Modeling and Prediction of Mechanical Properties of Mild Steel Weldments Using Artificial Neural Network (ANN) Technique Based on Simulation Software

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النمذجة والتنبؤ بالخصائص الميكانيكية لملحومات الفولاذ الطري باستخدام تقنية الشبكة العصبية الاصطناعية اعتماداً على برامج المحاكاة

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Abstract:
Tungsten Inert Gas welding, also known as Gas Tungsten Arc Welding (GTAW), is an advanced arc welding process that becomes a popular choice when a high level of weld quality or considerable precision welding is required. However, the major problems of the TIG welding process are its slow welding speed and limited ability to produce material with lower thickness in a single pass. In this work, TIG welding has been performed on a 10 mm thick EN-5A mild steel plate without using any filler material. They developed a model using the artificial neural network (ANN) technique based on the Japan Welding Engineering Society (JWES) software to find the significant effect between the welding inputs process parameters, namely current, velocity, and voltage, on the mechanical properties namely: HAZ maximum hardness Hv-5, and weld metal tensile strength. After the simulation process, the maximum hardness of HAZ, Hv-5, and the weld metal tensile strength of the weld were investigated by finding predicted and optimum values for each model. The implemented validation for each model was done using the mean absolute percentage error MAPE and Nash Sutcliffe efficiency (NSE), respectively. It was observed that the ANN technique gave a mean absolute percentage error MAPE low, and Nash Sutcliffe efficiency (NSE) high, indicating that each model is accurate and excellent. The ANN technique is an accurate prediction model of the HAZ maximum hardness Hv-5, and weld metal tensile strength of the weld. Therefore, they are recommended for predicting of the weld of the arc welding process.

Keywords: Tungsten Inert Gas welding, HAZ maximum hardness Hv-5, weld metal tensile strength, JWES, ANN, MAPE, and NSE.

الملخص:
يُعَدُّ اللحام بغاز التنغستن الخامل(TIG) ، المعروف أيضًا باسم لحام القوس بالتنغستن الخامل(GTAW) ، من عمليات اللحام القوسي المتقدمة التي تُستخدم على نطاق واسع عندما تكون هناك حاجة إلى جودة لحام عالية أو دقة كبيرة في عمليات اللحام. ومع ذلك، فإن من أبرز العيوب المرتبطة بهذه التقنية هو انخفاض سرعة اللحام ومحدودية قدرتها على لحام المواد ذات السماكات المنخفضة في تمريرة واحدة.
في هذه الدراسة، تم تنفيذ عملية لحام TIG على صفيحة فولاذية منخفضة الكربون من نوع EN-5A بسُمك 10مم دون استخدام أي مادة حشو. وقد تم تطوير نموذج إحصائي باستخدام منهجية سطح الاستجابة(RSM) ، بالإضافة إلى بناء نموذج باستخدام تقنية الشبكات العصبية الاصطناعية (ANN)بالاعتماد على برنامج جمعية هندسة اللحام اليابانية(JWES) ، وذلك لدراسة التأثيرات المهمة لمتغيرات عملية اللحام، وهي :التيار، والسرعة، والجهد الكهربائي، على الخصائص الميكانيكية المتمثلة في أقصى صلادة لمنطقة التأثير الحراري (HAZ) – Hv-5 وقوة الشد لمعدن اللحام.
بعد إجراء عملية المحاكاة، تم تحليل القيم المتوقعة والمثلى لكل نموذج لتحديد أقصى صلادة لمنطقة التأثير الحراري (Hv-5) وقوة الشد لمعدن اللحام. وتم التحقق من صحة كل نموذج من خلال متوسط نسبة الخطأ المطلق (MAPE) وكفاءة ناش-ساتكليف .(NSE) وقد أظهرت النتائج وتقنية ANN حقق قيمة منخفضة لمتوسط نسبة الخطأ المطلق (MAPE) وقيمة عالية لكفاءة ناش-ساتكليف(NSE) ، مما يشير إلى دقة وكفاءة كل نموذج في التنبؤ. وبالتالي، يمكن تقنية ANN أداة فعالة ودقيقة للتنبؤ بكل من أقصى صلادة لمنطقة التأثير الحراري (Hv-5) وقوة الشد لمعدن اللحام، ولذلك يُوصى باستخدامهما في عمليات التنبؤ بخصائص اللحام في عمليات اللحام القوسي.

الكلمات المفتاحية: لحام التنغستن الخامل (TIG)، أقصى صلادة لمنطقة التأثير الحراري (Hv-5)، قوة الشد لمعدن اللحام، جمعية هندسة اللحام اليابانية (JWES)، الشبكات العصبية الاصطناعية (ANN)، متوسط نسبة الخطأ المطلق (MAPE)، كفاءة ناش-ساتكليف (NSE).

Introduction

Welding localized, or connecting two metallic components at their flaying surfaces, is what welding entails. The part surfaces that need to be connected and are in touch or proximity are known as the faying surfaces. Although welding is typically used to join pieces made of the same metal, it can also be used to unite metals that are not the same. The American Welding Society has cataloged some fifty different types of welding operations. They use various types or combinations of energy to provide the required power (Mikell P., 2010). We can divide the welding processes into two major groups: fusion and solid-state. Fusion welding procedures to melt the base metals. A filler metal is frequently added to the molten pool during fusion welding operations to speed up the process and increase the welded junction's mass and strength. An autogenous weld is a fusion-welding procedure where no filler metal is supplied. TIG welding is commonly used to fabricate aluminum, mild steel, and stainless steel. It can weld mild steel plates up to a maximum thickness of 10 mm (AHIRWAR, 2015). Compared to other arc welding methods like manual arc welding or Metal Inert Gas (MIG) welding, TIG welding produces cleaner and more precise welds on mild steel. Mild steel is a ductile material that is easy to machine. Welding mild steel plates is essential for shaping them into different structural forms used in manufacturing various machine components. TIG welding is known for delivering high-quality welds and is highly versatile. It ensures strong weld integrity, especially at the root, while maintaining good weld speed. TIG welding machines are available in both high and low current ratings, typically ranging from 150 A to 350 A, making them suitable for welding thick, mild steel plate (CHANDRA MOI, 2019). The aim of this study the impact of the selected input welding parameters on the output welding parameter based on neural network analysis available through the Japan welding engineering society (JWES) website (www-it.jwes.or.jp/weld_simulator/en/cal6.jsp). This aim can be achieved by performing the followings objectives:

1. Build a model using the artificial neural network (ANN) technique via MATLAB R2013a GUI in order to predict namely: HAZ maximum hardness Hv-5, and weld metal tensile strength
2. Validation the results obtained through the model for ANN technique based on neural network analysis available through the Japan welding engineering society (JWES) website (www-it.jwes.or.jp/weld_simulator/en/cal6.jsp), by calculating the mean absolute percentage error (MAPE) and Nash-Sutcliffe Efficiency (NSE).

Literature review

The objective was to evaluate and compare the mechanical properties of the welded joints. The samples were cut, machined, and subjected to tensile testing, impact toughness testing, and hardness testing to determine their mechanical properties. In general, as the welding current increased, the hardness of the weld also increased for both samples, reaching peak values at 115A for mild steel and 116A for low carbon steel. However, further increases in welding current led to a decrease in hardness. The ultimate tensile strength decreased with increasing welding current but showed an improvement at 200A for mild steel and 115A for low carbon steel. Both yield strength and impact strength exhibited a decline for the two samples as the welding current increased (Owolabi, 2016). The objective of this study was to examine the impact of various input parameters—specifically welding current, arc voltage, and root gap—on the mechanical properties of mild steel 1018 grade during Metal Inert Gas (MIG) welding. The investigation focused on the microstructure, hardness, and tensile strength of the weld specimens. The three selected input parameters were varied across three levels, and nine experiments were conducted using the L9 orthogonal array based on Taguchi's methodology. Analysis of Variance (ANOVA) was applied to determine the significance levels of these input parameters. The results indicated that the root gap had the most significant influence on tensile strength, followed by welding current and arc voltage. In terms of hardness, arc voltage had the greatest effect, followed by root gap and welding current. The microstructure of the weld metal was found to consist of fine grains of ferrite and pearlite (Kumar, 2014). This study aimed to establish the relationship between welding parameters—specifically speed, current, and voltage—and the welded joint characteristics in butt joints (X-groove) of EN 235JR using the response surface method (RSM). Optimal joint conditions, considering design factors such as cost, manufacturing speed, strength, and surface finish, were determined through the multi-response surface (MRS) approach. The optimal welding parameters for cost-related design requirements were identified as 140.593 amps, 8.192 mm/s, and 29.999 volts. For manufacturing speed, the optimal settings were 149.88 amps, 9.261 mm/s, and 29.999 volts. In terms of joint strength and surface finish, the ideal parameters were 149.086 amps, 7.139 mm/s, and 28.541 volts, and 150.372 amps, 8.561 mm/s, and 29.877 volts, respectively (Lorza, 2016).

A recent study conducted a comparative evaluation of Taguchi, fuzzy logic, and response surface methodology (RSM) techniques for optimizing tungsten inert gas (TIG) welding parameters—specifically current, voltage, and gas flow rate—when applied to mild steel. Utilizing MATLAB for fuzzy logic modelling, Minitab for ANOVA and main effect analysis, and Design Expert for charting and graphical interpretations, the study demonstrated that all three methods exhibit effectiveness. However, fuzzy logic emerged as the most robust optimization tool, achieving a lower error range (1.8–5.4%) compared to RSM (0.72–12.3%) and Taguchi (0.79–33.54%). The findings suggest that fuzzy logic produced results that more closely approximated actual experimental outcomes, thereby offering a superior predictive capability relative to traditional optimization techniques (Afabor, 2025).

The selection of current, voltage, and velocity as input parameters in the present study is grounded in their proven influence on the mechanical properties of welded joints, as consistently demonstrated in prior research. Study employing Artificial Neural Networks (ANN) for mild steel welding, have highlighted the critical role of these parameters in controlling tensile strength, hardness, and microstructural features. The adoption of ANN approaches herein is justified by their established capabilities in modeling nonlinear relationships and optimizing complex welding processes, thus ensuring predictive accuracy and reduced experimental costs. Unlike traditional experimental designs alone, the integration of simulation-based prediction using the JWES model further enhances the robustness of the results by incorporating chemical composition impacts, addressing a gap noted in earlier studies where micro alloy element effects were less emphasized. The systematic variation of inputs through factorial design ensures comprehensive interaction analysis, while validation using MAPE and NSE metrics guarantees the reliability of the developed models. Ultimately, the careful selection and analysis of these input variables are crucial for accurately capturing the interdependencies that govern weld quality, thereby enabling precise control over mechanical performance outcomes.

Methodology

Material selection

Two mild steel specimens, each measuring 150 mm by 100 mm by 10 mm, served as the workpiece for this project. The V-shaped groove used to manufacture these specimens had the following dimensions: 30° for the groove angle, 3 mm for the root face, and 0.75 mm for the root gap. A surface grinder was then used to polish the faces of 24 pairs of these specimens with uniform groove angles and root faces (Das, 2013). Two plates with a constant root spacing of 0.75 mm were attached at both ends along the width to create a butt joint. Following welding, each plate was chopped to the proper shape to determine the penetration depth using a power hacksaw. A portable gas-cutting machine held the welding flame with a fixed arm that may move at various recognized speeds. The experiment's electrode was a 1.2 mm diameter mild steel wire coated in copper (Das, 2013). A roller drive system supplied the wire through the welding gun. CO2 was utilized as the shielding gas and delivered under control at a steady pressure and flow rate (Das, 2013). The welding specimen preparation and process shows in Fig. 1.

Table 1 and Table 2 give, respectively, the chemical compositions of the base metals and their mechanical properties. The welding process uses a shielding gas to protect the weld specimen from atmospheric interaction. For this study, 100% pure Argon gas was used. The weld samples were made from a 10mm thick mild steel plate; the plate was cut to size with the power hacksaw. The edges were ground, the surface was polished with emery paper, and the joints were welded. After that, the response (preheat temperature) was then measured and recorded (Das, 2013).

Table 1: Chemical Composition of EN-3A

		Elements (wt.%)									
Steel	ASTM	Cr	Ni	Mn	Mo	Si	N	C	P	S	Fe
Mild steel	EN-3A	-	-	0.78	0.76	0.22	-	0.15	0.029	0.021	Bal

Table 2: Mechanical Properties of EN-3A

Base metal	Tensile strength (MPa)	Yield strength (MPa)	Percentage Elongation (%)
EN-3A	724	289	24

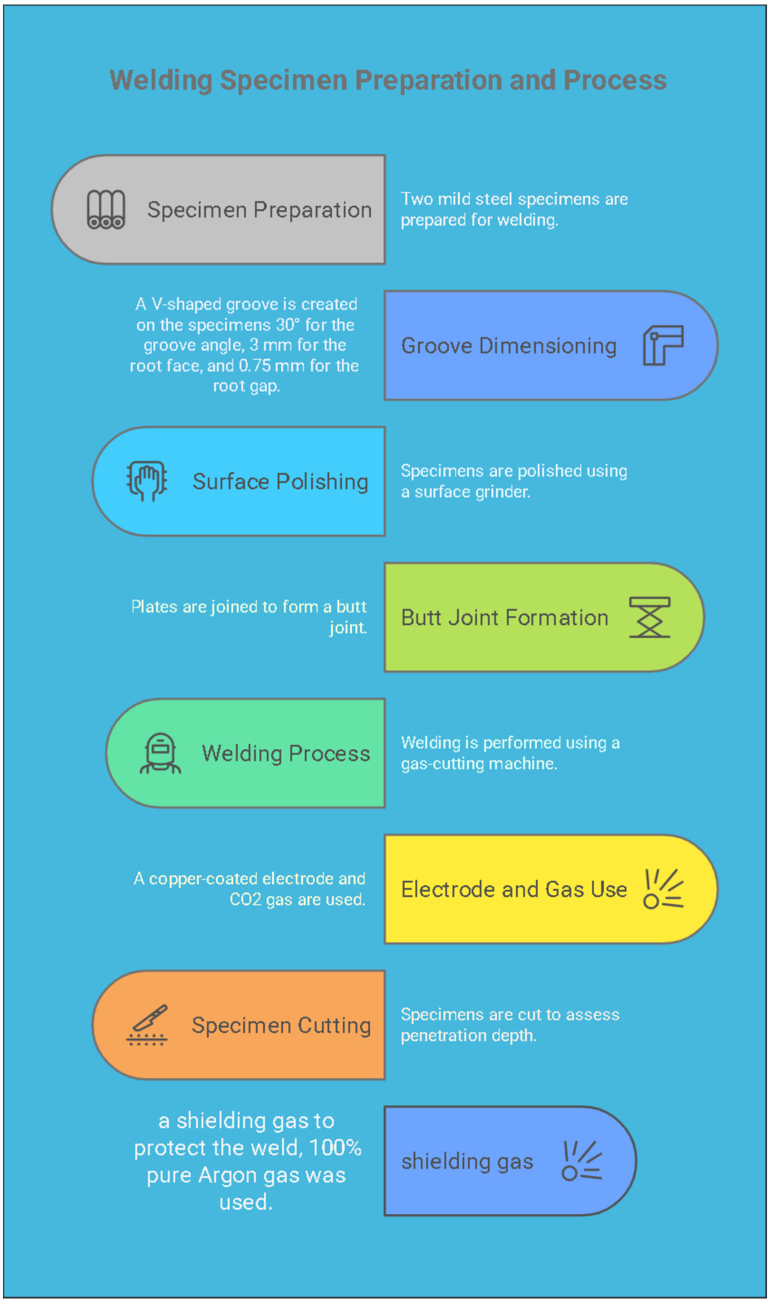

Figure 1: The welding specimen preparation and process.

Selection Welding Process Parameters
The key input process parameters considered in the study includes; current, voltage and velocity while the response or measured variables are HAZ maximum hardness estimated and weld metal tensile strength in welding process. The three input process parameters specified in Table 3 with their upper (+1) and lower (-1) levels as well as an appropriate design matrix had all been investigated. The outputs variables are specified in Table 4.

Table 3: Input process parameters and their levels.

No. S.	Factors	Notation	Unit	Level		
				-1	0	+1
1	Current	C	(A)	170	180	190
2	Voltage	V	(V)	21	23	25
3	velocity	S	(cm/min)	2	3.5	5

Table 4: The response selected for these experiments.

No. S.	Responses	Notation
1	HAZ Maximum Hardness estimated	Hv-5
2	Weld metal tensile strength	TS

Simulation and Prediction Models Approaches (JWES)

In this study, the simulation approach by means of utilizing simulation software will be implemented to represent the estimate the HAZ maximum hardness estimated and weld metal tensile strength in welding process. Moreover, the ANN technique will be utilized to develop two model. The JEWS website provides the required template to perform these predictive calculations based on the chemical composition with certain minimum and maximum limits for specific elements.

The Japan Welding Engineering Society (JWES) is a prominent professional organization dedicated to advancing the field of welding in Japan. Founded to foster progress in welding engineering and its applications, the JWES plays a pivotal role in connecting academicians, engineers, and researchers in the welding community. Additionally, JWES actively contributes to the establishment of quality standards in the welding industry, thereby ensuring the high quality of Japanese manufactured products. Through international collaborations, JWES enhances the global standing of Japan's welding industry(SAMPATH, 2022). The JEWS website provides the required template to perform these predictive calculations based on the chemical composition of Fe-C-Mn WMs with certain minimum and maximum limits for specific elements. Through its comprehensive computational analyses and simulations, the Japan Welding Engineering Society (JWES) enables engineers to make data-driven decisions and optimize welding processes. By simulating various welding scenarios, JWES researchers can identify potential issues, reduce the need for costly physical prototypes, and accelerate the development of new products. These simulations are instrumental in ensuring the highest quality and reliability of welded components, particularly in critical industries such as aerospace, automotive, and construction. On the JWES website, one can calculate and predict the temperature for 28 J CVN impact toughness or the absorbed the energy of Fe-C-Mn WMs based on their chemical composition, with certain minimum and maximum limits for specific elements. The prediction is performed using a neural network analysis by a software developed by D. J. C. MacKay at the University of Cambridge. The prediction is possible within the minimum and maximum limits for specific elements, and the prediction uses the extensive SMAW database developed at Oerlikon Welding Ltd., on low alloy high-strength steel WM. The tool facilitated balanced additions of Ti (and/or Zr), B, Al, N, and O to further reduce the actual TS temperature compared to the calculated value. The optimal content of Ti (and/or Zr), B, Al, N, and O was determined using an artificial neural network (ANN) model provided by the Japan Welding Engineering Society (JWES) through its website. This JWES ANN model allows for the adjustment of 16 elements in the weld metal (WM) composition, each within a defined range, to predict a temperature below −60°C for achieving 28 J of absorbed energy (T28J/°C) during Charpy V-notch (CVN) impact testing (SAMPATH, 2022).

Design of Experiments (DOE)

When conducting studies with multiple factors and needing to look into the combined impact of the factors on a response variable, factorial designs are frequently employed. Main effects and interactions are usually meant when we talk about joint factor effects. The fact that each of the k elements of interest has just two levels is a highly significant specific case of the factorial design. These designs are sometimes referred to as 2k factorial designs since every copy of such a design has precisely 2k experimental trials or runs (MONTGOMERY, 2013).

Factorial Design

Many experiments involve the study of the effects of two or more factors. In general, factorial designs are most efficient for this type of experiment. By a factorial design, we mean that in each complete trial or replicate of the experiment, all possible combinations of the levels of the factors are investigated. For example, if there are levels of factor A and b levels of factor B, each replicate contains all ab treatment combinations. When factors are arranged in a factorial design, they are often said to be crossed. The effect of a factor is defined to be the change in response produced by a change in the level of the factor. This is frequently called a main effect because it refers to the primary factors of interest in the experiment (MYERS, 2016).

Table 5 shows the statistical design of the experiment (doe) using the range and levels of the independent variables presented in Table 3. The total number of experimental runs that can be generated using the factorial design method is shown.

Table 5: Experimental result using factorial design**.**

Run	Current (A)	Voltage (V)	Velocity (cm/min)
1	180	23	210
2	190	23	300
3	180	21	210
4	170	21	210
5	180	21	300
6	180	25	120
7	170	25	300
8	180	23	300
9	190	25	120
2	190	21	120
11	170	25	210
12	180	21	120
13	180	23	120
14	170	25	120
15	170	21	300
16	180	25	300
17	190	23	210
18	190	21	210
19	190	25	210
20	190	25	300
21	190	23	120
22	170	23	120
23	170	21	120
24	170	23	210
25	180	25	210
26	170	23	300
27	190	21	300

Artificial Neural Network (ANN)

Is a computational technique when formulating an algorithmic solution for a problem becomes impossible or modeling tools for statistical data is not linear in a case with a lot of samples and the purpose of predicting the future. An artificial neural network (ANN) is a collection of artificial neurons that collaborate to solve nonlinear approximations, determine target functions, and other tasks. ANNs learn from samples in the same way that people do. The three major layers of ANNs are input, hidden, and output. They are made up of a sequence of nodes connected by weights. The input data is multiplied by the associated weight of the neuron, then a bias is applied to the outcome. The most common structure involves three layers: the inputs, which are the original predictors; the hidden layer, consisting of a set of constructed variables; and the output layer, made up of the responses. Each variable in a layer is called a node. Fig 2 shows a typical three-layer artificial neural network with inputs on the left and outputs on the right (MYERS, 2016). Artificial neural networks are a prominent area of research and application, especially for analyzing large, complex, and highly nonlinear problems. The issue of overfitting is often overlooked by many users and advocates of neural networks. Many individuals in the neural network community lack formal training in empirical model building, which leads to a diminished understanding of the difficulties that overfitting can cause. Additionally, many computer programs designed for implementing neural networks do not effectively address the overfitting problem. We believe that neural networks can complement traditional statistical tools such as regression analysis, response surface methodology (RSM), and designed experiments, but they should not replace them. While a neural network can provide a predictive model, it does not offer fundamental insights into the underlying mechanisms that generated the data. Furthermore, there is no evidence to suggest that the predictive capabilities of these models are superior to those obtained through a well-designed RSM study (MYERS, 2016).

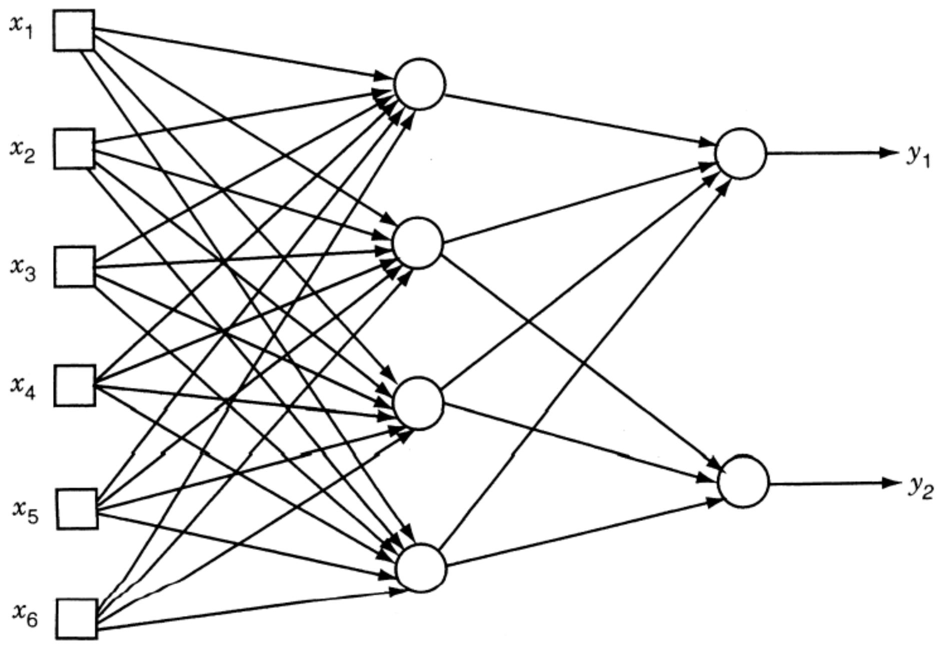

Figure 2: Artificial neural network with one hidden layer.

Results and Discussion

An artificial neural network (ANN), a predictive model, was applied to predict response variables beyond the experimental range. The neural network modeling utilized 27 experimental data points generated by replicating the factorial design matrix. The experimental data underwent normalization to address the potential issue of overtraining, a significant challenge in neural network modeling. This process scaled the input and output variables to values between 0 and 1, enabling practical network training and accurate modeling and prediction. A feed forward-back prop algorithm was implemented to train the neural network to the predict the HAZ maximum hardness and weld metal tensile strength, respectively. In contrast, the output layer employed a linear (purlin) transfer function. The hidden layers consisted of 10 neurons each, and the mean square error of the regression (MSE) was used to monitor network performance. The input data was divided into three sets during the network generation process: 60% for training, 25% for validation, and 15% for testing network performance. The train function, which updates weight and bias values according to Levenberg-Marquardt optimization, was employed for network training. This function is generally the fastest backpropagation algorithm available in the toolbox and is highly recommended as an initial choice for supervised learning despite its higher memory requirements. An optimal neural network architecture was developed using these parameters, as shown in Fig 3.

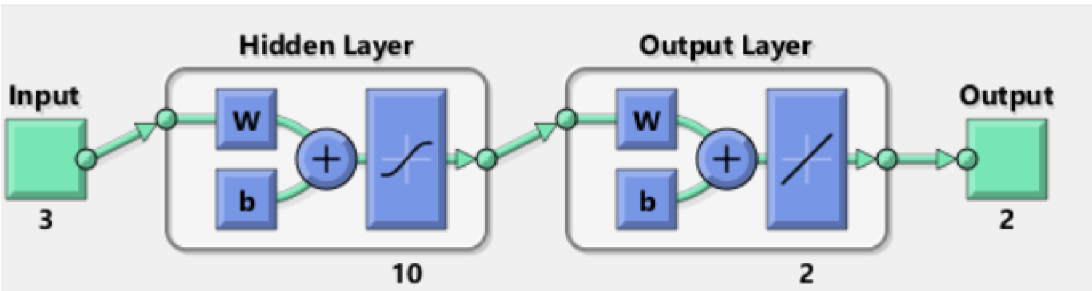

Figure 3: Artificial neural network architecture.

The regression plot which shows the correlation between the input variables (current, voltage and velocity) and the response variables (HAZ maximum hardness and weld metal tensile strength, respectively) coupled with the progress of training, validation and testing is presented in Fig 4. Based on the computed values of the correlation coefficient (R) as observed in Fig 4, it was concluded that the network has been accurately trained and can be employed to predict the HAZ maximum hardness and weld metal tensile strength, respectively. To test the reliability of the trained network, the network was thereafter employed to predict its own values of the HAZ maximum hardness and weld metal tensile strength, respectively using the same set of input parameters (current, voltage and gas velocity) generated from the factorial design.

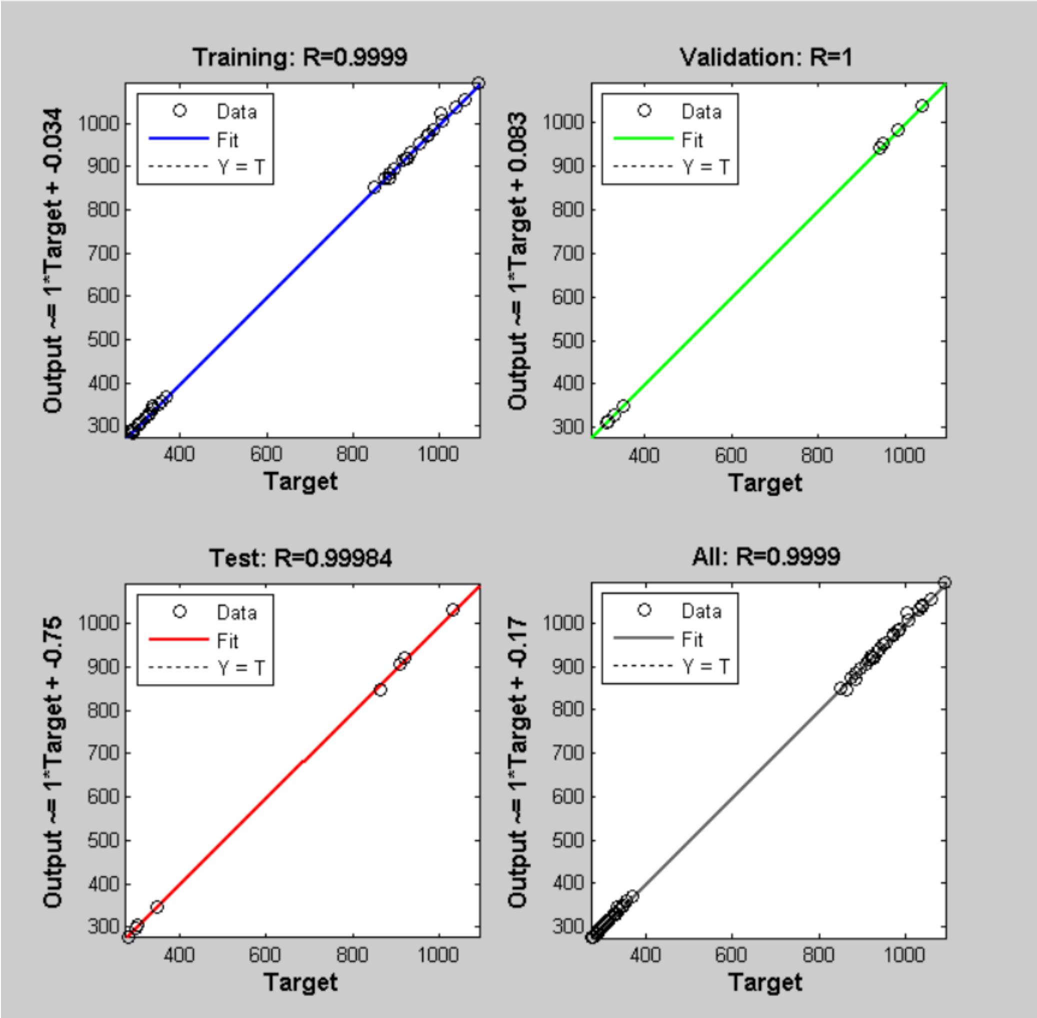

Figure 4: Regression plot showing the progress of training, validation and testing.

The ANN model developed in the present study is built using MATLAB R2013a GUI. For predicting the HAZ maximum hardness and weld metal tensile strength, respectively by ANN, the model is established using twenty-seven datasets. The responses/outputs (the HAZ maximum hardness and weld metal tensile strength, respectively) is considered. In ANN modeling, the input variables (current, voltage and velocity). Then, the predicted values, using the ANN model developed, of the HAZ maximum hardness and weld metal tensile strength, respectively were given in Table 6.

Table 6: The actual and the predicted values of the weld metal tensile strength and HAZ Maximum Hardness using JWES and ANN respectively.

Run	Inputs			Actual values		Predicted values	
	Current	Voltage	Velocity	HAZ Maximum Hardness Hv-5	Weld Metal Tensile Strength (MPa)	HAZ Maximum Hardness Hv-5	Weld Metal Tensile Strength (MPa)
1	160	28	22	324.5	971.5	324.4	971.2
2	140	24	16.5	325.2	973.1	325.7	974.2
3	140	28	22	347.2	1030.4	347.7	1031.5
4	160	24	22	349.8	1037.7	349.9	1037.8
5	180	28	22	306	925.4	303.1	919.1
6	180	26	19.3	298.7	907.4	298.5	906.8
7	140	24	22	368.7	1091.1	368.8	1091.3

8	140	24	19.3	350.3	1038.9	350.5	1039.5
9	160	26	19.3	315.3	948.3	316.3	951.4
2	180	26	22	317.9	954.8	317.9	954.7
11	180	24	22	330.5	986.6	329.8	984.9
12	180	28	16.5	274.8	848.1	276.9	851.0
13	180	28	19.3	289.5	884.7	285.0	872.3
14	160	26	22	336.8	1002.9	345.0	1024.2
15	160	24	19.3	328.8	982.3	329.0	982.7
16	160	24	16.5	304.1	920.6	304.6	921.7
17	180	24	19.3	309.2	933.1	309.2	932.9
18	180	24	16.5	289.7	885.1	289.7	885.1
19	160	28	19.3	304.6	922	303.0	919.8
20	140	28	16.5	301.5	914.2	301.5	914.1
21	140	26	22	357.6	1059.3	358.5	1053.4
22	140	28	19.3	324.5	971.5	324.3	971.0
23	180	26	16.5	281.2	864.3	276.5	847.9
24	160	28	16.5	285.5	874.8	285.3	874.2
25	140	26	19.3	337.5	1004.8	338.0	1006.1
26	160	26	16.5	293.6	894.9	293.7	895.1
27	140	26	16.5	312.1	940.5	312.2	940.8

Fig 5 and Fig 6 shows the actual versus the predicted values of the HAZ maximum hardness and weld metal tensile strength, respectively. Indicate accurately represents the ANN model's actual the HAZ maximum hardness and weld metal tensile strength, respectively values.

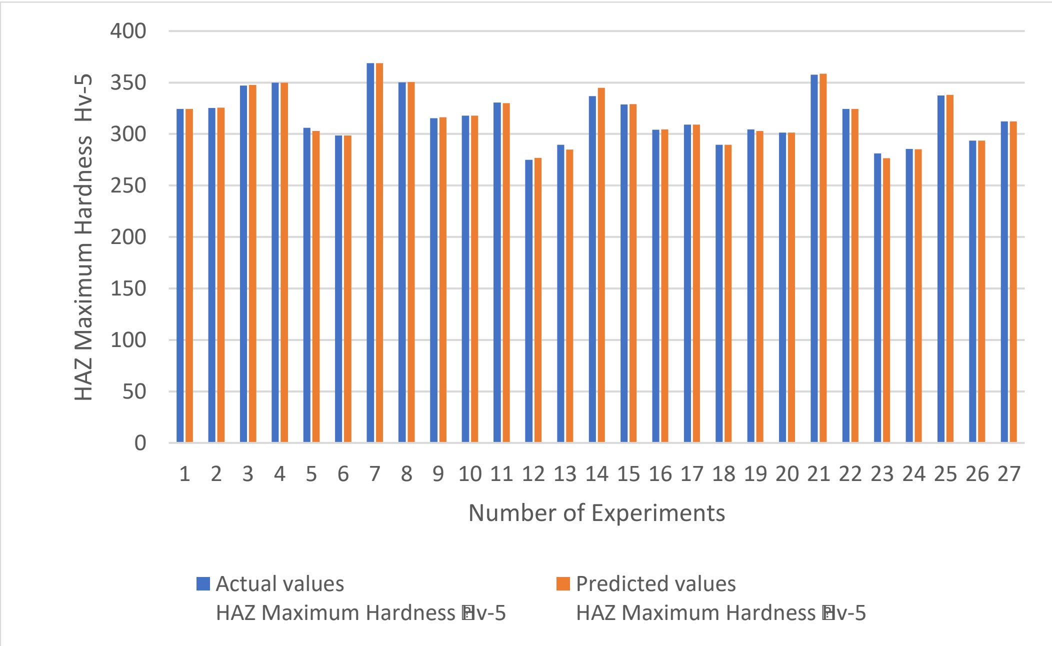

Figure 5: The actual versus the predicted values of HAZ maximum hardness by ANN.

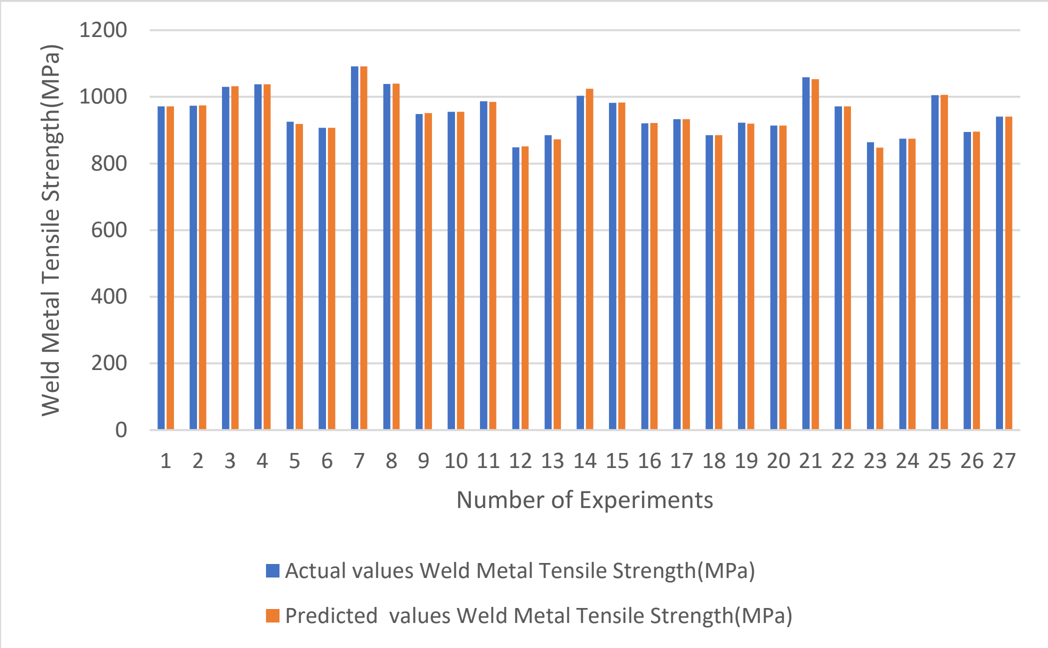

Figure 6: The actual versus the predicted values of weld metal tensile strength by ANN.

Validation Models for HAZ Maximum Hardness and Weld Metal Tensile Strength, Respectively by Using ANN

Based on the mean absolute percentage error (MAPE) value as given by equation 1. A comparison between the actual values and the anticipated values of HAZ maximum hardness and weld metal tensile strength, respectively is used to validate the ANN model. It was determined that (MAPE) was 0.4 % and 0.3 %, respectively. Indicate accurately represents the ANN model's HAZ maximum hardness and weld metal tensile strength, respectively.

$$\text{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{A-P}{A}\right| ☒ 100\% \qquad (1)$$

Where

A: The actual values

P: The predicted values

n: Number of Experiments

Based on the Nash-Sutcliffe Efficiency (NSE) value as given by equation 2. A comparison between the actual values and the anticipated values of HAZ maximum hardness and weld metal tensile strength, respectively is used to validate the ANN model. It was determined that (NSE) was 99.2% and %99.1%, respectively. Indicate accurately represents the RSM model's actual weld metal tensile strength (MPa) values. The Nash-Sutcliffe Efficiency (NSE) was also calculated to evaluate the model's efficiency by equation 2.

$$\text{NSE} = \frac{\sum(A-P)^2}{\sum(A-\overline{A})^2} \qquad (2)$$

Where

A: Actual values
$\overline{A}$: Average actual values
P: Predict a values

Analyzes the constitution of martensite volume fraction, that is, the size distribution of martensite units in quenched-transformed austenite in the microstructure. This correlates this distribution to the martensite shapestrain relaxation. The modes of relaxation a thermal/auto-accommodation or thermal-activated dislocation mobility and the sequential formation of the martensite units control the variation of the mean martensite volume as well as the uniformity of the transformation. Meaning that the faster the cooling, the higher the percentage of martensite as shown in Table 7 and Fig 7, respectively. The cooling time measurement in the temperature range 800-500 °C was the bead axis in all cases, are shown in Table 7.

Table 7: Results obtained for the t8/5 and Martensite Volume (%) by JWES software.

Numerical simulation	Martensite Volume (%)	Welding Cooling Time, t8/5(s)
1	44.9	10.434
2	45.3	10.355
3	57.4	8.012
4	58.6	7.759
5	34.9	13.091
6	31	14.435
7	68.7	6.097
8	58.8	7.719
9	39.9	11.653
10	41.3	11.29
11	48.1	9.732
12	18.1	21.382
13	26	16.531
14	51.5	9.046
15	47.2	9.925
16	33.9	13.423
17	36.6	12.574
18	26.1	16.485
19	34.2	13.329
20	32.5	13.901
21	62.8	7.051
22	44.9	10.434
23	21.6	18.94
24	23.8	17.621
25	51.9	8.97
26	28.2	15.523
27	38.2	12.111

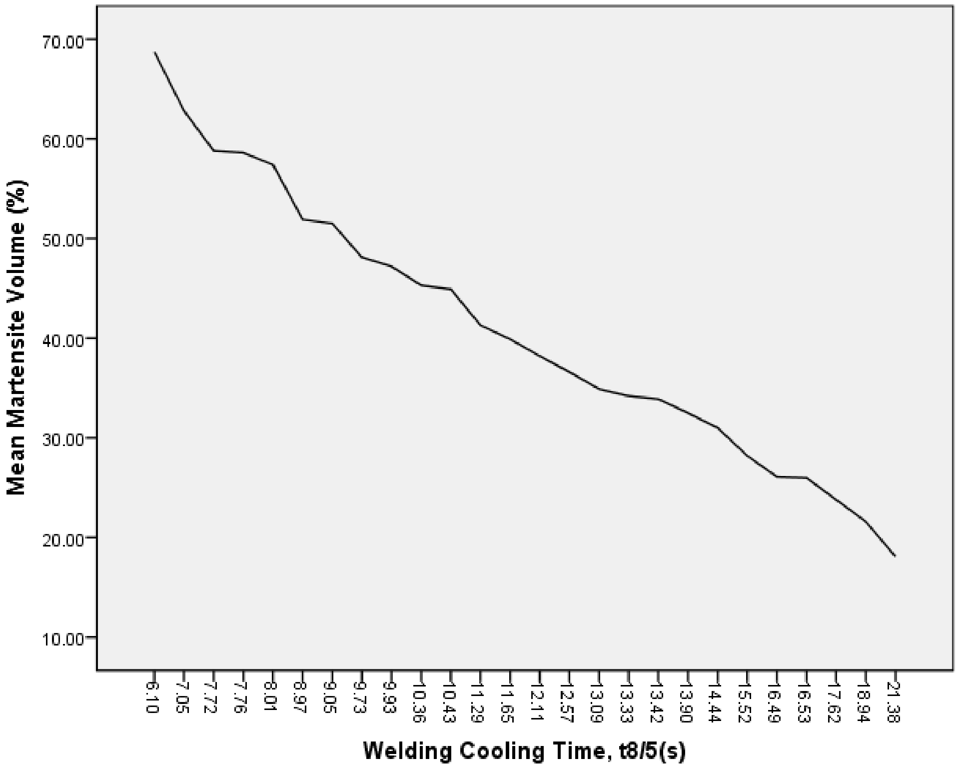

Figure 7: The effects of cooling time on martensite volume fraction %.

Conclusion

Based on the findings presented in this research, the study comprehensively explored the prediction of mechanical properties specifically weld metal tensile strength and HAZ maximum hardness using Artificial Neural Networks (ANN) based on JWES software. The findings of the present investigation can be summarized into the following points:

1. **Model Accuracy and Performance:**
   - Artificial Neural Network (ANN) models both demonstrated exceptional predictive accuracy for weld metal tensile strength and heat-affected zone (HAZ) maximum hardness.
   - The ANN model yielded slightly higher MAPE values of **0.3%** for weld metal tensile strength and **0.4%** for HAZ maximum hardness.
   - Nash-Sutcliffe Efficiency (NSE) scores were consistently high with ANN achieving 99.2**%** for weld metal tensile strength and **99.1%** for HAZ maximum hardness.
2. **Cooling Time and Martensite Volume Relationship:**
   - The welding cooling time (t8/5) directly influences martensite volume. Faster cooling times increase martensite formation, with the highest observed martensite volume being **68.7%** at a cooling time of **6.097 s**.
   - This relationship emphasizes the need for precise control over cooling rates to achieve desired microstructural properties in welded joints.

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