the model has difficulty identifying. The cook's distance plot was created for each response in order to identify any potential outliers in the experimental data. When an outlier is removed from the analysis, how much the regression would change is determined on the cook's distance. A point that stands out from the others by having an extremely high distance value should be looked into. Figure 1b shows the generated cook's distance for the weld strength component.

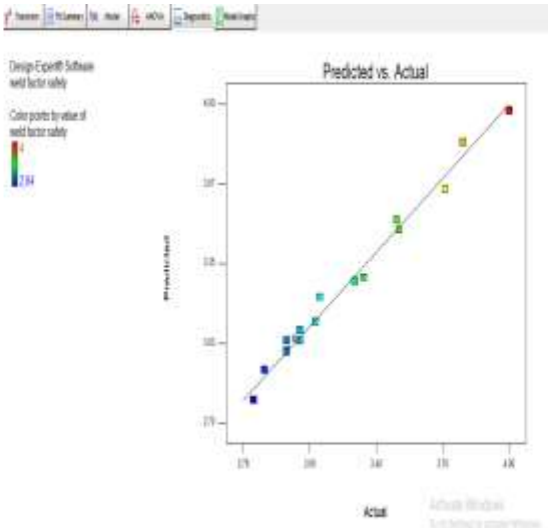


**Figure 1a:** Plot of Predicted Vs Actual for weld factor of safety

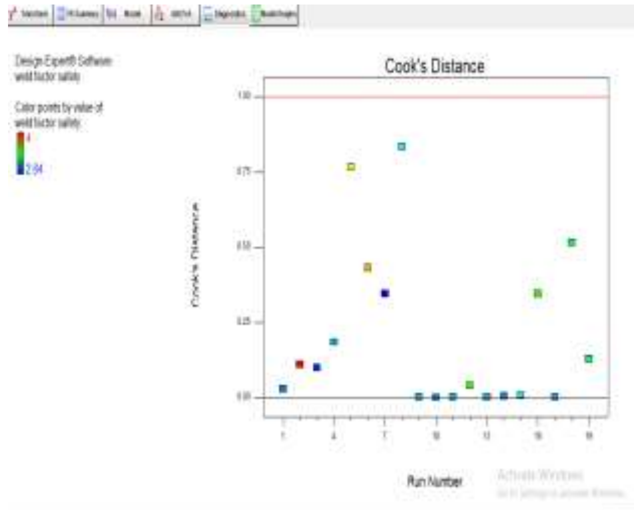


Figure 1b: cook's distance plot for weld factor of safety.

The 3D surface plots in Figure 2a and 2b were created to examine the influence of many input variables on the weld factor of safety generated as follows

.

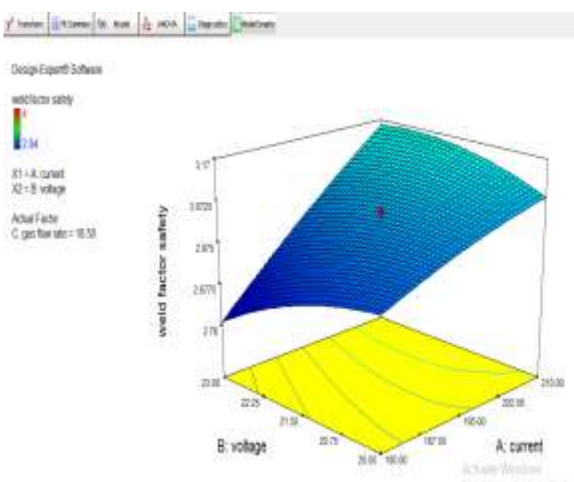


**Figure 2a:** Effect of current and voltage on weld factor of safety

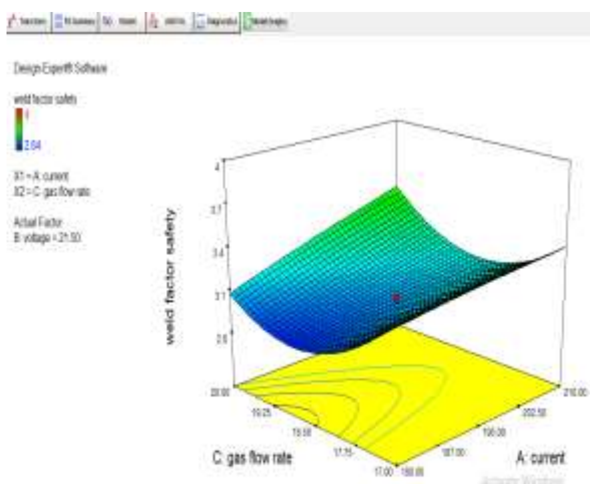


**Figure 2b:** Effect of current and gas flow rate on weld factor of safety

**Weld factor of safety analysis**

It is recommended that a set of data be set aside for validation and testing, therefore, that data obtained from this research were broken into three segments with 70% of the experimental sample data, used for training

15% used for validation, while the remaining 15% was used to test the neural network model the diagram of partitions. The ANN network architecture has 3 inputs, figure 3 depicts the safety weld factor of the network topology, which has ten hidden layer neurons and one output layer neuron.

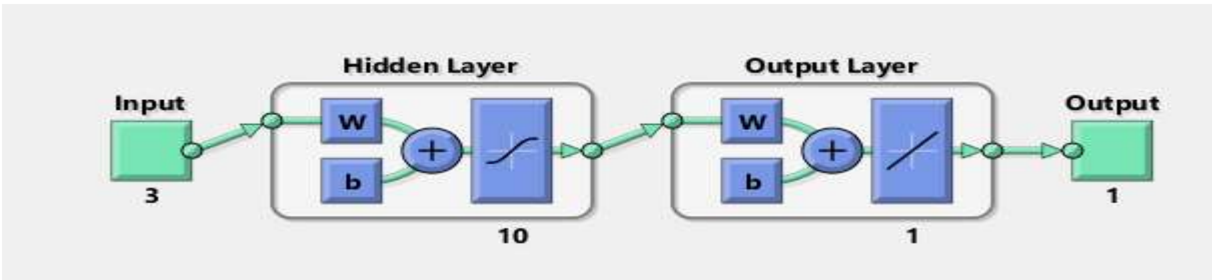


**Figure 3:** Artificial neural network architecture for predicting weld factor of sfety

The Training interphase for the weld factor of safety network, it was noticed that the training of the network model provided a correlation having 99.9% with a mean square error of 3.246E-4. The validation of the network model produced a correlation of 98.7% with a mean square error of 3.679E-2. the testing of the network model produced a correlation of 77.3% with mean square error 1.985E-1.

The performance plot for weld factor of safety was produced to check for network learning. Epoch 3 yielded the best validation performance which is shown in figure 4a. A gradient function plot is produced for the weld factor of safety network. it displays how many epochs were employed as part of the training procedure. 1 epoch denotes one full algorithm training cycle. There were 5 epochs used, and figure 4a demonstrates that the best forecast was made at the third epoch. The gradient function diagram is presented in figure 4b.

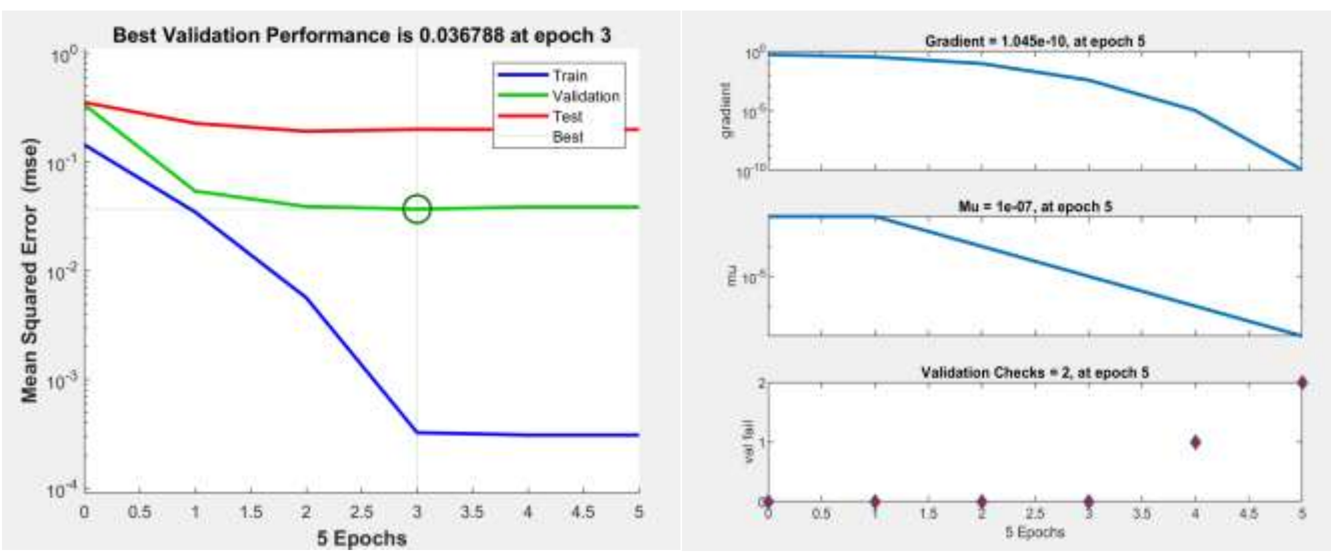


**Figure 4a:** Performance curve for weld factor of safety Figure 4b: gradient function plot for predicting weld factor of safety

A regression plot was produced to check the relationships between the observed values and the network predictions. The regression plot for the weld factor of safety network is presented in figure 5.

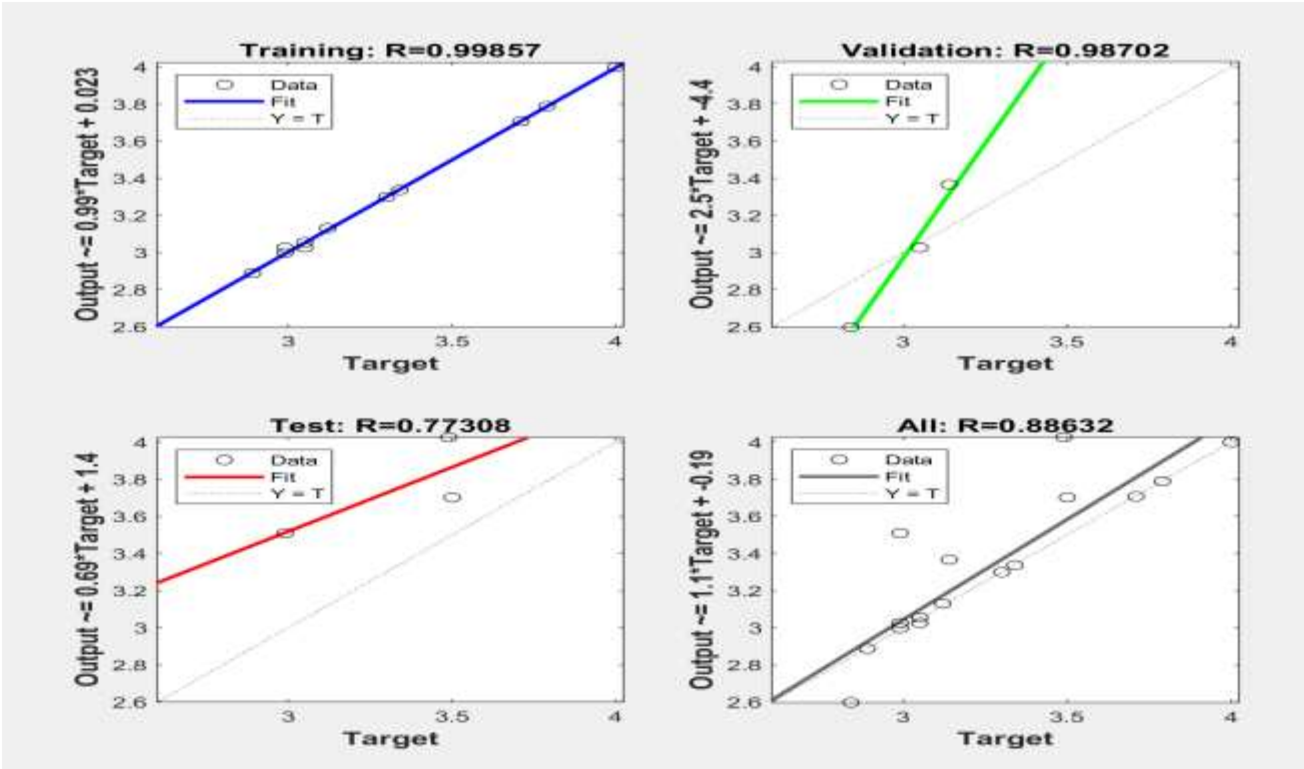


**Figure 5:** Regression plot for the weld factor of safety

Figure 6 illustrates a time series plot that can be used to understand the graphical contrast between the experimental result and the network output for the weld factor of safety.

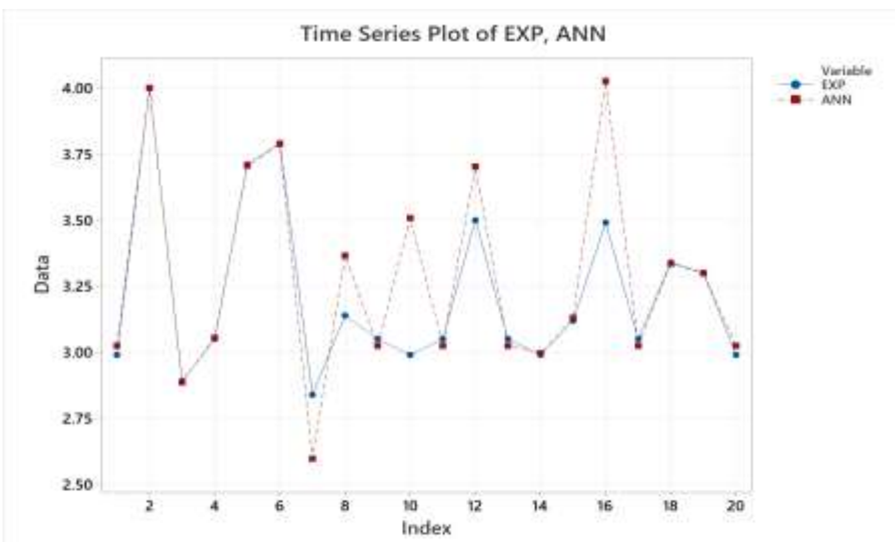


Figure 6: A time series plot for weld factor of safety

Equation 1 presents the regression equation for the weld factor of safety.
EXP = 0.8272 + 0.7290 ANN

Table 6 displays the results of the model summary statistics for the weld factor of safety network, which illustrate the output strength of the network

.

**Table 6:** ANN Model Summary for weld factor of safety

| S | R-sq | R-sq(adj) |
|---|---|---|
| 0.153234 | 78.56% | 77.37% |

The analysis of variance for the network output to check for the significance of the network as shown in table 7.

**Table 7:** Artificial Neural Network Analysis of Variance for weld factor of safety

| Source | DF | SS | MS | F | P |
|---|---|---|---|---|---|
| Regression | 1 | 1.54840 | 1.54840 | 65.94 | 0.000 |
| Error | 18 | 0.42265 | 0.02348 | | |
| Total | 19 | 1.97105 | | | |

A fitted plot for the artificial network output was done to ilustrate the correlation between the experimental and the weld factor of safety model developed,which is shown in figure 7

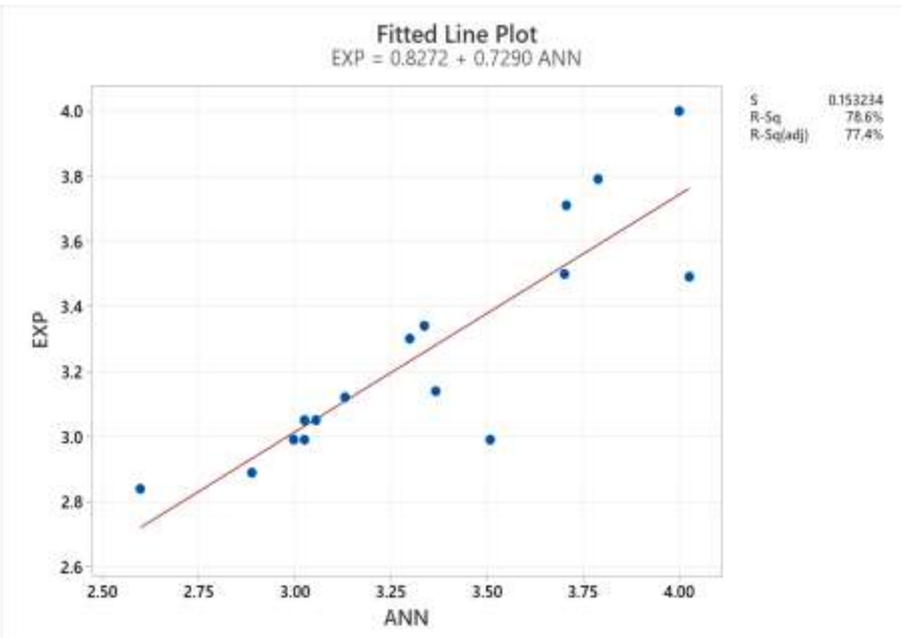


**Figure 7:** fitted line plot for the weld factor of safety

## 4.4 DISCUSSION

In this study, the weld factor of safety was predicted and optimized using the Response Surface methodology and artificial neural network methods. The input parameters include voltage, current, and gas flow rate, while the response is the weld factor of safety. With a coefficient of correlation of 0.9842, the link involving the procedure variables and the weld strength is quadratic and demonstrates a significant correlation between the variables of current, voltage, and weld strength. The ANOVA table demonstrates the model's importance and has a P-value of less than 0.0001 and a very good fit. The goodness of fit statistics provided a Coefficient of determination R2 of 0.9842, indicating how well the model can predict the chosen variables' values that will optimize the weld factor of safety, validating the model's importance and suitability based on its capacity to maximize the weld strength factor. The model has a noise to signal ratio of 29.157, which is larger than 4 is preferred and denotes a strong signal. The same statistical diagnostics was employed for the weld factor of safety response. From the result, it was seen that there is a strong correlation between the current had a strong correlation with the weld factor of safety with coefficient of correlation values of 0.9817 and 0.9882 respectively, the result obtained showed that the variance inflation factor (VIF) was 1.00 which is expected.

Lastly, numerical optimization was carried out to determine whether the entire model was desirable. We request the design specialist to increase the weld factor of safety during the numerical optimization phase. According to table 4.10's data, a weld with a weld factor of safety of 3.6253 will be produced by a current of 210.00 amps, a voltage of 22.66 volts, and a gas flow rate of 20 litres per minute. Design experts determined that this option, which has a desirability rating of 0.880, is the best one. The study demonstrates effective application of artificial neural networks in predicting the weld factor of safety for tungsten inert gas welding of mild steel plates. The mean square error was used to measure the performance of the network in each run. The network's mean square performance index is a quadratic function. Three sets of the input data are generated at random. 15% are used to verify the network performance after 15% are used to train the network and 15% are used for the test. For the training interphase the network provided a correlation value of 99.8% with a mean square error of 2.766E-7. The validation of the network model produced a correlation value of 94.0% with a mean square error of 1.040E-4. the testing of the network model produced a correlation of 97.7% with mean square error 1.003E-5. The performance plot showed that the model developed was learning, which is expected of a very good network. Lastly the artificial network model produced predicted values for the weld strength, weld quality index and weld factor of safety of which the predicted values and the experimental values of the responses, closely fit and are in reasonable agreement with a high coefficient of correlation.

## Conclusion

The assessment of a weld's integrity hinges on the weld bead's quality index and strength. A weld with elevated strength and a robust factor of safety corresponds to heightened integrity and dependability. In this investigation, both the response surface method and the artificial neural network model were harnessed to prognosticate and enhance the aforementioned output parameters. Analysis of the outcomes underscores the preference for the response surface methodology as the superior predictive model, surpassing the Artificial Neural Network in virtue of its lower mean square error value. Through the development of a mathematical model employing the Response Surface Methodology and the Artificial Neural Networks, the optimization and prediction of the weld factor of safety were achieved, thereby augmenting the longevity and integrity of welded joints. Rigorous testing and validation have attested to the model's robustness, precision, and effectiveness.

The findings derived from this study indicated a robust correlation between current and the mean weld strength factor, signifying that the manipulation of current holds the potential to enhance the weld strength factor. The independent term's variance inflation factor had a value of 1, while the combined and quadratic terms of the input factors demonstrated a value of 1.04. The outcomes unveiled the superiority of the enhanced second-order gradient technique, recognized as the Levenberg Marquardt Back Propagation training algorithm, which was chosen as the optimal learning rule for shaping the network architecture. Notably, the training algorithm was configured with 10 hidden neurons in both the input and output layers.

## References

[1] Dak, G.; Pandey, C. Experimental investigation on microstructure, mechanical properties, and residual stresses of dissimilar welded joint of martensitic P 92 and AISI 304 L austenitic stainless steel. *Int. J. Press. Vessel. Pip.* 2021, *194*, 104536.

[2] Khan, M.; Dewan, M.W.; Sarkar, M.Z. Effects of welding technique, filler metal and post-weld heat treatment on stainless steel and mild steel dissimilar welding joint. *J. Manuf. Processes* 2021, *64*, 1307–1321.

[3] Ramakrishnan, A.; Rameshkumar, T.; Rajamurugan, G.; Sundarraju, G.; Selvamuthukumaran, D. Experimental investigation on mechanical properties of TIG welded dissimilar AISI 304 and AISI 316 stainless steel using 308 filler rod. *Mater. Today Proc.* **2021**, *45*, 8207–8211.

[4] Satputaley, S.S.; Waware, Y.; Ksheersagar, K.; Jichkar, Y.; Khonde, K. Experimental investigation on effect of TIG welding process on chromoly 4130 and aluminum 7075-T6. *Mater. Today Proc.* 2021, *41*, 991–994.

[5] https://www.reddit.com/r/Welding/comments/347bgd/struggling_with_tig_on_stainless_steel/

[6] https://www.youtube.com/@weldHAGOJIBI/about

[7] Anbarasu, P.; Yokeswaran, R.; Godwin Antony, A.; Sivachandran, S. Investigation of filler material influence on hardness of TIG welded joints. *Mater. Today Proc.* 2020, *21*, 964–967.

[8] Kausar, A. Study of Weld Quality characteristics of Tungsten Inert Gas Welding of Dissimilar Metals SS 316L and IS 2062 Plates. *Int. J. Res. Appl. Sci. Eng. Technol.* 2019, *7*, 759–767.

[9] Hazari, H.R.; Balubai, M.; Suresh Kumar, D.; Haq, A.U. Experimental investigation of TIG welding on AA 6082

and AA 8011. In *Materials Today: Proceedings*; Elsevier: Amsterdam, The Netherlands, 2019; pp. 818–822.

[10] Sayed, A.R.; Kumbhare, Y.V.; Ingole, N.G.; Dhengale, P.T.; Dhanorkar, N.R. A Review Study of Dissimilar Metal Welds of Stainless Steel and Mild Steel by TIG Welding Process. *Int. J. Res. Appl. Sci. Eng. Technol.* 2019, *7*, 370–373.

[11] Kumar, A.; Sharma, V.; Baruaole, N.S. Experimental Investigation of TIG welding of Stainless Steel 202 and Stainless Steel 410 using Taguchi Technique. *Mody Univ. Int. J. Comput. Eng. Res.* 2017, *1*, 96–99.

[12] Maeda K, Suzuki R, Suga T, Kawahito Y (2020) Investigating delayed cracking behaviour in laser welds of high strength steel sheets using an X-ray transmission in-situ observation system. Sci Technol Weld Joi 25(5):377–382

[13] Ramadan, N.; Boghdadi, A. Parametric Optimization of TIG Welding Influence on Tensile Strength of Dissimilar Metals SS-304 and Low Carbon Steel by Using Taguchi Approach. *Am. J. Eng. Res.* 2020, *9*, 7–14.

[14] Vennimalai Rajan, A.; Mathalai Sundaram, D.C.; Vembathurajesh, A.; Nagaraja, R.; Chakravarthy Samy Durai, J.; Nagaraja, R. Analysis and Experimental investigation of Weld Characteristics for TIG Welding in Dissimilar Metals. *Int. J. Emerg. Trends Eng. Res.* 2020, *1*, 278–287.