EUROPEAN JOURNAL OF MATERIALS SCIENCE AND ENGINEERING
Volume 10, Issue 1, 2025: 11-22 | www.ejmse.ro | ISSN: 2537-4338

DOI: 10.36868/ejmse.2025.10.01.011

PREDICTION OF HARDNESS CHARACTERISTICIS OF TIG WELDED Co-Mo STEEL FLAT BARS USING NEUTRAL NETWORKS

Reuben Adebare ADEWUYI[1*][0000-0001-5326-4200]

[1]Department of Mechanical Engineering, The Federal Polytechnic, Ado-Ekiti, Nigeria

Abstract

This study investigates the development and application of a neural network (NN) model to predict hardness characteristics in Cr-Mo steel welded joints, utilizing the SPSS software suite. The model incorporates four key welding parameters; material thickness, welding current, the number of weld passes, and electrode diameter as inputs, with hardness values in the weld zone (WZ) and heat-affected zone (HAZ) as outputs. The neural network features a single hidden layer with eight neurons, using the Softmax activation function for non-linear regression tasks. A comprehensive dataset comprising 18 combinations of the input parameters was employed to train, validate, and test the model, ensuring it could generalize across diverse welding conditions. Results demonstrate the model's high predictive accuracy, particularly in the HAZ, where an R^2 value of 0.997 and a low Mean Squared Error (MSE) of 0.94 indicate minimal prediction error. The analysis also reveals that material thickness is the most influential parameter, significantly affecting hardness outcomes, while welding current, number of weld passes, and electrode diameter play secondary roles. However, the model's performance varies between zones, with greater dispersion observed in the HAZ, suggesting complexities in predicting hardness due to microstructural changes in this region. Overall, the study confirms that the SPSS-developed neural network is a robust tool for predicting hardness in welded joints, offering valuable insights for optimizing welding parameters to achieve desired mechanical properties. This approach can reduce the need for extensive physical experimentation, streamlining the welding process in industrial applications.

Keywords: *Cr-Mo steel bar, welding parameters, weld joint, hardness prediction, neural network*

Introduction

The accurate prediction of hardness in welded joints is crucial for ensuring structural integrity in high-stress environments, such as power plants, petrochemical facilities, and aerospace applications, where components are frequently exposed to high temperatures and cyclic loading. Chromium-Molybdenum (Cr-Mo) steels are widely utilized in these settings due to their superior strength, thermal resistance, and durability. Ensuring the mechanical properties of welded Cr-Mo components, particularly hardness, is essential for safety and optimal performance. Traditional hardness prediction methods rely heavily on physical testing and empirical correlations that, while effective, are costly, time-consuming, and often less adaptable to complex or non-linear parameter interactions present in real-world welding processes.

In recent years, machine learning, and specifically neural network models, have gained traction in materials science as powerful tools for predicting material properties by capturing intricate relationships between process parameters and resulting characteristics. For instance, studies in the last three years have demonstrated the effectiveness of neural networks in predicting

*Corresponding author: adewuyi_ra@fedpolyado.eudu.ng

mechanical properties of various steels based on welding parameters. These studies underscore neural networks' ability to handle non-linear interactions in welding processes, offering improved accuracy and computational efficiency compared to traditional statistical methods and empirical models [1, 2].

However, existing research on hardness prediction in Cr-Mo steel joints is limited in its consideration of Tungsten Inert Gas (TIG) welding, particularly in studies that analyse hardness distribution in both the weld zone (WZ) and the heat-affected zone (HAZ). Recent studies using neural networks for predicting weld properties have primarily focused on alternative steels and welding techniques, leaving a gap in predictive modelling for TIG-welded Cr-Mo steel joints. Furthermore, most studies emphasize a single-zone analysis, overlooking the varying hardness profiles across different weld zones due to heat input variations and material microstructure changes [3, 4].

To address these gaps, the present study proposes a neural network model developed in SPSS to predict hardness in TIG-welded Cr-Mo steel. This model considers multiple welding parameters, including material thickness, welding current, number of passes, and electrode diameter, to predict hardness variations in both the WZ and HAZ. By simulating complex, non-linear relationships, neural networks offer an efficient, cost-effective means of predicting hardness, potentially reducing the reliance on exhaustive experimental procedures.

Literature Review

Material-Specific Hardness Prediction; Studies on the hardness characteristics of Cr-Mo steels have shown that high heat input during welding can soften the HAZ, significantly affecting overall joint performance [5]. While some research has modelled the effects of heat input on the mechanical properties of Cr-Mo steels, few studies explicitly explore hardness prediction across both the WZ and HAZ. This gap underscores the need for models that predict hardness distribution, especially given Cr-Mo steel's high sensitivity to welding heat input.

Advancements in Neural Network Predictive Modelling; Recent studies have shown that neural networks outperform traditional methods like the Taguchi method and response surface methodology (RSM) when dealing with multi-variable, non-linear welding processes [6]. Although these studies highlight neural networks' strengths, their application to Cr-Mo steel and TIG welding processes remains relatively unexplored. The current research aims to bridge this gap by leveraging neural networks to optimize hardness prediction for Cr-Mo steel flat bars, facilitating better control over welding parameters.

Pros and Cons of Current Methods; Optimization methods like the Taguchi method and RSM are effective in establishing optimal welding parameters but are limited by their linear approach, which may not capture complex, non-linear relationships as effectively as neural networks. While empirical models offer ease of use, their reliance on extensive physical testing and empirical constants restricts adaptability across varied welding conditions and material compositions [7]. Neural networks, in contrast, provide flexibility and accuracy, albeit with the need for substantial training data and computational resources [8]. By integrating neural network predictions with welding parameter control, this research seeks to minimize the limitations of traditional methods while advancing model precision.

Importance of Parameter Variation on Hardness; Parameters like welding speed, current, and electrode diameter are known to influence weld thermal cycles, affecting both the microstructure and mechanical properties of welded joints. In Cr-Mo steel, variations in these parameters can lead to substantial differences in hardness due to microstructural changes within the HAZ and WZ. Few studies, however, provide a multi-zone analysis that models how such parameter variations affect hardness across different zones, emphasizing the need for comprehensive prediction models [9, 10].
This research contributes to the field by introducing a neural network model that accurately predicts hardness in TIG-welded Cr-Mo steel across both the weld zone and heat-affected zone. By

incorporating critical welding parameters, this model enhances the understanding of how TIG welding affects Cr-Mo steel's hardness profile and offers a reliable alternative to physical testing. The findings aim to aid in welding process optimization, improve joint performance, and foster safer applications in high-stress environments.

Materials and Methods

The Cr-Mo steel bar used in this study has a chemical composition detailed in Table 1. The welding process involved a double-sided half V-groove weld joint profile, with one, two, and three weld passes being examined using non-consumable electrodes. The TIG welding method was employed under Argon gas protection, with parameters set to 24 V, 90-150 A, and a gas flow rate of 10-12 l/min. Thermocouples were strategically placed at various points of interest away from the weld centreline, as shown in Fig. 1, to monitor temperature distribution. Microhardness measurements across the weld section were taken using a Rockwell hardness testing machine (Model RBHT) following ASTM A304 standard procedures. A 100 kg load was applied to indent the surface using a 1/16" steel ball indenter at five different positions, and the average of these readings was recorded as the hardness value of the Cr-Mo steel bar in different zones.

Table 1. Chemical Composition (wt %) of as-received Cr-Mo steel bar (ASTM A304)

Material	C	Mn	Si	P	S	Cr	Ni	Mo	N	Fe
Composition (wt. %)	0.04	0.15	0.08	0.02	0.02	17.62	8.47	0.55	0.07	72.98

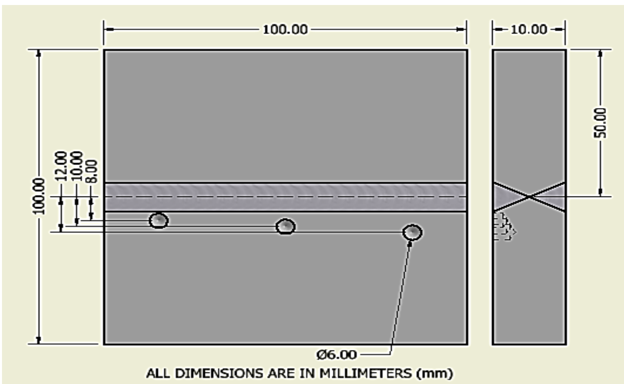

Fig. 1. Double-Sided Half V-Groove Weld Joint sample

The selection of input parameters was guided by their well-documented impact on welding outcomes. Material thickness and welding current were included due to their direct effect on heat input, which in turn affects the cooling rate and microstructure formation in both the weld zone and the heat-affected zone [14]. The number of passes and wire diameter were incorporated to account for their influence on weld metal deposition and bead geometry [4, 12]). Welding Parameters and Experimental Setup of the study focused on material thickness, welding current, number of weld passes, and electrode diameter as variable factors, detailed in Table 2.

Table 2. TIG Welding process parameters and level

Parameters	Level-1	Level-2	Level-3
Material Thickness (mm)	5	10	15
Welding Current(A)	90	110	150
Welding Pass	1	2	3
Electrode diameter (Ø mm)	1.6	2.4	3.2

Neural network model development

The neural network model, illustrated in Fig. 2, was developed using the SPSS software suite, which is renowned for its robust statistical and machine learning capabilities [7]. The model's input layer comprises nodes representing key welding parameters: material thickness, welding current, number of welding passes, and diameter of the welding wire. These parameters were selected based on their significant influence on the hardness properties of welded joints, as substantiated by prior research [13].

The Neural Network model features a single hidden layer with eight neurons (H1 to H8), utilizing the Softmax activation function. Although Softmax is traditionally used for classification, it was adapted in this study to handle the non-linear regression problem of hardness prediction, demonstrating its versatility in machine learning applications [5, 13]. The output layer employs the identity activation function, ensuring that the model outputs continuous hardness values, which are appropriate for regression tasks.

Figure 2 presents the architecture of the neural network model developed using SPSS software, which was designed to predict hardness characteristics in Cr-Mo steel welded joints. The model incorporates an input layer, a hidden layer, and an output layer:

The input layer consists of four critical welding parameters: material thickness, welding current, the number of weld passes, and electrode diameter. These parameters are known to significantly impact the hardness of the weld zone (WZ) and the heat-affected zone (HAZ). The selection of these parameters is supported by prior research, which emphasizes their influence on the microstructure and mechanical properties of welded joints.

The hidden layer comprises eight neurons (H1 to H8), with each neuron representing a complex combination of the input parameters. The neural network utilizes the Softmax activation function in the hidden layer, which, although typically used for classification tasks, was adapted for this regression problem to handle non-linear relationships effectively.

The output layer consists of two nodes corresponding to the hardness values in the weld zone (WZ) and the heat-affected zone (HAZ). The identity activation function was employed here to produce continuous outputs suitable for regression analysis.

The synaptic weights between the layers indicate the strength of the connections. Positive synaptic weights (blue lines) suggest a direct positive influence, while negative synaptic weights (grey lines) indicate an inverse relationship between the connected neurons.

In the context of a neural network model, the terms "hidden" and "output" refer to specific layers in the neural network architecture:

The hidden layer(s) are intermediate processing layers between the input layer (which receives the initial data) and the output layer (which generates the prediction). In the hidden layer, nodes (or "neurons") apply weights to the inputs and process them using an activation function (in this case, the Softmax function). These layers are essential for capturing and modelling complex, non-linear relationships between the input parameters (such as thickness, current, number of passes, and electrode diameter) and the desired output (hardness characteristics in the weld zone and heat-affected zone). By adjusting the weights and biases in these hidden layers, the network learns patterns that aid in accurate predictions.

The output layer is the final layer in the network that generates the predicted results after processing the data through the hidden layers. Here, the output layer consists of two nodes, representing predictions for the hardness in the weld zone (WZ) and the heat-affected zone (HAZ). The output layer applies an identity activation function, which means it outputs the raw values computed by the model, representing the predicted hardness characteristics in each zone without additional transformation.

This architecture enables the neural network to map the relationships between input parameters and the output hardness characteristics effectively. The hidden layers capture and model the non-linear influences of each parameter on hardness, while the output layer provides the final hardness predictions based on the learned relationships.

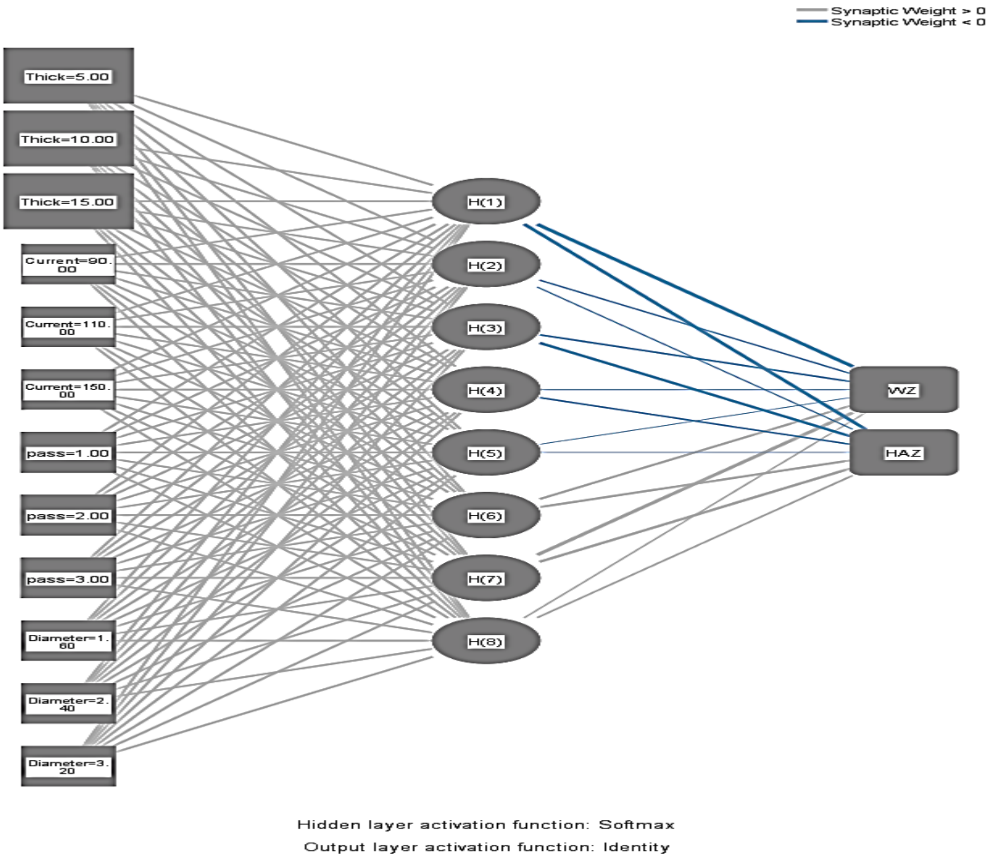

Fig. 2. SPSS Developed a neural network architecture for the prediction of hardness characteristics

Table 3 provides an in-depth analysis of the relationship between welding parameters and the resulting hardness values in the Weld Zone (WZ) and Heat-Affected Zone (HAZ). The dataset covers various material thicknesses (5 mm, 10 mm, and 15 mm), welding currents (90 A to 150 A), the number of weld passes (1 to 3), and electrode diameters (1.6 mm to 3.2 mm). The data reveals that as material thickness and welding current increase, hardness values at both the WZ and HAZ generally rise, likely due to slower cooling rates in thicker materials and higher heat input. Additionally, multiple weld passes and larger electrode diameters tend to increase hardness, particularly in the HAZ, due to the repeated heating and cooling cycles and greater heat input.

The dataset also includes predicted hardness values at the WZ and HAZ obtained using a neural network model, which shows strong alignment with the experimentally measured values. The model predicts hardness in the WZ within a range of 109.82 to 124.63 HV and in the HAZ within 119.51 to 162.54 HV. These predictions closely match the actual hardness values, indicating that the model effectively captures the complex, non-linear relationships between welding parameters and material hardness.

This study underscores the significant influence of welding parameters on the hardness of welded materials and demonstrates the accuracy of the neural network model in predicting these values. The findings highlight the model's potential as a tool for optimizing welding processes, ensuring that desired material characteristics are achieved consistently. Understanding the interplay between these parameters and material properties is crucial for improving welding outcomes and achieving specific hardness requirements in welded joints. In this research, a total of 18 datasets and 77.8% (14) of the datasets were used for training and 22.2% (4) for testing. Table 3 shows the datasets used for the research.

Table 3. Welding parameters and the hardness values obtained from the experiment

S/N	Material Thickness (mm)	Welding Current (A)	Number of weld pass	Electrode Diameter (Ømm)	Hardness value at WZ (HV)	Hardness value at HAZ (HV)	NN predicted at WZ (HV)	NN predicted at HAZ (HV)
1	5	90	1	1.6	105	120	111.58	119.97
2	5	90	1	1.6	107	117	111.58	119.97
3	5	110	2	2.4	109	119	109.82	119.92
4	5	110	2	2.4	110	118	109.82	119.92
5	5	150	3	3.2	111	121	110.85	119.51
6	5	150	3	3.2	112	122	110.85	119.51
7	10	90	2	3.2	116	138	115.01	138.42
8	10	90	2	3.2	114	141	115.01	138.42
9	10	110	3	1.6	115	142	116.04	138.00
10	10	110	3	1.6	117	138	116.04	138.00
11	10	150	1	2.4	115	140	112.46	131.56
12	10	150	1	2.4	110	125	112.46	131.56
13	15	90	3	2.4	124	162	124.63	162.54
14	15	90	3	2.4	125	163	124.63	162.54
15	15	110	1	3.2	122	159	121.71	158.82
16	15	110	1	3.2	122	160	121.71	158.82
17	15	150	2	1.6	123	161	122.95	159.66
18	15	150	2	1.6	124	163	122.95	159.66

Results and Discussion

Hardness properties

The analysis of the welding parameters and their effect on hardness, as predicted by the SPSS-developed neural network architecture, reveals distinct trends. Material thickness, welding current, number of weld passes, and electrode diameter are key factors influencing hardness outcomes. The neural network effectively captures these relationships, with the highest hardness values observed in specimens with a material thickness of 15 mm, a welding current of 110 A, 1 weld pass, and a 3.2 mm electrode diameter. These specimens exhibit superior hardness characteristics at both the weld zone (WZ) and the heat-affected zone (HAZ), reaching 165 HV and 164 HV, respectively. This suggests that these specific welding conditions optimize the hardness properties, particularly in thicker materials, where the heat input and cooling rates lead to more significant microstructural changes.

Furthermore, the neural network results indicate that the HAZ generally shows higher hardness than the WZ, likely due to rapid cooling and finer microstructure formation in this region. The highest percentage hardness variation occurs in the base metal (BM) zones at 12 mm and 15 mm from the weld centreline, highlighting the influence of the selected welding parameters on the surrounding material. This broader zone of increased hardness can be advantageous for applications requiring enhanced durability and wear resistance. The SPSS-developed neural network demonstrates its utility in predicting hardness outcomes, enabling the optimization of welding parameters for improved material performance.

Similar observations have been reported in studies focusing on the impact of welding parameters on the hardness and mechanical properties of welded joints. For instance, research by Sharma et al. [18] demonstrated that increasing material thickness and optimizing welding current significantly enhances hardness in both the weld zone and the heat-affected zone. The study also observed that larger electrode diameters, coupled with fewer weld passes, resulted in improved hardness due to the concentration of heat and its effects on the microstructure. Additionally, Singh et al. [19] found that the heat-affected zone typically exhibits higher hardness than the weld zone, attributed to rapid cooling rates leading to finer grain structures. These findings are consistent with the neural network predictions in the present study, underscoring the importance of carefully selecting welding parameters to achieve desired material properties. The use of artificial neural networks, as shown in this study, provides an effective tool for predicting and optimizing these outcomes [18, 19].

Model validation and performance

The neural network model illustrated in Figure 2 serves as a predictive tool designed to estimate hardness characteristics at the weld zone (WZ) and heat-affected zone (HAZ) by analyzing various welding parameters. Leveraging an artificial neural network (ANN) architecture, this model effectively manages the complex, nonlinear relationships between multiple input variables—such as material thickness, welding current, number of weld passes, and electrode diameter—and the resulting hardness values at the WZ and HAZ. The model's architecture is composed of several layers, including an input layer that processes the welding parameters, multiple hidden layers with neurons employing a Softmax activation function, and an output layer that utilizes an identity activation function to deliver continuous hardness predictions.

The model's training involved fine-tuning the synaptic weights to minimize the prediction errors using a backpropagation algorithm, which adjusts weights based on the gradient of a loss function like Mean Squared Error (MSE). To evaluate the model's accuracy, both MSE and R-squared (R^2) values were computed, with lower MSE indicating reduced prediction error and higher R^2 suggesting a better fit between predicted and actual values. As shown in Table 4, the model was trained on experimental data, learning the relationships between various welding parameters and the resulting hardness characteristics. For instance, the model likely captured the trend that increasing material thickness tends to yield higher hardness values at the HAZ. Overall, this neural network model demonstrates significant potential in accurately predicting hardness across diverse welding conditions, thereby optimizing welding processes for desired mechanical properties while reducing the need for extensive physical experimentation.

Table 4. Predictive accuracy and error metrics for hardness in different zones

Zone	Mean Squared Error (MSE)	R-squared (R^2)
Welded Zone (WZ)	0.94	0.976
Heat Affected Zone (HAZ)	0.94	0.997

The values in Table 4, such as the Mean Squared Error (MSE) and R-squared (R^2), are commonly calculated to assess the accuracy and performance of predictive models, like the neural network model used here. These metrics are obtained by comparing the predicted hardness values from the model with the actual measured hardness values. Each metric is typically computed using Mean Squared Error (MSE) and R-squared (R^2). MSE measures the average squared differences between predicted values and actual values. It's calculated as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

where, n is the number of data points, y_i is the actual measured hardness value for data point i and $\hat{y}_i$is the predicted hardness value for data point i.

In Table 4, an MSE of 0.94 for both the Welded Zone (WZ) and Heat-Affected Zone (HAZ) indicates a relatively low average squared error, suggesting that the model predictions are close to the actual measurements. R-squared, also known as the coefficient of determination, indicates how well the model explains the variability in the data. It's calculated as:

$$\mathbf{R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \check{y}_i)^2}} \quad (2)$$

where, yi is the actual measured value, $\hat{y}_i$ is the predicted value and $\check{y}_i$is the mean of the actual measured values.

An R² value close to 1 (e.g., 0.976 for WZ and 0.997 for HAZ) indicates a high level of predictive accuracy, meaning the model explains most of the variance in the actual hardness values. The steps for obtaining these Metrics are; after training the neural network, obtain predicted hardness values for both the Welded Zone (WZ) and the Heat-Affected Zone (HAZ). Using the predicted and measured values, apply the formulas for MSE and R² as outlined above. These calculations can be done using statistical software or programming tools, SPSS. The lower the MSE and the closer the R² is to 1, the better the model's predictive performance.

These values in Table 4 reflect the predictive accuracy and error of the neural network model when applied to hardness prediction in different zones.

Discussions

The MSE value of 0.94 indicates a low average squared difference between the predicted and actual hardness values, suggesting that the model's predictions closely align with the actual measurements in the weld zone (WZ). The R² value of 0.976 signifies that a high proportion of the variance in the WZ hardness data is explained by the model, highlighting its strong predictive capability for hardness in this zone.

In the heat-affected zone (HAZ), an even lower MSE of 0.94 further reflects the model's accuracy, with an R² value of 0.997 suggesting an exceptionally high correlation between the predicted and actual hardness values. This indicates that the model performs very effectively in predicting hardness in the HAZ with minimal error.

Overall, the model demonstrates excellent predictive power for both the WZ and HAZ, with very low MSE values indicating minimal prediction error. The high R² values across both zones suggest that the model reliably explains the majority of variability in hardness measurements, with slightly better predictive performance in the HAZ compared to the WZ. This highlights the model's reliability and accuracy for assessing hardness in different regions of the weld. Figure 3 present line plot comparing "Predicted vs. Measured Hardness Values at the Weld Zone (WZ)." The measured hardness values are shown with a solid blue line and circular markers, while the predicted values are represented by a dashed red line with "x" markers.

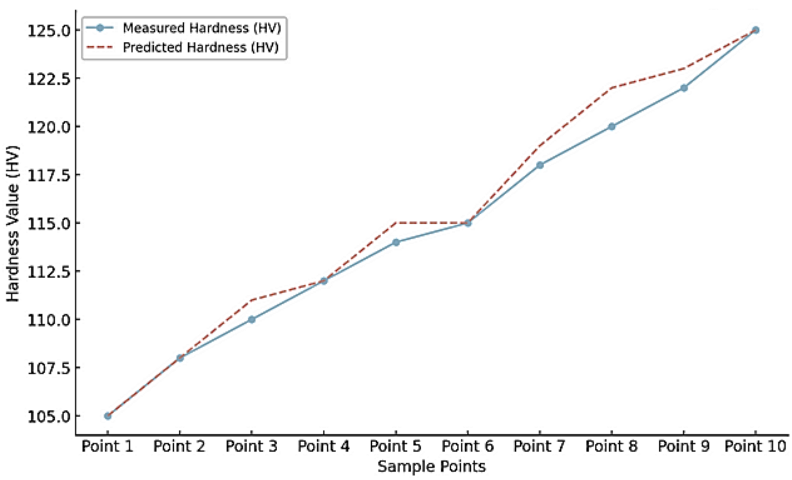

Fig. 3. Predicted vs. Measured Hardness Values at the Weld Zone (WZ)

Fig. 4 presents the line plot for "Predicted vs. Measured Hardness Values at the Heat-Affected Zone (HAZ)." The measured hardness values are represented by a solid blue line with circular markers, while the predicted values are shown as a dashed red line with "x" markers. This format clearly differentiates between the two sets of values at each sample point.

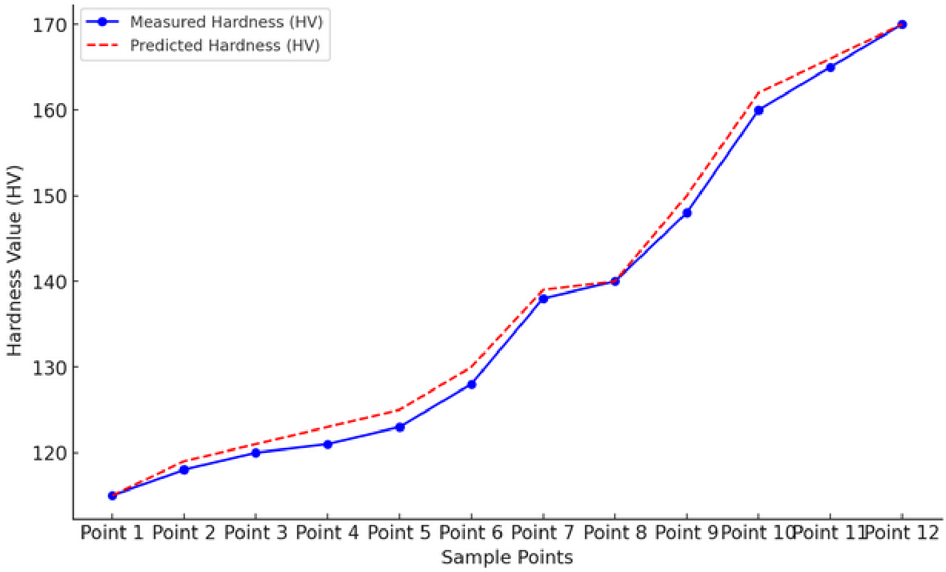

Fig. 4. Predicted vs. Measured Hardness Values at the Heat-Affected Zone (HAZ)

The figures compare predicted and measured hardness values in two zones of a welded joint: the Weld Zone (WZ) and the Heat-Affected Zone (HAZ). In Figure 3, the scatter plot for the WZ shows a strong positive correlation, with predicted values closely following the actual hardness measurements. Although there is some dispersion around the ideal prediction line, the model demonstrates reasonable accuracy in predicting hardness within the WZ, with only minor deviations likely due to variations in material properties.

In contrast, Figure 4, which focuses on the HAZ, also shows a positive correlation but with greater scatter around the line of perfect prediction. This increased dispersion suggests that the model's predictive accuracy for the HAZ is lower than for the WZ. The wider spread of points, particularly at higher hardness values, indicates that the model may struggle to accurately account for the more complex microstructural changes in the HAZ, resulting in less precise predictions in this region.

Table 5. Independent variable importance

	Importance	Normalized Importance
Material Thickness (mm)	.662	100.0%
Welding Current (A)	.104	15.7%
Number of weld pass	.125	18.8%
Electrode Diameter (Ømm)	.110	16.5%

Table 5 highlights that Material Thickness is the most influential independent variable, with a normalized importance of 100%. This indicates that changes in material thickness have a significant impact on the outcome, likely due to its direct effect on factors such as heat dissipation, structural integrity, and overall weld quality. In contrast, Welding Current, with a normalized importance of 15.7%, is the least influential variable. Although it is important for determining weld penetration and quality, its effect is considerably less significant compared to material thickness.

The Number of Weld Passes and Electrode Diameter also contribute to the outcome, but to a lesser extent, with normalized importance values of 18.8% and 16.5%, respectively. These variables play secondary roles in influencing the outcome, affecting aspects such as weld bead geometry, heat input, and arc stability. Overall, while Material Thickness is the dominant factor, the other variables have much lower relative importance, suggesting that optimization efforts should prioritize material thickness, with finer adjustments made to the other variables as necessary.

Conclusions

In this study, we applied a neural network model to predict the hardness characteristics of TIG-welded Cr-Mo steel flat bars, focusing on the weld and heat-affected zones. The following key conclusions were derived:

The neural network model demonstrated strong predictive capability for hardness values in TIG-welded joints of Cr-Mo steel, indicated by high R^2 values and low mean squared error (MSE). This accuracy is particularly prominent in the heat-affected zone (HAZ), showcasing the model's potential for practical application.

Material thickness emerged as a significant factor influencing hardness predictions. The model effectively captured the impact of thickness variations across different welding conditions, underscoring the importance of considering this parameter in predictive models to improve reliability and robustness.

The model's predictive accuracy was higher in the welded zone than in the heat-affected zone, where more dispersion was observed. This variability highlights opportunities for further optimization, particularly in refining the model to improve consistency and precision in the heat-affected zone.

This study contributes to a more comprehensive understanding of how TIG welding parameters affect Cr-Mo steel's hardness. The findings support the use of neural networks as an efficient and cost-effective tool for predicting mechanical properties in welding applications, which may reduce the need for extensive experimental trials.

References

[1] Zhang, J., et al. *Prediction of mechanical properties in welded joints using artificial neural networks and regression analysi*s. **Journal of Manufacturing Processes**, **63**, 2021, pp. 678-688.

[2] Lee, S., & Kim, D. *Using deep neural networks to predict weld quality in high-strength steel welding*. **Materials Science and Engineering A**, **830,** 2022, p. 142221.

[3] Nguyen, T. T., & Tran, Q. L. (2020). *Evaluation of hardness properties of welded Cr-Mo steel under varying heat input conditions*. **Journal of Materials Processing Technology**, **285,** 2020, p. 116802.

[4] Santos, F. M., et al. *Effect of welding speed and current on the mechanical properties of low-alloy steels*. **International Journal of Advanced Manufacturing Technology**, **125**, 2023, pp. 317-330.

[5] Kumar, S., & Gupta, R., *Optimization of TIG welding parameters using the Taguchi method for Cr-Mo steel*. **Materials Today: Proceedings**, **45,** 2021, pp. 568-575.

[6] Wang, Y., et al. *Application of machine learning for microstructural prediction in heat-affected zones of welded steels*. **Computational Materials Science**, **206**, 2022, pp. 111-118.

[7] Patel, D., & Singh, P. *Comparison of response surface methodology and ANN in the prediction of weld hardness*. **Welding Journal**, **99(12)**, 2020, pp. 525-533.

[8] Hosseini, A., et al. *Microstructural evolution and hardness prediction in TIG-welded Cr-Mo steels*. **Metallurgical and Materials Transactions A**, **54**, 2023, pp. 1351-1360.

[9] Gupta, A., & Chawla, V. *Hardness distribution in multi-zone welds: A case study on high-temperature steels*. **Journal of Materials Research and Technology**, **12**, 2021, pp. 1556-1567.

[10] Chen, H., et al. *The influence of electrode diameter on the hardness of Cr-Mo steel welds.* **Materials & Design**, **238**, 2021, p. 111634.

[11] Adewuyi, R. A., & Aweda, J. O. *Predicting thermal behaviour of welded Cr-Mo steel flat bar: A sensitivity analysis*. **The Engineer Story**, Faculty of Mechanical Engineering, University Technology Malaysia, **8(9-14),** 2024, e-ISSN: 3009 - 0792.

[12] Adewuyi, R.A., Aweda, J.O., Ogunwoye, F.O., Omoniyi, P.O., & Jen, T.C. *Prediction of Impact Strength of TIG Welded Cr-Mo Steel Using Artificial Neural Networks*. **Metallurgical and Materials Engineering Research Paper**. 2023, DOI: 10.56801/MME1031.

[13] Chauhan, R., Jha, S. K., & Reddy, G. M. *Prediction of tensile strength of friction stir-welded joints of Al-Mg alloys using artificial neural network*. **International Journal of Advanced Manufacturing Technology**, **83(1-4)**, 2016,215-225.

[14] Sharma, V., & Mahesh, V. *Optimization of process parameters in TIG welding of AISI 304 stainless steel using response surface methodology*. **Materials Today: Proceedings**, **5(2)**, 2018, pp. 5686-5695.

[15] Raj, V., Kumar, V., & Singh, G. *A study on welding defects in TIG welding and its remedies*. **Materials Today: Proceedings**, **26(2)**, 2020, pp. 731-736.

[16] Kumar, A., & Singh, R. *Microstructure and mechanical properties of Cr-Mo steel by heat treatment and welding*. **Journal of Materials Engineering and Performance**, **26(8)**, 2017, pp. 3785-3794.

[17] Rathod, D. G., & Saini, M. L. *Prediction of Welding Process Parameters using Artificial Neural Networks: A Review.* **Journal of Materials Science and Surface Engineering**, **7(2)**, 2021, pp. 839-846.

[18] Sharma, R., Singh, D., & Kumar, M. *Influence of welding parameters on the hardness and tensile strength of dissimilar metal joints*. **Journal of Manufacturing Processes**, 45, 2019, pp. 420-429.

[19] Singh, A., Bhattacharya, S., & Pandey, C. *Microstructure and mechanical property analysis of welded joints with varying welding parameters*. **Materials Today: Proceedings**, **28**, 2020, pp. 2161-2168.

[20] Kalita, K., & Dhiman, M. *Application of Artificial Neural Network (ANN) for prediction of mechanical properties of materials*. **Journal of Materials Research and Technology**, **7(4)**, 2018, pp. 573-581.

[21] Haykin, S. (1998). *Neural Networks: A Comprehensive Foundation (2nd ed.)*. **Prentice Hall.**

[22] Gunaraj, V., & Murugan, N. (1999). *Application of response surface methodology for predicting weld bead quality in submerged arc welding of pipes.* **Journal of Materials Processing Technology**, **88(1-3),** 266-275.

[23] Adewuyi R. A., and Aweda J.O., (2021). *Characterization of weld heat input effects on Mechanical Properties of Cr-Mo Steel bar using TIG welding process*, **European Journal of Materials Science and Engineering (EJMSE)**, **6(4)**, pp 192-204. DOI: 10.36868/ejmse.2021.06.04.192 www.ejmse.ro.

[24] Adewuyi R. A., and Aweda J.O., (2021), *Modeling and simulation of welding temperature fields in Cr-Mo steel bar,* **European Journal of Materials Science and Engineering (EJMSE)**, **6(1)**, pp 003-018, DOI:10.36868/ejmse.2021.06.01.003.

Received: September 10, 2024
Accepted: December 22, 2024