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# Prediction of Impact Strength of TIG Welded Cr-Mo Steel Using Artificial Neural Networks

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***Abstract:*** Welding is a critical and energy-intensive process with significant importance in the manufacturing industry, enabling the creation of joints capable of withstanding diverse loads without failure. Accurate prediction of welding parameters' effects on the thermal cycle and strength of metals during and after welding is essential to ensure the reliability of welds. This study investigates the influence of welding parameters such as welding current, material thickness, number of weld passes, and electrode diameter on the impact strength of Cr-Mo steel bars. Pure tungsten with 2% thoriated Tungsten Inert Gas (TIG) electrodes was used to join the metal sheets autogenously. Artificial neural network (ANN) was used in creating the model that predicts the impact strength of the steel. Sample with welding parameters of 15 mm thickness, 90 A current, 3 weld passes, and Ø2.4 mm electrode size exhibited the highest impact strength. Furthermore, the analysis of variance (ANOVA) results show that the material thickness and number of weld passes contribute significantly to the impact strength of the steel. The ANN model trained by the Levenberg-Marquardt algorithm had an average training dataset root mean square error (RSME) of 4.12%. This study contributes to the reliability and performance of welded joints in various applications.

***Keywords:*** Cr-Mo steel bar, Taguchi, TIG, welding parameters, Weld joint.

## 1. Introduction

Welding is a material-joining process that produces the fusion of materials by heating the material to melting temperatures [1, 2]. Permanent joints are achieved by welding processes [3]. Most of the areas of application of welding in manufacture are railway wagons, machine frames, structural works, tanks, automobile bodies, furniture, boilers, general repair work, and shipbuilding [4].

One prominent application of chromium molybdenum steel is in the turbine blades of power plants, as it can operate at elevated pressures and temperatures [5]. Chromium molybdenum (Cr-Mo) is a metal with good weldability, and different fusion welding processes have been used in joining this material. Tungsten inert gas (TIG) welding is an economical and common welding process which have been found suitable for welding Cr-Mo steels. However, there is still a need to further study the response/behavior/multiphysics of this material during cycles of heating and cooling [6]. Welding parameters such as current, gas flow rate, voltage, welding speed, and electrode thickness plays vital roles in the quality of joint produced in any material [7]. Different works of literature have examined the influence of these parameters on weld quality.

One parameter Amraei et al. [8] identified is heat input, which was observed to affect the elongation of high-strength steels significantly. The higher the heat input, the lower the ductility of the material. In another study by Maduraimuthu et al. [5], high hardness was observed due to high carbon in a solid solution, which in turn is caused by high heat input. So also is the increment in impact toughness as heat input increases. Similarly, tensile strength increased with increasing welding current and weld speed. Conversely, an increase in electrode diameter causes a decrease in tensile strength, which may result from inadequate coalescence of the filler material [8].

Optimization of process parameters plays an important role in the quality of welds, and several optimization tools have been developed to tackle these challenges. One of the major tools used is artificial intelligence (AI), in which machine learning (ML) and artificial neural network (ANN) are subset [9]. Choudhury et al. [10] used ANN and Teacher learning-based optimization tools in optimizing gas tungsten arc welding (GTAW) parameters of Inconel 825 sheets to obtain an improved ultimate tensile strength (UTS). Their results show that the 4-7-1 architecture of ANN, i.e., four inputs, seven layers of hidden neurons, and an output layer, gave the least effective error. It shows that welding current significantly affects the UTS, followed by welding speed. In another study by Johnson et al. [11], ANFIS was compared to ANN in optimizing the parameters of resistance of welding of DP780 sheets for improved nugget diameter (ND). It was observed that the ANFIS performed slightly better than the ANN model. Furthermore, their study confirmed welding current as the most important parameter influencing welds' quality. Genetic algorithm and ANN have also found their use in optimizing ultrasonic welding parameters. The algorithm has been found to produce models with minimized error [12].

The reviewed literature has highlighted the effect of the welding parameters, such as the welding current, welding speed, gas flow rate, and electrode diameter, on the mechanical properties of welds. However, there is still a need to understand how these parameters interact to affect the mechanical properties such as hardness, impact strength, and ultimate tensile strength in Cr-Mo steel welded using TIG welding. The need to have models that are balanced is also important, making this research adopt the ANN in optimizing the welding parameters such as material thickness, electrode diameter, welding current, and number of welds passes on the impact strength of Cr-Mo steel.

## 2. Materials and method

100 × 50 × 10 mm Cr-Mo steel bar with the chemical composition given in Table 1 was joined using tungsten inert gas welding. Before welding, the faying surface was cut to a double-sided half V-groove, as shown in Figure 1 and cleaned with acetone to remove impurities. The steel was joined using butt configuration using the parameters presented in Table 2. The parameters were carefully selected based on the review of works of literature and the need to achieve a full weld penetration. Argon gas with 99.99% purity at a flow rate of 12 l/min was used as shielding gas, with three weld passes carried out.

The impact strength of each sample was carried out on the Avery Denison Universal Izod Impact–Testing machine. Three identical samples of 75 x 10 x 10 mm of Cr-Mo steel bar were prepared, and an impact test was conducted on notched samples at a depth of 2 mm in the middle and a notch tip radius of 0.25 mm at an angle of 45° following the ASTM E23 [13, 14].

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

| 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 |

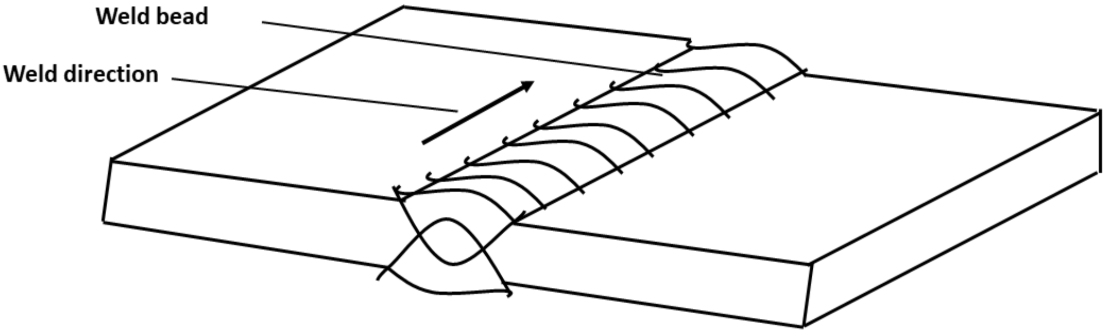

**Figure 1.** *Schematics of TIG weld*

**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 |

### *2.1 Artificial Neural Network Architecture*

Neural networks are tools that can use existing data to create an experience or learning and then use these experiences to predict the outcome of an occurrence [10]. In using the ANN tool, the input and output parameters must be known, and, in this research, the welding speed, material thickness, number of weld passes, and electrode diameter were used as the input, and the impact strength was used as the output. The artificial neural network (ANN) architecture is shown in Figure 2. One of the factors considered in ANN is the number of neurons and the number of hidden layers, as this determines whether the outcome model is underfitted or overfitted [12]. The development of ANN also involves data selection, normalization of datasets, network training, model validation, and testing [10]. In this research, the number of neurons varied between 7-12, using one hidden layer. The number of neurons with the least error is reported.

Table 3 shows the impact strength test results of the welds. Dataset selection is based on the data distribution used in the neural network training, model validation, and testing. Dataset distribution ensures that the model is not overfitted. Furthermore, the validation and testing dataset ensures the optimum performance of the model. According to Choudhury et al. [10], there is a need for better representation of parameters with higher influence with the suggestion of using training and testing data set to be in the ratio of 1:3 with the validation dataset being about 10-20% of the total dataset.

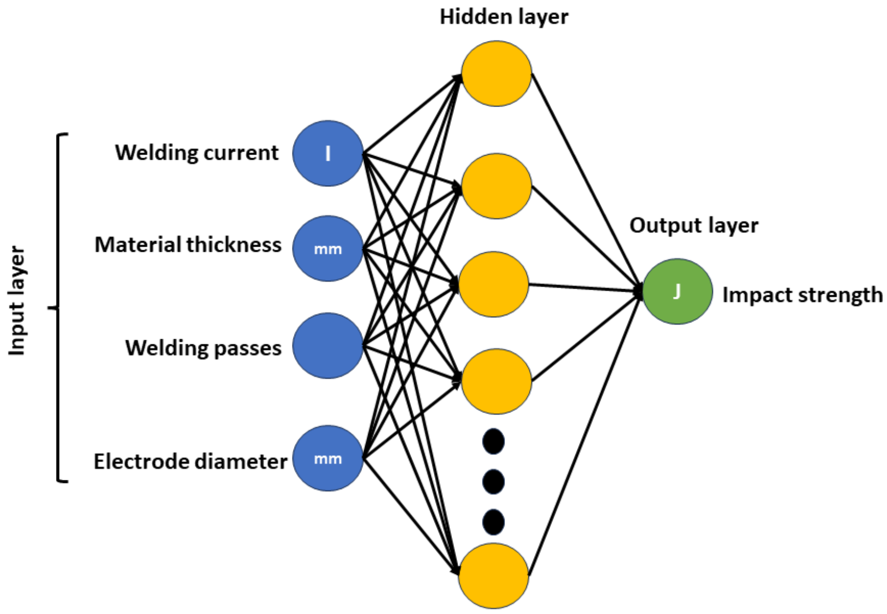

**Figure 2.** *ANN architecture is used in the optimization of welding parameters.*

Equation 1 shows the probabilistic approach to determining the minimum number of training datasets. P is the ratio of the incorrect predictions to total prediction, and *(1-P)* is the probability of the neural network making correct predictions for *m* number of testing data sizes.

$$P = (1 - P)^{m} \tag{1}$$

In this research, a total of 18 datasets and 70% (12) of the datasets were used for training, 20% (4) for validation and 10% (2) for testing. Table 2 shows the datasets used for the research.

**Table 3.** *Welding parameters and the impact strength obtained from the experiment.*

| Material Thickness (mm) | Welding Current (A) | Number of Weld Passes | Electrode Diameter (Ø mm) | Impact Strength (J) |
|---|---|---|---|---|
| 5 | 90 | 1 | 1.6 | 38.1 |
| 5 | 90 | 1 | 1.6 | 43.38 |
| 5 | 110 | 2 | 2.4 | 38.34 |
| 5 | 110 | 2 | 2.4 | 43.12 |
| 5 | 150 | 3 | 3.2 | 44.09 |
| 5 | 150 | 3 | 3.2 | 44.89 |
| 10 | 90 | 2 | 3.2 | 44.98 |
| 10 | 90 | 2 | 3.2 | 45.43 |
| 10 | 110 | 3 | 1.6 | 46.78 |
| 10 | 110 | 3 | 1.6 | 46.89 |
| 10 | 150 | 1 | 2.4 | 41.07 |
| 10 | 150 | 1 | 2.4 | 45.33 |
| 15 | 90 | 3 | 2.4 | 49.12 |
| 15 | 90 | 3 | 2.4 | 49.43 |
| 15 | 110 | 1 | 3.2 | 48.53 |
| 15 | 110 | 1 | 3.2 | 48.7 |
| 15 | 150 | 2 | 1.6 | 48.86 |
| 15 | 150 | 2 | 1.6 | 48.95 |

There is also a need to normalize the datasets to lie in the range of [0, 1] to ensure equal contribution of each parameter during training. Equation 2 is used to normalize the data. Where *x* is the actual parameter value, $x_{min}$, and $x_{max}$ are the minimum and maximum values of parameters.

$$x_i = \frac{\left(x_i - x_{min}\right)}{\left(x_{max} - x_{min}\right)} \tag{2}$$

Equation 3 shows the node activation function of the element of ANN that enables the solution of a complex non-linear function, where *b* is the net weighted input to the neuron.

$$f(x) = 1 \big/ \left(e^{-2b} + 1\right) \tag{3}$$

Equation 4 shows the root mean square error function used for the backpropagation neural network. Where N is the dataset number, $x_i$ is the experimental value of the dataset, and ¯x is the predicted value.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \bar{x}_i\right)^2}{N}} \tag{4}$$

## 3. Results and discussion

### *3.1 Impact strength*

The impact properties of 19 tested samples under four different welding parameters. Each piece was tested four times to obtain accurate and reliable results. The impact properties of these samples are presented in Figure 3, which provides a graphical representation of the impact values of each sample under different welding parameters. The samples with 15 mm, 90 A, 3 p, and Ø2.4 mm welding demonstrated the highest impact strength values of 49.43 J among the four tested welding parameters. Generally, it is observed that welds with a higher number of weld passes have higher impact strength, which could be attributed to the refining of the grain structure of the material after repeated heating and cooling. Furthermore, higher current results in an increase in impact strength and has been attributed to the ability of the material's thickness to withstand the existing materials with more thickness and to have higher impact strength than material with lower thickness [15]. It is important to note that impact testing measures a material's ability to absorb energy when subjected to a sudden load or force. A higher impact value indicates that the material has a greater ability to absorb energy and is, therefore, more resistant to fracture or failure. This implies that the samples with welding parameters of 15 mm, 90 A, 3 p, and Ø2.4 mm had a higher fracture or failure resistance than the other samples tested. This could be attributed to the presence of coarse ferrite within the microstructure of the material, as shown in Figure 4. This phenomenon is also observed by Yan et al. [16]. The lowest impact strength was recorded at 38.1 J, with a welding current of 90A, 1 number of weld passes, and a 5 mm thick plate. Therefore, these parameters may be considered optimal for welding applications that require high impact resistance, such as in the construction industry.

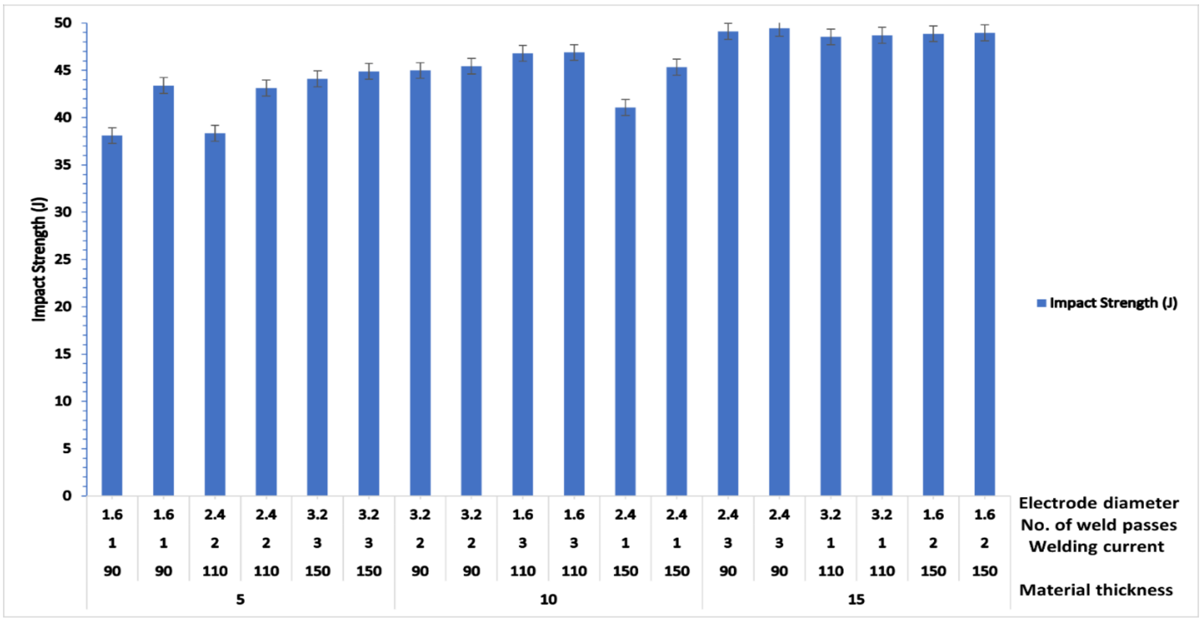

**Figure 3.** *Effect of welding parameters on the impact strength of welded samples*

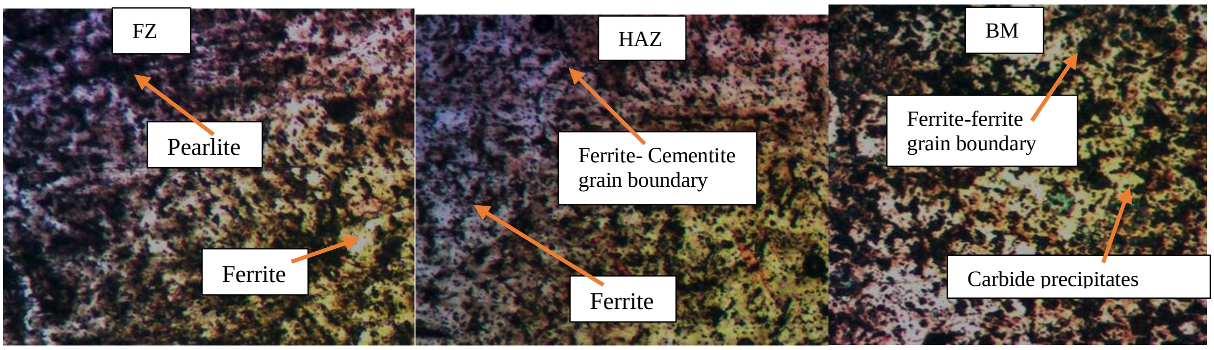

**Figure 4.** *Typical microstructure of the Cr-Mo steel showing grain structure at the fusion zone (FZ), heat affected zone (HAZ), and the base material (BM)*

### *3.2 Model Validation*

Table 4 shows the analysis of variance (ANOVA), a statistical tool that gives information on each parameter's significance to the material's impact strength. Material thickness has the highest contribution with 68.30%, then the number of weld passes comes second with 10.77%. Only a marginal effect is observed for the other parameters, such as the welding current and the electrode diameter. The ANOVA results further confirm that the material with the highest thickness has the highest impact strength, and those with multiple weld passes also have increased impact strength. The source code was run using MATLAB version R2023a, with the Lavenberg-Marquart used for the machine learning algorithm. The Lavenberg-Marquart algorithm was developed in the 1960s to solve nonlinear least square problems and can be applied to the trend of results from the experiment [17]. The codes were run using different weights to minimize mean square error. Table 5. shows the different architectures of the neurons, giving the least error. The 4-10-1 architecture with 10 neurons has the least error and has been used in predicting the impact strength of the welds.

Table 6 compares the predicted ANN values to the experimental values. The highest error value for the training data set is 8.48%, while the lowest is 0.33%, and the average error is 2.88%. The validation set has a maximum error of 6.87% and a minimum of 2.19%. The test dataset has a minimum error of 2.81% and a maximum error of 14.38%. All the error margins for all data set categories show that the ANN predicted results are not overfitted, and the model is suitable for predicting the impact strength of TIG welded Cr-Mo steel. The parameter combination of 15 mm material thickness, 90 A current, 2.4 mm electrode diameter, and 3 welded passes gave the highest predicted impact strength of 48.04 J, and that of the experimental results had 49.43 J using the welding parameters of 90 A current, 15 mm material thickness, 2.4 electrode diameter, and 3 weld passes, making it the best parameter combination for welding.

**Table 4.** *Analysis of variance (ANOVA) results of the impact strength of the welded material*

| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| Material Thickness (mm) | 2 | 145.274 | 68.30% | 145.274 | 72.6371 | 18.71 | 0.001 |
| Welding Current (A) | 2 | 0.663 | 0.31% | 0.663 | 0.3316 | 0.09 | 0.919 |
| Number of Weld Passes | 2 | 22.916 | 10.77% | 22.916 | 11.4579 | 2.95 | 0.103 |
| Electrode Diameter (Ø mm) | 2 | 8.919 | 4.19% | 8.919 | 4.4595 | 1.15 | 0.359 |
| Error | 9 | 34.931 | 16.42% | 34.931 | 3.8812 | | |
| Total | 17 | 212.703 | 100.00% | | | | |

**Table 5.** *Neural network architecture with different numbers of neurons*

| SN | ANN Architecture | Root mean square error (RSME) | | |
|---|---|---|---|---|
| | | Training | Testing | Error |
| 1 | 4-7-1 | 1.6987 | 2.8083 | 1.11 |
| 2 | 4-8-1 | 0.8920 | 3.7341 | 2.84 |
| 3 | 4-9-1 | 0.1659 | 4.7972 | 4.63 |
| 4 | 4-10-1 | 1.7436 | 1.5033 | 0.24 |
| 5 | 4-11-1 | 1.3940 | 0.3817 | 1.01 |
| 6 | 4-12-1 | 1.4201 | 0.6288 | 0.79 |

**Table 6.** *ANN predicted results.*

| SN | Material thickness (mm) | Welding current (A) | Number of weld pass | Electrode diameter (mm) | Impact strength (J) | | Percentage error |
|---|---|---|---|---|---|---|---|
| | | | | | Experimental | ANN predicted | |
| **Training datasets** | | | | | | | |
| 1 | 5 | 90 | 1 | 1.6 | 38.1000 | 39.6996 | 4.1984 |
| 2 | 5 | 90 | 1 | 1.6 | 43.3800 | 39.6996 | 8.4841 |
| 3 | 5 | 110 | 2 | 2.4 | 43.1200 | 43.8550 | 1.7045 |
| 4 | 5 | 150 | 3 | 3.2 | 44.0900 | 43.7727 | 0.7174 |
| 5 | 5 | 150 | 3 | 3.2 | 44.8900 | 43.7737 | 2.4868 |
| 6 | 10 | 90 | 2 | 3.2 | 44.9800 | 45.1303 | 0.3341 |
| 7 | 10 | 90 | 2 | 3.2 | 45.4300 | 45.1301 | 0.6597 |
| 8 | 10 | 110 | 3 | 1.6 | 46.8900 | 45.4651 | 3.0388 |
| 9 | 10 | 150 | 1 | 2.4 | 45.3300 | 43.8919 | 3.1725 |
| 10 | 15 | 90 | 3 | 2.4 | 49.4300 | 48.0435 | 2.8050 |
| 11 | 15 | 110 | 1 | 3.2 | 48.5300 | 47.5630 | 1.9926 |
| 12 | 15 | 150 | 2 | 1.6 | 48.8600 | 46.4546 | 4.9231 |
| **Validation datasets** | | | | | | | |
| 13 | 10 | 150 | 1 | 2.4 | 41.0700 | 43.8919 | 6.8710 |
| 14 | 15 | 90 | 3 | 2.4 | 49.1200 | 48.0435 | 2.1916 |
| 15 | 15 | 110 | 1 | 3.2 | 48.7000 | 47.5630 | 2.3347 |
| 16 | 15 | 150 | 2 | 1.6 | 48.9500 | 46.4546 | 5.0979 |
| **Test datasets** | | | | | | | |
| 17 | 5 | 110 | 2 | 2.4 | 38.3400 | 43.8550 | 14.3845 |
| 18 | 10 | 110 | 3 | 1.6 | 46.7800 | 45.4651 | 2.8108 |

## 4. Conclusions

In this study, the analysis of experimental results and the use of ANN to predict the impact strength of TIG-welded joints of the Cr-Mo flat steel bar have been carried out. The results have contributed to the reliability of TIG welding of Cr-Mo steel through the following conclusions:

1. Parameter selection plays an important role in the quality of welds as there are complex Multiphysics in the interplay during the welding process.
2. The impact strength property of the welded specimens is also significantly influenced by the material thickness and number of weld passes, resulting in higher impact values and percentage impact variation compared to the control experiment.
3. The ANN model shows a satisfactory performance with an average validation dataset root mean square error of 4.12%., showing that the model has a low generalized error and is not overfitted.
4. Parameter combination of 3 weld passes, 90 A current, and 2.4 mm electrode thickness resulted in the highest impact strength.

Employing prediction tools to forecast the microstructural and mechanical properties of Cr-Mo steel will give engineers an advantage in planning and avoiding material failure. Furthermore, further parameter optimization, such as gas flow rate, voltage, and joint configuration, is recommended to enhance the prediction accuracy further. In addition, the effect of parameter interactions will also improve the prediction model.

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