Multidisciplinary | Peer-Reviewed
Open Access | Research Journal
ISSN: 3139-2954

Article ID: IRJIST-2026-081
Volume 1 | Issue 3 | 2026
DOI: https://doi.org/10.67308/irjist.081

International Research Journal of Innovation in Science and Technology

Machine Learning-Based Prediction of Tensile Strength and Hardness in GTAW-Welded IS 2062 E250 Mild Steel Under Varying Heat Input

Jadhav Priyanka Jalindar[1], Pooja Kulkarni[2], Ganesh Bhavar[3]

[1]Research Scholar, Deogiri Institute of Engineering and Management Studies Chhatrapati Sambhjinagar, India
[2]Assistant Professor, Deogiri Institute of Engineering and Management Studies Chhatrapati Sambhjinagar, India
[3]Student, Deogiri Institute of Engineering and Management Studies Chhatrapati Sambhjinagar, India
Correspondence: pj0401443@gmail.com

Abstract

Gas Tungsten Arc Welding (GTAW) joints in structural mild steel exhibit a nonlinear, current-dominated relationship between tensile strength, hardness, and heat input that is difficult to capture using classical linear regression. A 16-run Taguchi L16 experimental design was conducted on IS 2062 Grade E250 mild steel (current: 120–150 A; voltage: 10–16 V), with heat input for each run (1.20–2.40 kJ/mm) calculated using the standard heat-input equation. Six regression algorithms Linear Regression, Decision Tree, Random Forest, Support Vector Regression (SVR), XGBoost, and Artificial Neural Network (ANN) were trained and evaluated using leave-one-out cross-validation (LOOCV), which is statistically appropriate for the limited sample size. XGBoost produced the most accurate tensile-strength predictions ($R^2 = 0.953$, RMSE = 19.71 MPa), while the ANN achieved the best hardness predictions ($R^2 = 0.992$, RMSE = 0.63 HB). In contrast, linear regression performed poorly for tensile strength ($R^2 = -0.099$) because the relationship peaked at 130 A rather than varying monotonically with current. ANOVA identified welding current as the statistically dominant factor influencing both responses ($p < 0.001$). The findings demonstrate that tree-based and neural-network models substantially outperform conventional linear regression for modelling nonlinear GTAW response surfaces, even with a limited dataset, providing a practical and cost-effective approach for pre-screening welding parameters prior to experimental validation, while highlighting the need for future validation using larger, replicated datasets.

Keywords: Gas Tungsten Arc Welding; IS 2062 E250; heat input; machine learning; tensile strength; hardness; Taguchi design

1. Introduction

Gas Tungsten Arc Welding (GTAW) is a fusion welding process widely used in structural fabrication because it produces clean, metallurgically sound joints with precise heat-input control [1]. IS 2062 Grade E250 is a low-carbon structural steel (minimum yield strength of 250 MPa) whose in-service performance depends less on its bulk chemistry than on the thermal history imposed during welding [2]. Heat input, governed by welding current, arc voltage, and travel speed, is the single most influential GTAW parameter. Excessive heat input coarsens the weld and heat-affected zone (HAZ) microstructure, reducing strength and hardness, whereas insufficient heat input results in rapid cooling and the formation of brittle constituents [3,4]. Because tensile strength and hardness often respond to heat input in a coupled, non-monotonic manner, selecting process parameters that satisfy both requirements is a genuinely nonlinear optimisation problem. Nevertheless, most GTAW parameter studies still rely on Taguchi signal-to-noise analysis or low-order polynomial regression, which assume additive and monotonic effects [5].

Machine learning (ML) regression can represent nonlinear, interaction-dominated relationships without assuming a functional form in advance, and tree-based ensembles, kernel methods, and neural networks have outperformed linear regression for weld-property prediction across several processes and materials [6–9]. Recent studies have further demonstrated the effectiveness of machine learning-based predictive models for manufacturing process optimisation, quality prediction, and industrial risk assessment across various manufacturing applications, highlighting their growing importance in intelligent manufacturing systems [10,11]. However, few studies have applied and rigorously cross-validated multiple ML algorithms specifically to GTAW of plain structural steels such as IS 2062 E250, and fewer still have employed cross-validation schemes appropriate for the small (9–16 run) datasets typically generated by Taguchi-designed welding experiments. This paper addresses that gap by benchmarking six regression algorithms on a genuine 16-run GTAW dataset for IS 2062 E250 using leave-one-out cross-validation (LOOCV), the approach that is statistically most appropriate for this sample size, and reporting which model family is best suited for predicting each mechanical property.

2. Materials and Methods

The base metal was IS 2062 Grade E250 (C ≤ 0.23%, Mn ≤ 1.50%, Si ≤ 0.40%; UTS 410–540 MPa, hardness 120–170 HB), welded using ER70S-6 filler with a 2.4 mm thoriated tungsten electrode, DCEP polarity, and 100% argon shielding at a flow rate of 10 L/min. A single-V groove with a 3 mm root gap was prepared, and the interpass temperature was maintained below 120°C. A Taguchi L16 orthogonal array was employed to vary the welding current (120, 130, 140, and 150 A) and arc voltage (10, 12, 14, and 16 V) at a constant travel speed of 60 mm/min, resulting in sixteen unique experimental combinations. Each combination was welded and tested once for tensile strength using a Universal Testing Machine (UTM), as shown in Figure 1, and for hardness, as shown in Figure 2. Heat input for each run was calculated using:

$$HI = \frac{V \times I \times 60}{S \times 1000}$$

Where, HI is the heat input expressed in kJ/mm.

resulting in sixteen distinct heat-input values (1.20–2.40 kJ/mm), rather than the four level-averaged values used in the Taguchi design.

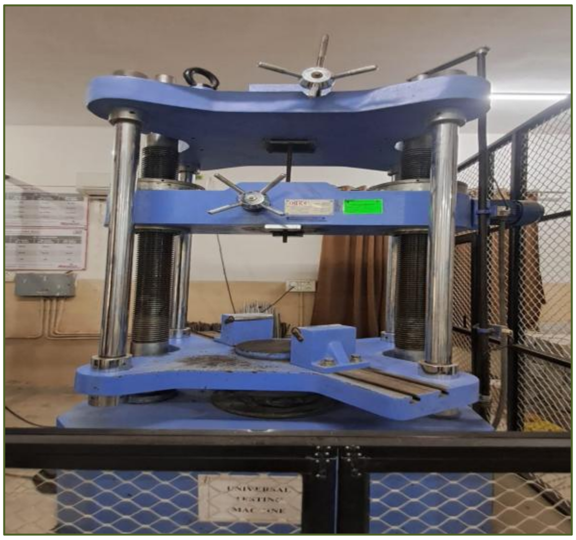

Figure 1: *Tensile Test*

Figure 2: *Hardness Test*

Current and voltage, standardized to zero mean and unit variance, were used as the two machine learning (ML) input features. Heat input, being a deterministic function of these two variables, was excluded from the feature set to avoid multicollinearity and was used only for correlation and visualization. With **n = 16**, leave-one-out cross-validation (LOOCV) was employed throughout the study. Each model was trained on 15 data points and tested on the remaining held-out point, with the process repeated for all 16 data points, as shown in Table

1. Six algorithms were evaluated: Linear Regression; Decision Tree (maximum depth = 3); Random Forest (200 trees, maximum depth = 4); Support Vector Regression (SVR) with an RBF kernel (C = 100, ε = 5); XGBoost (150 estimators, maximum depth = 3, learning rate = 0.1); and an Artificial Neural Network/Multi-Layer Perceptron (ANN/MLP) with two hidden layers of 8 and 4 neurons, ReLU activation, and the L-BFGS solver. Model performance was evaluated using pooled LOOCV predictions based on the coefficient of determination (R^2), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE).

Table 1: *Experimental dataset: welding parameters, derived heat input, tensile strength and hardness (n = 16).*

Current (I)	Voltage (V)	Heat Input (kJ/mm)	Tensile Strength (MPa)	Hardness (HRC)
120	10	1.20	255.52	48
120	12	1.44	290.93	46
120	14	1.68	318.81	45
120	16	1.92	260.00	42
130	10	1.30	390.24	40
130	12	1.56	440.00	38
130	14	1.82	487.91	36
130	16	2.08	400.26	33
140	10	1.40	265.82	36
140	12	1.68	305.27	34
140	14	1.96	332.24	32
140	16	2.24	270.00	29
150	10	1.50	170.72	30
150	12	1.80	195.79	28
150	14	2.10	211.38	26
150	16	2.40	170.25	24

3. Results and Discussion

3.1 Effect of Current, Voltage and Heat Input

ANOVA (Table 2) confirms welding current as the statistically dominant factor for both responses ($p < 0.001$), explaining 91.0% and 88.6% of the modelled variance in tensile strength and hardness respectively, versus 8.9% and 11.4% for voltage. Hardness decreases monotonically with current and heat input ($r = -0.930$ and $r = -0.705$, $p < 0.01$), consistent with grain coarsening at higher heat input. Tensile strength, by contrast, peaks at 130 A (1.56-1.82 kJ/mm; maximum 487.9 MPa at 130 A/14 V) and declines sharply at 150 A, giving only a weak, non-significant linear correlation with current ($r = -0.515$) and heat input ($r = -0.176$) - the relationship is real and strong, but not linear.

Table 2: *Two-way ANOVA for tensile strength and hardness.*

Response Variable	Factor	df	F-value	p-value
Tensile Strength	Current	3	380.95	8.5×10^{-10}
Tensile Strength	Voltage	3	37.44	2.1×10^{-5}
Hardness	Current	3	1992.50	5.1×10^{-13}
Hardness	Voltage	3	257.50	4.9×10^{-9}

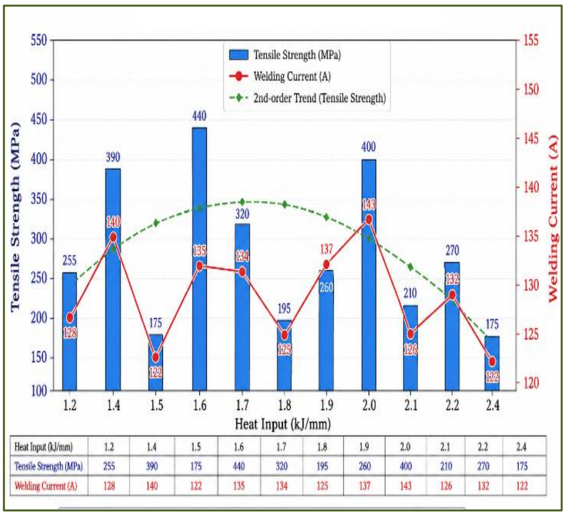

Figure 3: *Non-monotonic effect of heat input on tensile strength (peak near 1.7-1.8 kJ/mm).*

3.2 Machine Learning Model Comparison

Table 3 and Figure 4 report the LOOCV performance of all six models. For tensile strength, XGBoost performs the best (R^2 = 0.953), followed by the ANN (R^2 = 0.877), whereas Linear Regression fails outright (R^2 = −0.099), numerically confirming its inability to represent the non-monotonic current–strength relationship. For hardness, the relationship is closer to linear; consequently, Linear Regression performs strongly (R^2 = 0.968) but is narrowly outperformed by the ANN (R^2 = 0.992). SVR was the weakest nonlinear model for both responses, likely reflecting the difficulty of reliably tuning its three hyperparameters (C, ε, γ) with n = 16.

Table 3a: *LOOCV performance for tensile-strength prediction (MPa units).*

Model	R2	RMSE	MAPE
XGBoost	0.953	19.71	5.70%
ANN (MLP)	0.877	31.90	8.63%
Decision Tree	0.830	37.46	11.32%
Random Forest	0.822	38.41	11.69%
SVR	0.672	52.10	12.77%
Linear Regression	-0.099	95.40	28.42%

Table 3b: *LOOCV performance for hardness prediction (HRC units).*

Model	R2	RMSE	MAPE
ANN (MLP)	0.992	0.63	1.62%
Linear Regression	0.968	1.26	2.88%
XGBoost	0.935	1.80	4.73%
Random Forest	0.908	2.14	5.49%
Decision Tree	0.735	3.63	10.21%
SVR	0.561	4.68	11.31%

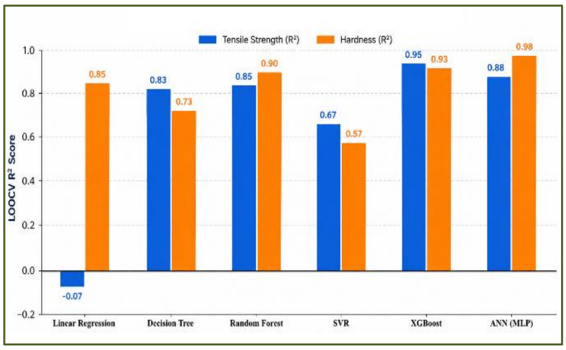

Figure 4: *LOOCV R^2 comparison across all six models for both responses.*

These findings extend previous reports of ML outperforming linear regression for weld-property prediction in other processes and materials—e.g., GMAW steel and TIG-welded SS304H, where XGBoost similarly emerged as the best-performing model among several ML algorithms [6,7]—to plain low-carbon structural steel and a substantially smaller dataset evaluated using LOOCV. The optimum parameter window identified in this study (130–140 A, 14 V) simultaneously provides near-base-metal tensile strength and balanced hardness, consistent with the qualitative optimum reported for GTAW mild-steel joints elsewhere [1,2].

3.3 Limitations

The dataset comprises only sixteen unreplicated observations across two varying input parameters (current and voltage). Travel speed and gas flow were held constant, and no microstructural characterisation (SEM/EBSD) was performed to directly confirm the grain-coarsening mechanism inferred from the mechanical trends. LOOCV mitigates, but cannot eliminate, the risk of overfitting in the more flexible models (RF, XGBoost, and ANN) at this sample size. The reported models should therefore be regarded as a proof of concept for ML-assisted GTAW parameter screening and should be validated using a larger, replicated dataset before industrial application.

4. Conclusions

This study investigated the effects of welding current and voltage on the tensile strength and hardness of GTAW-welded IS 2062 E250 mild steel using a Taguchi L16 experimental design. In addition, six machine learning models were evaluated to predict the mechanical properties from the welding parameters. Based on the experimental and machine learning analyses, the following conclusions are drawn:

i. Welding current is the statistically dominant factor controlling both tensile strength and hardness of GTAW-welded IS 2062 E250, as confirmed by ANOVA ($p < 0.001$).

ii. Hardness decreases monotonically with increasing current and heat input ($r = -0.930$ and -0.705, respectively), whereas tensile strength exhibits a non-monotonic response, reaching its maximum at 130 A (1.56–1.82 kJ/mm).

iii. XGBoost provides the most accurate prediction of tensile strength ($R^2 = 0.953$), while the Artificial Neural Network (ANN) achieves the highest prediction accuracy for hardness ($R^2 = 0.992$). In contrast, Linear Regression fails to accurately predict tensile strength ($R^2 = -0.099$), demonstrating that model selection should reflect the underlying behaviour of each response.

iv. Leave-one-out cross-validation (LOOCV) is both necessary and appropriate for Taguchi-scale (9–16 run) welding machine learning studies, providing a more reliable evaluation than conventional k-fold cross-validation for small datasets.

v. Within the investigated parameter window, a welding current of 130–140 A at 14 V provides the best balance between tensile strength and hardness. However, these findings should be validated using a larger, replicated dataset before industrial implementation.

References

[1] Elfallah, S. S. (2024). *Mechanical properties and microstructure analysis of mild steel welding made by GTAW. Journal of Mechanical Engineering*, 21(3), 333–355.

[2] Elfallah, S. S. S., Abdullah, H. Z., & Idris, M. I. (2022). *Effect of GTAW on the mechanical properties of mild steel. Journal of Advanced Mechanical Engineering Applications*, 3(2), 57–65.

[3] Sales, A. M., Ramirez, A. J., & Modenesi, P. J. (2016). *Effect of welding heat input on microstructure and mechanical properties*

of steel welds. *Welding in the World*, 60(5), 877–882.
[4] Matsunaga, H., Nishimoto, K., & Ogawa, T. (2013). *Effect of welding thermal cycle on microstructure and properties of stainless steel welds*. *Science and Technology of Welding and Joining*, 18(3), 225–232.
[5] Ogbonna, O. S., Akinlabi, S., Madushele, N., *et al.* (2023). *Multi-response optimization of TIG dissimilar welding of AISI 1008 mild steel and AISI 316 stainless steel using grey-based Taguchi method*. *The International Journal of Advanced Manufacturing Technology*, 126, 749–758.
[6] Ansari Dezfoli, A. R., Lin, L.-S., Hadidchi, S., & Huang, Y.-J. (2026). *Machine learning prediction of tensile strength in gas metal arc welding: Gradient boosting, neural networks and random forests*. *The International Journal of Advanced Manufacturing Technology*, 142(5–6), 2251–2258.
[7] Saha, S., Haldar, B., Joardar, H., Das, S., Mondal, S., & Tadepalli, S. (2025). *Supervised machine learning models for predicting SS304H TIG-welding properties using ANN, KNN, SVR, RF, GBR, and XGBoost*. *Crystals*, 15(6), 529.
[8] Boucetta, B., Boumediene, F., Ait Chikh, M. A., & Afia, A. (2026). *An improved artificial neural network using gradient-based optimizer for precise ultimate tensile strength prediction in GTAW of Inconel 825*. *The International Journal of Advanced Manufacturing Technology*, 142(5–6), 2771–2783.
[9] Somatkar, A. A., Dwivedi, R., Pol, R. S., & Aher, V. N. (2024, December). *Comparative Analysis of Dry and Lubricated Conditions for Enhanced Surface Quality with Optimization of Roller Burnishing Process*. In *International Conference on Advances in Materials and Manufacturing Technology* (pp. 423–438). Singapore: Springer Nature Singapore.
[10] Chaudhari, K. S., More, N. B., & Somatkar, A. (2026). *Risk Assessment in Automated Manufacturing Systems: A Hybrid Framework for Industry 4.0 and Beyond*. *International Research Journal of Innovation in Science and Technology (IRJIST)*, 1(2), 54–63.
[11] Sudake, M., Pujari, A., Somatkar, A., & Chahare, V. (2026). *Surface roughness optimization in hard turning of AISI D2 steel using RSM and machine learning*. *International Research Journal of Innovation in Science and Technology (IRJIST)*, 1(2), 8–15.

Publisher's Note & Copyright

IRJIST Journals remains neutral regarding jurisdictional claims in published maps and institutional affiliations; the views expressed are solely those of the authors.