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Prediction of HAZ Maximum Hardness in Tig Welding Process by Using Response Surface Methodology Based on JWES ANN Model

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التنبؤ بصلابة المنطقة المتأثرة بالحرارة في عملية اللحام غاز التنجستن باستخدام منهجية سطح الاستجابة بناءاً على نموذج JWES ANN

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Abstract:
This study presents a developing modeling approach integrating Response Surface Methodology (RSM) with the JWES (ANN) model to predict the maximum hardness of the Heat Affected Zone (HAZ) in Tungsten Inert Gas (TIG) welding. Using EH36 TMCP steel as the base material, experimental design through Central Composite Design (CCD) was conducted by varying welding current, voltage, and velocity. The HAZ maximum hardness values were predicted via JWES ANN model and compared against those derived from RSM-based regression equations. The model demonstrated high accuracy, with a Predicted R^2 of 0.9821 and Adequate Precision ratio of 84.226. Statistical analysis confirmed the significance of key process parameters. The results validate the effectiveness of combining JWES ANN model predictions with RSM optimization in achieving accurate HAZ maximum hardness modeling.

Keywords: TIG welding, HAZ hardness, JWES ANN, Response Surface Methodology, Regression model, Welding parameters.

الملخص
تقدّم هذه الدراسة نموذجاً متطورًا في النمذجة من خلال دمج منهجية سطح الاستجابة (RSM) مع نموذج الشبكة العصبية الاصطناعية (ANN) التابع للجمعية اليابانية لهندسة اللحام(JWES) ، بهدف التنبؤ بالصلابة القصوى لمنطقة التأثير الحراري (HAZ) في لحام التنجستن بالغاز الخامل (TIG)تم استخدام فولاذ EH36 TMCP كمادة أساسية، كما تم إجراء تصميم تجريبي باستخدام التصميم المركزي المركب (CCD) من خلال تغيير تيار اللحام، الجهد الكهربائي، وسرعة اللحام. تم التنبؤ بقيم الصلابة القصوى لـ HAZ باستخدام نموذجJWES ANN ، وتمت مقارنتها بالنتائج المستخلصة من معادلات الانحدار المستندة إلى RSM. أظهر النموذج دقة عالية، حيث بلغ معامل التحديد التنبؤي $R^2 = 0.9821$، ونسبة الدقة الملائمة 84.226. وأكد التحليل الإحصائي أهمية المتغيرات العملية الأساسية. وتثبت النتائج فعالية الدمج بين تنبؤات نموذج JWES ANN وتحسينات RSM في تحقيق نمذجة دقيقة للصلابة القصوى لمنطقة التأثير الحراري.

الكلمات المفتاحية: لحام TIG، صلابة HAZ، نموذج JWES ANN، منهجية سطح الاستجابة، نموذج انحدار.

Introduction

Welding is a method of joining two similar or dissimilar metals, with or without the use of filler material. One of the well-known conventional Arc welding processes is Tungsten Inert Gas welding, commonly referred to as TIG welding. This method is used due to its powerful and controllable features, which enable it to transmit heat to the welding line locally. The TIG fusion zone size is narrower compared to other single-pass arc welding processes (Sattarpanah Karganroudi et al., 2021). In the TIG arc welding process, a non-consumable tungsten electrode is used to create an arc on the workpiece. This welding method was applied to the metals using an inert gas as the shielding gas for the weld pool. Experiences have demonstrated that the TIG welding method is a reliable welding process, producing high-quality welds. Spatters and fumes are rarely encountered during this process. The low productivity of this method restricts it to limited industries. One of the current methods for increasing productivity in the TIG welding process involves increasing current and scanning speed. However, under high-current TIG welding, due to a significantly increased heat input on the base material (BM), some defects, such as discontinuities and undercuts, can form (Sattarpanah Karganroudi et al., 2021). The manufacturing industry is growing rapidly to create components or engineering systems that impart the desired combination of properties to materials, enabling them to perform their intended function within their expected working life. The manufacturing process involves turning raw materials into finished materials products (i.e., goods) that are intended for use in some useful purpose. The key manufacturing processes include metal forming, metal cutting, and metal joining, among others. These manufacturing processes are applied to raw materials to create a variety of parts. However, the selection of a manufacturing technique depends on the complexity of the component's geometry, the number of parts to be made, the properties of the materials, the accuracy required, etc. (CHANDRA MOI, 2019). Within the last few decades, the focus has been on creating complex shape parts by joining welding materials that can withstand ever-increasing stress, temperatures, and impact strength, among other factors. Welding is a well-recognized technique worldwide today as a remarkably versatile means of metal fabrication and material repair, joining similar or dissimilar materials permanently with or without the application of heat, pressure, and filler material, ranging from simple constructions to complex systems with high safety requirements. The welding process is efficient, economical, and dependable as a means of joining metals (CHANDRA MOI, 2019. This study aims to develop an accurate predictive model for estimating the HAZ maximum hardness in TIG welding using a hybrid approach that integrates the JWES ANN model with Response Surface Methodology (RSM). By analyzing the effects of welding current, voltage, and velocity, the study aims to identify significant process parameters and enhance the quality and reliability of welded joints through data-driven modeling. This aim can be achieved by performing the following objectives:

1. Develop a statistical model and find the significant effect of the welding input process parameters on HAZ Maximum Hardness Hv-5 by applying the Response Surface Methodology (RSM) via Minitab software and Design Expert software.
2. Validation of the model based on neural network analysis available through the JWES ANN model by calculating the coefficient of determination (R-squared), comparing actual values with predicted values.

Literature Review

In the (Sampath & Varadarajan, 2023) presented the balanced Ti (and/or Zr), B, Al, N, O content can be ascertained using an artificial neural network (ANN) model offered by the Japan Welding Engineering Society (JWES) at its website. The JWES ANN model allows one to manipulate 16 elements of the WM compositions, each within a specified range and seek a lower predictive temperature range for achieving28 J absorbed energy (T28J/C) during CVN impact testing. (Tahara et al., 2013) summarized the contents of JWES WES7700 along with a verification of repair welding procedures, such as minimum required grind out thickness for thermal removal of flaws, minimum required throat thickness of fillet welds for patched plates by experimental pressure tests and FEM analysis and some comparison. (Oyinbade, 2023) Presented defects in welding can compromise the quality and strength of weld joints, creating challenges for fabricators in achieving optimal joint strength and quality in a weld structure. A fuzzy logic-based therapy was designed to predict tensile strength in welding. A total of 30 fusion experiments were conducted, and the resulting tensile strength was recorded. The crisp variables were transformed into fuzzy sets. The fuzzy logic tool was discovered to be most effective in predicting the tensile strength of TIG-welded mild steel, with an R2 value of 0.99. (Sampath, 2024) performed a study of consumable electrodes for fusion welding of HSSs used in the fabrication of demand-critical applications such as structures in earthquake-prone locations, aircraft carriers, submarines and pressure vessels can immensely benefit from the above understanding of the relationships among actual chemical composition, austenite-to-ferrite TS temperature and cooling rate to form predominantly AF in WM microstructures with exceptional combination of higher strength and superior impact toughness. (Afabor, 2025) A study was conducted to compare 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 primary 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. (Al-Fazani & M. Elmabrok, 2025) implemented 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 the weld of the arc welding process. Although significant advancements have been made in modeling various aspects of the TIG welding process such as temperature distribution, weld bead geometry, tensile strength, and metallurgical characteristics, limited research has specifically focused on the prediction of Heat Affected Zone (HAZ) maximum hardness (Hv-5). Existing studies primarily emphasize mechanical and thermal parameters without establishing direct predictive models for HAZ hardness, especially through hybrid computational methods. These approaches often lack integration with robust statistical techniques such as Response Surface Methodology (RSM) for optimization and parameter significance analysis. Consequently, a comprehensive hybrid model that combines the predictive capability of ANN (specifically the JWES ANN model) with the statistical rigor of RSM for HAZ hardness prediction remains underexplored. JWES was chosen because it is specifically designed for welding process modeling and is accredited by the Japanese Welding Society. The program is capable of modeling the chemical composition of the welded metal and analyzing its effects on the mechanical properties of the welded metal using algorithms supported by advanced artificial neural networks. Compared to other programs, such as Simufact and Abaqus, it offers accurate physical analyses; however, these require more comprehensive materials engineering and modeling, which are beyond the scope of this study.

Material Selection and Process Settings

In (Shin et al., 2015), prepared the base material used in this study is EH36 TMCP steel plate with 20 mm thickness, which is equivalent to ASTM A131 steel. The TMPC steel is widely used in ship buildings and is guaranteed for use in cold environments. Table 1 and Table 2 shows the chemical composition and the mechanical properties of the base metal based on the mill test certificate. Bevel butt joint configuration with the root gap of 6 mm, as shown in Figure 1, has been prepared for joining the plates in order to secure the notch position at the weld metal and the HAZ in the impact test specimen.

Table 1 Chemical composition of EH36 (Shin et al., 2015)

Base metal	**Mn**	**Si**	**C**	**P**	**S**
EH36	1.5	0.32	0.08	0.008	0.003

Table 2 Mechanical properties of EH36 (Shin et al., 2015)

Base metal	**Ultimate strength (MPa)**	**Yield stress (MPa)**	**Elongation (%)**	**Charpy impact energy (J)**
EH36	572	500	22	429

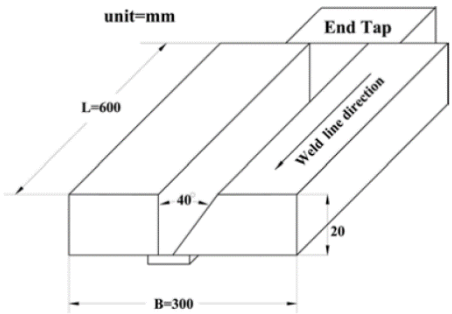

Figure 1: Joint Configuration and Weld Specimen Size (Shin et al., 2015)

The key input process parameters considered in the study include welding current, welding voltage and welding speed selected depends on (Shin et al., 2015), while the response variable is HAZ Maximum Hardness estimated in welding process the selected depended on research gap. 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 (Shin et al., 2015). The output variable is specified in Table 4.

Table 3 Input process parameters and their levels (Uwoghiren & Erhunmwunse, 2022)

No. S.	Input process parameters	Notation	Unit	Level		
				-1	0	+1
1	welding current	C	(A)	100	140	180
2	welding voltage	V	(V)	16	19	22
3	welding speed	S	(cm/min)	10	35	60

Table 4 The response selected for these experiments

No. S.	Response	Notation
1	HAZ Maximum Hardness	Hv-5

Simulation and Prediction Models Approaches

In this study, the simulation approach by means of utilizing simulation software will be implemented to represent the estimate the HAZ Maximum Hardness estimated in welding process. Moreover, the statistical approach namely RSM, technique will be utilized to develop the accurate 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 ANN Model) 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, 2023). Figure 2 illustrates the interface of JWES ANN model.

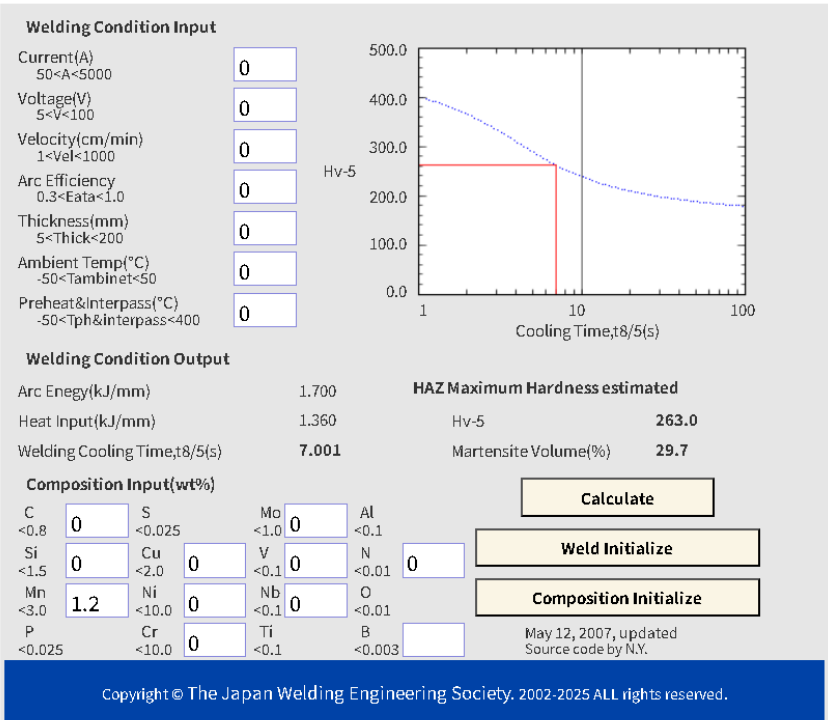

Figure 2: The interface for JWES ANN model

Response Surface Methodology Approach

The design of experiment (DOE) method is a statistical method for studying a process with a limited number of tests. Response surface methodology (RSM) is a common and powerful regression-based modeling approach that uses a mathematical model to determine the relationship between multiple complicated factors and process responses It also has significant uses in the development, formulation, and design of new items as well as in the improvement of designs for already-existing ones (MYERS, 2016). Using the range and levels of the independent variables presented in Table 5, statistical design of experiment (DOE) using central composite design (CCD) method was done. The total number of experimental runs that can be generated using the CCD method.

Table 5. Experimental Result using CCD.

Run	Current (A)	Voltage (V)	Velocity (cm/min)
1	100	16	10
2	180	16	10
3	100	16	60
4	180	16	60
5	100	22	10
6	180	22	10
7	100	22	60
8	180	22	60
9	100	19	35
10	180	19	35
11	140	19	10
12	140	19	60
13	140	16	35
14	140	22	35
15	140	19	35

Results and Discussion

The effects of the three input process parameters current, voltage, and velocity and their effects on the response HAZ maximum hardness is analyzed and studied using the experimental values. The JWES ANN model is implemented to calculate the HAZ maximum hardness for each run. The values of the HAZ maximum hardness are also presented in Table 6.

Table 6. Results of The Calculated HAZ maximum hardness as Actual Values by ANN model.

Run	Factors			Response
	Current (A)	Voltage (V)	Velocity (cm/min)	HAZ Maximum Hardness (Hv-5)
1	100	16	10	295.1
2	180	16	10	258.7
3	100	16	60	360.1
4	180	16	60	348
5	100	22	10	274.7

Run	Factors			Response
	Current (A)	Voltage (V)	Velocity (cm/min)	HAZ Maximum Hardness (Hv-5)
6	180	22	10	240.6
7	100	22	60	354.2
8	180	22	60	338.5
9	100	19	35	343.9
10	180	19	35	323
11	140	19	10	263.8
12	140	19	60	349.7
13	140	16	35	339
14	140	22	35	327.4
15	140	19	35	333.2

The analysis of variance in Table 7 presents a Model F-value of 796.31, indicating that the model is statistically significant. There is only a 0.01% chance that an F-value this large could occur due to noise. "Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case, A, B, C, AC, BC, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (excluding those required to support the hierarchy), model reduction may improve your model.

Table 7 Analysis of variance for the HAZ maximum hardness.

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	
Model	21670.57	10	2167.06	796.31	< 0.0001	significant
A-A	29.53	1	29.53	10.85	0.0301	
B-B	42.83	1	42.83	15.74	0.0166	
C-C	916.29	1	916.29	336.70	< 0.0001	
AB	0.21	1	0.21	0.078	0.7944	
AC	227.91	1	227.91	83.75	0.0008	
BC	24.70	1	24.70	9.08	0.0394	
A^2	2.69	1	2.69	0.99	0.3766	
B^2	1.53	1	1.53	0.56	0.4946	
C^2	1695.47	1	1695.47	623.02	< 0.0001	
ABC	4.35	1	4.35	1.60	0.2747	

Source	Sum of Squares	df	Mean Square	F-Value	p-value Prob > F	
Residual	10.89	4	2.72			
Cor Total	21681.46	14				

Table 8 shows the estimated regression coefficient for HAZ maximum hardness, representing the p-values determining whether the effects are significant or insignificant. The "Pred R-Squared" of 0.9821 is in reasonable agreement with the "Adj R-Squared" of 0.9982; i.e., the difference is less than 0.2. Adeq Precision" measures the signal-to-noise ratio. A ratio greater than 4 is desirable. Your ratio of 84.226 indicates an adequate signal. This model can be used to navigate the design space.

Table 8 Analysis of variance for the HAZ maximum hardness.

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	368.77	1	6.33	351.20	386.34	
A-A	-59.61	1	18.10	-109.85	-9.37	98.22
B-B	-6.14	1	1.55	-10.44	-1.84	8.81
C-C	28.42	1	1.55	24.12	32.72	8.81
AB	-0.57	1	2.04	-6.24	5.10	8.81
AC	18.68	1	2.04	13.01	24.35	8.81
BC	4.73	1	1.57	0.37	9.09	7.25
A^2	12.52	1	12.60	-22.47	47.51	98.52
B^2	0.77	1	1.03	-2.08	3.63	1.30
C^2	-25.68	1	1.03	-28.53	-22.82	1.30
ABC	-2.58	1	2.04	-8.25	3.09	7.25
	Std. Dev.	1.65		R-Squared	0.9995	
	Mean	316.66		Adj R-Squared	0.9982	
	C.V. %	0.52		Pred R-Squared	0.9821	
	PRESS	387.51		Adeq Precision	84.226	

Equation 1, in terms of coded factors, can be used to make predictions about the response for given levels of each factor. By default, the high levels of the factors are coded as +1, and the low levels of the factors are coded as -1 The coded equation is useful for identifying the relative impact of the factors by comparing the factor coefficients.

$$\text{HAZ maximum hardness}=368.77 -59.6* A -6.14* B + 28.4 * C - 0.5* AB +18.68* AC +4.73 * BC +12.52 * A^2+ 0.77 * B^2 -25.67 * C^2 -2.58 * ABC \quad (1)$$

Where

A: current, B: voltage, and c: velocity.

The goal is to predict a response that is impacted by a number of factors through an accurate experiment design in Table 9. The response data was considered as the actual values using the JWES ANN model. Subsequently, the data were inputted into Minitab software. Then, the predicted values, using the devolved mathematical model, of the HAZ maximum hardness were also given in Table 9.

Table 9 The actual and the predicted values of the HAZ maximum hardness using JWES ANN model and RSM, respectively.

Run	Factors			Response	
	Current (A)	Voltage (V)	Velocity (cm/min)	HAZ Maximum Hardness (Hv-5) by the JWES ANN model	HAZ Maximum Hardness (Hv-5) by predicted RSM
1	100	16	10	295.1	293.47
2	180	16	10	258.7	259.28
3	100	16	60	360.1	360.54
4	180	16	60	348	347.70
5	100	22	10	274.7	274.92
6	180	22	10	240.6	240.08
7	100	22	60	354.2	353.54
8	180	22	60	338.5	340.05
9	100	19	35	343.9	345.52
10	180	19	35	323	321.68
11	140	19	10	263.8	265.14
12	140	19	60	349.7	348.66
13	140	16	35	339	339.90
14	140	22	35	327.4	326.80
15	140	19	35	333.2	332.58

Figure 3 shows the actual versus the predicted values of the which indicates the accuracy of the model based visual comparison.

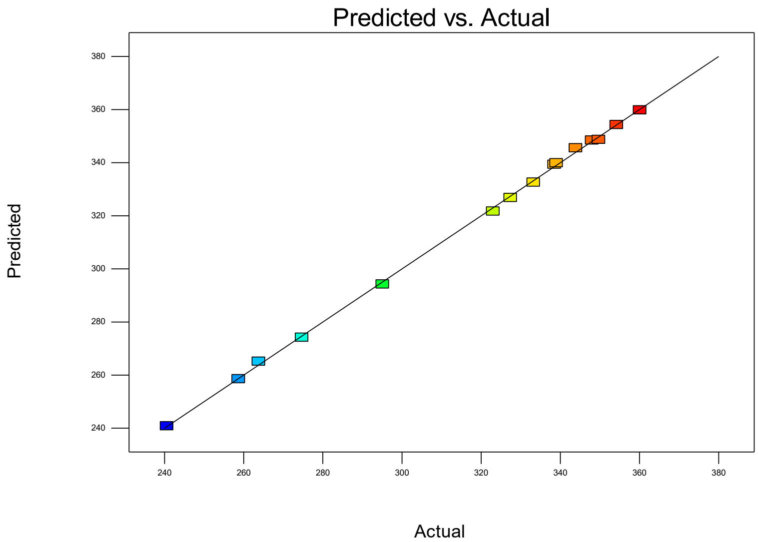

Figure 3: The Actual Versus the Predicted Values for HAZ maximum hardness**.**

The model graphs, which illustrate the interactions between the combined variables and the measured responses, were evaluated using a counterplot, as shown in Figures 4, 5, and 6, respectively. Figure 4 shows that the variation in current and voltage significantly affects the maximum hardness of the HAZ as the current and voltage decrease. The HAZ maximum hardness is high, reaching a point where further reduction in velocity and current indicates a decrease, as shown in Figure 5. Figure 6 shows that the voltage decreases and the velocity increases to the maximum hardness of the HAZ.

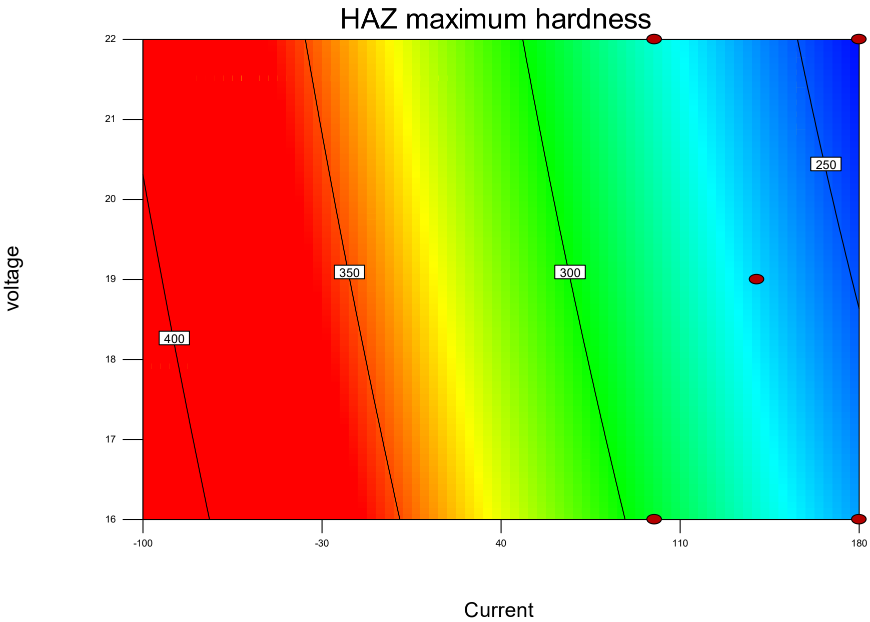

Figure 4: Effect of Current and Voltage on the HAZ maximum hardness.

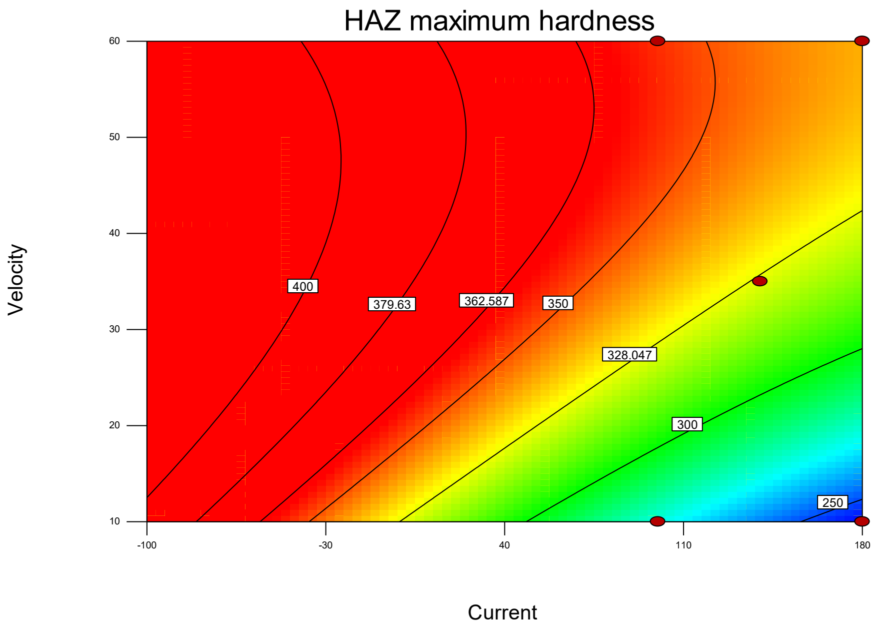

Figure 5: Effect of Current and velocity on the HAZ maximum hardness.

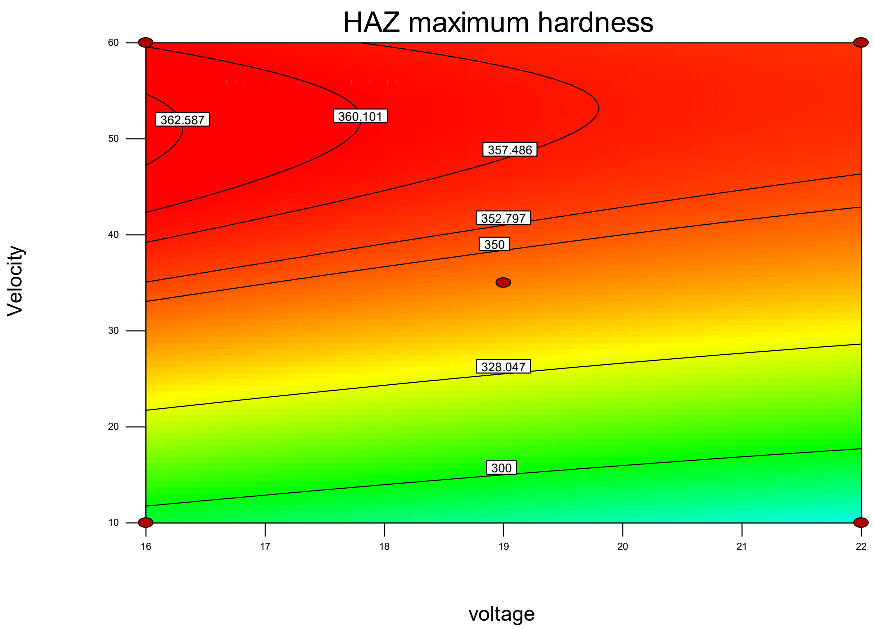

Figure 6: Effect of voltage and velocity on the HAZ maximum hardness.

Conclusion

This study successfully developed a predictive model combining Response Surface Methodology (RSM) with the JWES ANN model to estimate the maximum hardness of the Heat Affected Zone (HAZ) in TIG welding. Using EH36 TMCP steel as the base material and applying a Central Composite Design (CCD) experimental setup, the research examined the effects of welding current, voltage, and velocity. The analysis revealed that welding speed was the most influential parameter affecting HAZ hardness, followed by interaction effects between current and voltage. The developed models showed a high level of accuracy, with a predicted R^2 of 0.9821 and an Adequate Precision ratio of 84.226, indicating strong predictive capability and statistical reliability. The integration of ANN and RSM proved to be highly effective, offering a robust framework for understanding and optimizing welding parameters to control the mechanical properties of the welded joint. Moreover, the results demonstrate the practical value of combining machine learning techniques with statistical analysis in engineering applications. The model provides a reliable tool for engineers to optimize welding conditions, improve material performance, and reduce experimental costs by accurately predicting outcomes before physical trials. Therefore, the hybrid modeling approach proposed in this study is recommended for broader industrial adoption, particularly in applications where precision and weld quality are critical.

Recommendation and Future Study

Based on the findings of this study, it is recommended that the developed hybrid model combining RSM and the JWES ANN be utilized in industrial applications to optimize TIG welding parameters, particularly for controlling HAZ maximum hardness. The model's high predictive accuracy supports its use in minimizing experimental costs and improving weld quality. For future research, it is suggested to extend the model's application to other materials, incorporate additional mechanical properties in multi-objective optimization, and integrate real-time process data to enhance prediction capabilities. Further microstructural analysis is also encouraged to deepen the understanding of hardness variations within the HAZ.

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