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OPTIMIZATION AND PREDICTION OF TENSILE STRENGTH OF AN S235JR MILD STEEL WELD USING RESPONSE SURFACE METHOD AND ANALYTICAL HIERARCHY PROCESS (AHP)

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Abstract

Tensile strength in welding operation is very important as it is the maximum pulling stress in which a welded joint can withstand before failure. The higher the tensile strength, the stronger and more resistant the weld joint which is a critical indicator of the weld quality. Predicting tensile strength using the testing machines can be expensive and time consuming. Introducing machine learning processes like Analytical Hierarchy Process (AHP) through decision tree algorithm and Response Surface Method (RSM) which is a statistical computation can predict the tensile strength of a weld joint. This study applies RSM and AHP to predict the tensile strength of an S235JR mild steel weld.

Keyword: Mild Steel, Response Surface Method, Analytical Hierarchy Process, Tensile Strength, Tungsten Inert Gas welding, Decision Tree

Twenty (20) experimental runs were carried out using Tungsten Inert Gas (TIG) welding process while focusing on four key input parameters – Current (A), Voltage (V), Gas flow rate (L/min) and Ambient Temperature (°C). the experimental result was compared with RSM and AHP result to show the range in values and the predictability in the use of the RSM and AHP to predict tensile strength in welding operations. The Tensile Strength from the

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experiment, RSM and AHP process at maximum and minimum level was observed to be 565MPa and 428MPa, 565.18MPa and 527.59MPa, 549.67MPa and 466.75MPa respectively where the input parameters (voltage, current and temperatures) were 23V and 24V, 190A and 220A, 38°C and 28°C accordingly. While RSM is better suited for capturing intricate relationships and performing multi-objective optimization, the AHP using Decision Tree provides a simpler, interpretable framework for understanding general trends.

Introduction

Welding is an essential manufacturing process widely utilized in industries such as automotive, aerospace, shipbuilding, construction, and pipeline manufacturing. It involves the joining of materials, typically metals, through the application of heat, pressure, or both, to form a cohesive bond (Abukhshim *et al*, 2005). Residual stress in weldments arises due to uneven heating and cooling during the welding process, causing localized expansion and contraction within the weld zone. These stresses can manifest as tensile, compressive, or shear forces and may significantly influence the mechanical properties of the welded joint. High levels of tensile residual stress, in particular, can lead to premature failure through fatigue cracking or distortion, while compressive residual stress may reduce the material's load-bearing capacity (Sousa *et al*., 2020). Crack propagation is a significant threat to weld integrity when residual tensile stress is present. Even microscopic flaws or imperfections within the weld metal or heat-affected zone can act as stress concentrators, where cracks can initiate and propagate under the influence of residual stress (Cook *et al.,* 1963). Factors contributing to residual stress include welding parameters such as current, voltage, gas flow rate, and ambient temperature, as well as material properties and environmental conditions (Abhang and Hameedullah, 2010). To address the challenges associated with residual stress, computational techniques have emerged as valuable tools for optimization and prediction. Response Surface Methodology (RSM) is widely used for optimizing welding parameters, providing insights into the relationships between input variables and response outcomes. It employs statistical and mathematical techniques to model and analyze the effects of several variables, aiming to find optimal conditions that minimize residual stress (Adibi-Sedeh *et al*, 2005). Meanwhile, machine learning techniques, particularly Decision Trees, have gained attention for their predictive accuracy and ability to model complex nonlinear relationships without requiring explicit mathematical formulations (Otimeyin *et al*., 2025). Integrating RSM and Decision Tree approaches enables researchers to optimize welding processes while accurately predicting residual

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stress outcomes. This hybrid approach can significantly enhance welding quality and reliability, offering solutions to long-standing challenges in welding engineering. In recent times, researcher such as Gumus *et al*, 2025, Ikponwosa-Eweka and Ozigagun, 2023, have applied hybrid approach to enhance welding quality.

PROBLEM STATEMENT

During welding processes, residual stresses are inherent and can affect the weld quality. Without precise control over residual stress and weldments, there usually arises a complicated stress and optimization (Zhu and Xie, 2021). The traditional experiment and analytical methods often fall short due to inherent limitations when predicting and controlling residual stress (Ogbeide and Etin-osa 2023). To address these challenges associated with residual stress, computational techniques such as Response Surface Method (RSM) is widely used for optimizing welding parameters, providing insights into the relationship between input variables and response outcome (Otimeyin *et al*, 2025).

RESEARCH OBJECTIVES

1. investigate the influence of welding parameters (current, voltage, gas flow rate, material temperature) on tensile strength
2. develop a model to optimize and predict tensile strength
3. optimize welding parameters for tensile strength using RSM and AHP
4. compare the predicted results with the actual result

RESEARCH QUESTIONS

1. How do welding parameters affect tensile strength of a weld joint
2. What is the optimal parameter combination for maximizing tensile strength using RSM and AHP

RESEARCH METHOD

This study applied Response Surface Method (RSM) and Analytical Hierarchy Process (AHP) to optimize and predict tensile strength of a mild steel weld. S235JR Mild steel plates were used as the base material due to its widespread industrial application and susceptibility to residual stress during welding operations. A Tungsten Inert Gas welding machine was employed to conduct the welding operations with the capacity to adjust process parameters such as current, voltage, and gas flow rate. Shielding gas was supplied through a calibrated gas flow regulator to ensure consistent delivery during welding.

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Data Collection

Data collection focused on four key input parameters: Voltage (V), Current (A), Gas Flow Rate (L/min), and Ambient Temperature (°C), which were varied systematically to investigate their effects on tensile strength responses

TABLE 1: WELDING PARAMETERS

Parameters	Value	
	Low	High
Current (A)	190	220
Voltage (V)	21	24
Gas flow rate (L/min)	13	16
Material Temperature (°C)	28	38

Model Building

The table 2 below show the experimental results obtained for tensile strength using the universal testing machine. Using the data obtained and fitting to the central composite design (CCD), a second –order polynomial regression model for the tensile strength was developed. The regression equations were fitted by including linear, interaction and quadratic terms.

Model Analysis

The model analysis used is RSM and AHP. The RSM and AHP analysis in this study comprehensively assessed the relationship between the welding input parameters and the tensile strength response variables using various statistical and graphical tools. The fit summary helped to identify the most suitable model—linear, interaction, or quadratic—based on statistical metrics such as R^2, adjusted R^2, and predicted R^2. The lack-of-fit test determined the adequacy of the model by comparing the variation due to the model with that due to experimental error. Analysis of variance (ANOVA) evaluated the significance of each input factor and their interactions, while the fit statistics provided insights into model precision and reliability and AHP validated the model. The predictive capability of the Decision Tree (DT) algorithm is evaluated for estimating key response variables based on the input factors. The performance and reliability of the DT model were examined through a series of graphical diagnostics and visualizations, including the decision tree graph (to visualize model structure), predictor importance plot (to identify the most influential variables), and 3D surface plots (to understand factor-response relationships).

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RESULTS

With the universal testing machine, the results for each run are presented. Each row in the table corresponds to a unique combination of the input process parameters (Current, Voltage, Gas Flow Rate, and Ambient Temperature), and the measured output response (Tensile Strength). A careful observation of the data reveals how variations in welding parameters significantly affect the tensile strength of the mild steel weldments

TABLE 2 EXPERIMENTAL RESULTS WITH 20 RUNS

		Factor 1	Factor 2	Factor 3	Factor 4	Response 1
Std	Run	A: Current	B: Voltage	C: Gas Flow Rate	D: Ambient Temp	Tensile Strength
		A	V	L/min	oC	MPa
5	1	200	22	14	30	516
11	2	200	22	14	30	517
8	3	200	22	14	32	525
18	4	200	22	14	31	516
2	5	200	22	14	32	521
6	6	210	23	15	33	508
9	7	210	21	15	34	480
12	8	210	24	15	36	467
3	9	190	23	15	28	565
4	10	220	23	15	34	517
20	11	210	23	13	35	487
10	12	210	23	16	37	509
16	13	190	21	13	29	531
15	14	190	24	13	35	488
14	15	220	21	13	28	522
13	16	220	24	13	38	428
1	17	190	21	16	34	502
19	18	190	24	16	30	553
7	19	220	21	16	37	477
17	20	220	24	16	38	484

RSM Analysis

The RSM analysis in this study comprehensively assessed the relationship between the welding input parameters and the response variables using various statistical and graphical tools. The tables below show the fit summary, lack of fit test and analysis of variance

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Table 3: Fit Summary for **Tensile Strength**

Source	Model p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Design Model	< 0.0001	0.2523	0.9871	0.9742	
Linear	< 0.0001	0.0187	0.7931	0.7231	
2FI	0.3811	0.0183	0.8093	-0.5737	
Quadratic	**< 0.0001**	**0.5941**	**0.9960**	**0.8572**	**Suggested**
Cubic	0.5941		0.9955		**Aliased**

Presents the fit summary for the tensile strength response, highlighting the statistical significance and model adequacy of different model types. The design model, with a p-value of less than 0.0001 and a lack of fit p-value of 0.2523, indicates a highly significant and reliable fit, with excellent model performance metrics—an adjusted R^2 of 0.9871 and a predicted R^2 of 0.9742. The quadratic model is chosen for further analysis of tensile strength due to its optimal statistical properties.

Table 4: Lack of Fit Tests for **Tensile Strength**

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Linear	2918.42	13	224.49	52.82	0.0187	
2FI	1609.65	7	229.95	54.11	0.0183	
Quadratic	**10.31**	**3**	**3.44**	**0.8088**	**0.5941**	**Suggested**
Cubic	0.0000	0				Aliased
Pure Error	8.50	2	4.25			

Table 4 presents the lack of fit test results for the tensile strength model, providing critical insight into the adequacy of the different model forms. The quadratic model exhibits the most desirable statistical performance, with a very low sum of squares (10.31), low mean square (3.44), and a non-significant p-value of 0.5941, indicating that the model's deviation from the actual data is not statistically significant—making it a good fit for the observed data and the suggested model for further analysis. Overall, the quadratic model provides the best fit with minimal lack of fit, justifying its use in modeling tensile strength.

Table 5: ANOVA for **Tensile Strength**

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	17897.74	14	1278.41	339.78	< 0.0001	significant
A-Current	451.89	1	451.89	120.10	0.0001	
B-Voltage	105.81	1	105.81	28.12	0.0032	
C-Gas Flow Rate	0.5214	1	0.5214	0.1386	0.7249	

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Prof. Saeid Eslamian [IRAN]

Source	Sum of Squares	df	Mean Square	F-value	p-value	
D-Ambient Temp	34.91	1	34.91	9.28	0.0285	
AB	4.88	1	4.88	1.30	0.3062	
AC	17.28	1	17.28	4.59	0.0850	
AD	61.71	1	61.71	16.40	0.0098	
BC	440.71	1	440.71	117.13	0.0001	
BD	55.25	1	55.25	14.69	0.0122	
CD	34.26	1	34.26	9.10	0.0295	
A^2	536.18	1	536.18	142.50	< 0.0001	
B^2	585.65	1	585.65	155.65	< 0.0001	
C^2	40.63	1	40.63	10.80	0.0218	
D^2	52.05	1	52.05	13.83	0.0137	
Residual	18.81	5	3.76			
Lack of Fit	10.31	3	3.44	0.8088	0.5941	not significant
Pure Error	8.50	2	4.25			
Cor Total	17916.55	19				

Table 5 provides the Analysis of Variance (ANOVA) results for the tensile strength response, confirming the statistical significance of the developed quadratic model. The model has an extremely high F-value of 339.78 and a p-value of less than 0.0001, indicating that the variation explained by the model is highly significant compared to the residual error. Among the main effects, current (A), voltage (B), and ambient temperature (D) significantly influence tensile strength, with p-values of 0.0001, 0.0032, and 0.0285 respectively, while gas flow rate (C) is not significant ($p = 0.7249$). Interaction effects such as AD, BC, BD, and CD are also statistically significant, implying that combinations of these parameters considerably affect the response. Furthermore, the quadratic terms A^2, B^2, C^2, and D^2 are all significant ($p < 0.05$), emphasizing the need for a quadratic model to accurately capture the curvature in the response surface. The low residual sum of squares (18.81) and a non-significant lack of fit ($p = 0.5941$) further confirm that the model fits the experimental data well. This strong statistical performance justifies the use of the quadratic model for predicting and optimizing tensile strength in mild steel weldments.

The Model

The equation below represents the quadratic regression model derived for predicting Tensile Strength as a function of four key input parameters: Current (A), Voltage (B), Gas Flow Rate (C), and Ambient Temperature (D).

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$$Tensile\ Strength = 81.59620 - 54.52318 \cdot A + 523.17603 \cdot B - 273.71894 \cdot C + 140.13279 \cdot D + 0.248164 \cdot (A \cdot B) + 0.376066 \cdot (A \cdot C) - 0.439288 \cdot (A \cdot D) + 18.34720 \cdot (B \cdot C) - 4.90639 \cdot (B \cdot D) - 2.72272 \cdot (C \cdot D) + 0.138175 \cdot A^2 - 15.26499 \cdot B^2 - 4.38190 \cdot C^2 + 1.55510 \cdot D^2 \quad \text{eqn. 1}$$

The model captures not only the main effects of each factor but also the interaction effects (e.g., A·B, B·C) and quadratic terms (e.g., A^2, B^2), making it a comprehensive representation of the complex relationships influencing tensile strength in welding.

Analytical Hierarchy Process

the Decision Tree model for predicting Tensile Strength, revealing a clear, interpretable structure that highlights the influence of key input variables. The root node splits based on Ambient Temperature (x4), demonstrating its dominant role in determining tensile strength outcomes.

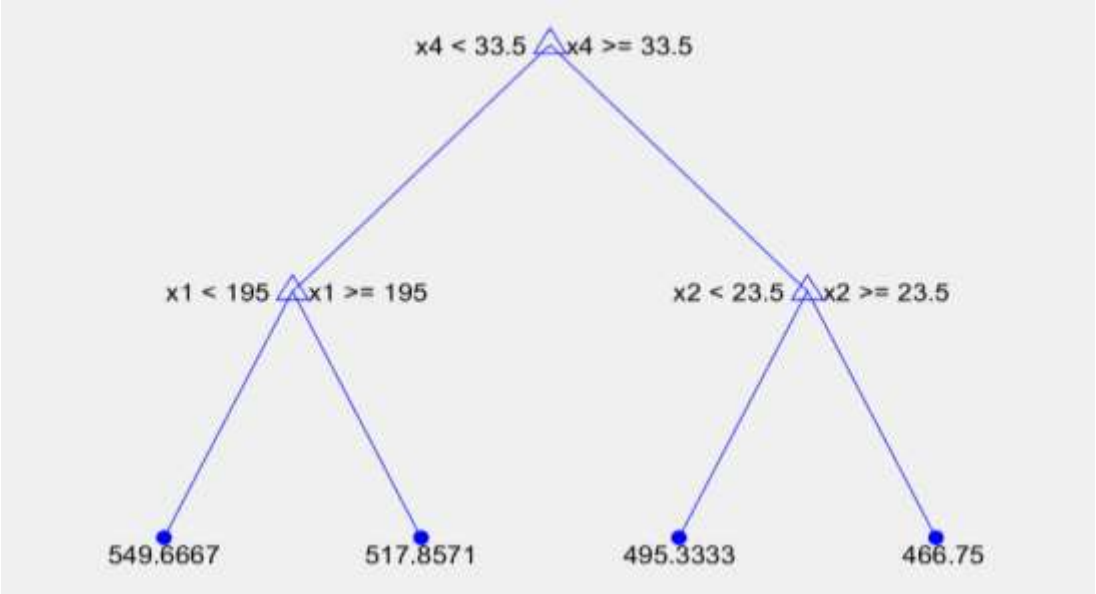


Figure 1: **Decision Tree for Tensile Strength**

If the ambient temperature is below 33.5°C, the model proceeds to evaluate Current (x1); lower current values (<195 A) are associated with the highest predicted tensile strength (549.67 MPa), while higher current values yield slightly lower strength (517.86 MPa). On the other hand, if the ambient temperature is equal to or above 33.5°C, the model considers Voltage (x2): voltages below 23.5 V predict a moderate strength (495.33 MPa), whereas higher voltages result in the lowest predicted strength (466.75 MPa). Notably,

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Prof. Saeid Eslamian [IRAN]

Gas Flow Rate (x3) does not appear in the decision path, suggesting it had minimal influence in this model's structure. Overall, the tree indicates that tensile strength is primarily influenced by ambient temperature, followed by current and voltage, and supports the conclusion that lower ambient temperatures and lower electrical input parameters are conducive to achieving higher tensile strength in the welding process.

Table 6: Predicted result of RSM vs Decision Tree to Experimental Results for Tensile Strength

S/N	Input Parameters				Tensile Strength MPa		
	Current (A)	Voltage (V)	Gas Flow Rate (L/min)	Ambient Temp. (°C)	EXP	RSM	Decision Tree
1	190	21	13	32	516.00	516.61	517.85
2	200	21	14	33	517.00	516.61	517.85
3	210	21	15	29	525.00	521.87	517.85
4	220	21	16	30	516.00	517.69	517.85
5	190	22	14	34	521.00	521.87	517.85
6	200	22	13	28	508.00	506.37	517.85
7	210	22	16	37	480.00	480.71	495.33
8	220	22	15	35	467.00	467.27	466.75
9	190	23	15	31	565.00	565.18	549.66
10	200	23	16	36	517.00	517.81	495.33
11	210	23	13	36	487.00	487.75	495.33
12	220	23	14	38	509.00	509.24	495.33
13	190	24	16	29	531.00	530.87	549.66
14	200	24	15	34	488.00	488.04	466.75
15	210	24	14	37	522.00	521.86	517.85
16	220	24	13	35	428.00	427.59	466.75
17	190	22	13	32	502.00	502.05	495.33
18	200	21	15	28	553.00	552.97	549.66
19	210	23	16	30	477.00	476.61	495.33
20	220	24	14	36	484.00	484.01	466.75

Table 6 shows the Predicted result of RSM vs Decision Tree to Experimental Results for Tensile Strength, compares the performance of Response Surface Methodology (RSM) and a Decision Tree model in predicting tensile strength against experimental (EXP)

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results under varying input conditions such as Current, Voltage, Gas Flow Rate, and Ambient Temperature. While both models generally capture the trends in tensile strength, the RSM predictions align more closely with the experimental values, showcasing its ability to model complex, non-linear relationships effectively. In contrast, the Decision Tree model exhibits larger deviations in certain cases, such as rows 9 and 10, where it significantly underpredicts tensile strength, and rows 7 and 8, where it overpredicts or underpredicts depending on the input combinations. This suggests that while the Decision Tree provides reasonable approximations for general trends, it lacks the precision of RSM in capturing sharp variations or extreme values observed in the experimental data.

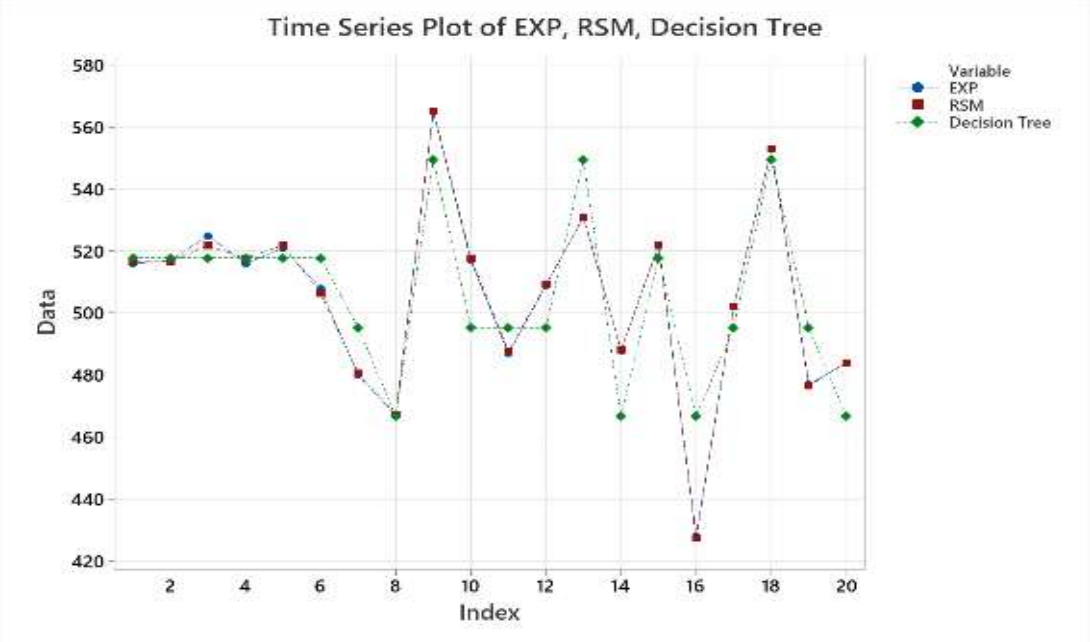


Figure 2: Time Series **plot of Exp, RSM and DT for Tensile Strength**

The Time Series Plot of EXP, RSM, and Decision Tree for Tensile Strength in Figure 2. compares the experimental (EXP), Response Surface Methodology (RSM), and Decision Tree (DT) predictions over a series of data points indexed from 1 to 20. The plot reveals that all three methods generally follow the overall trend of the experimental data but exhibit varying degrees of accuracy. The experimental data (blue line) shows significant fluctuations, with peaks and troughs at different indices. The RSM predictions (red line) closely track the experimental values, capturing most of the trends and sharp changes effectively, indicating its robustness in modeling complex relationships. In contrast, the Decision Tree predictions (green line) tend to smooth out some of the finer details,

showing less sensitivity to rapid changes in the experimental data. While the Decision Tree captures the general pattern, it underpredicts or overpredicts in certain regions, particularly where the experimental data exhibits sharp variations. This highlights the trade-off between the flexibility of RSM and the simplicity of the Decision Tree, with RSM providing more precise tracking of the experimental trends compared to the Decision Tree's broader, generalized approach.

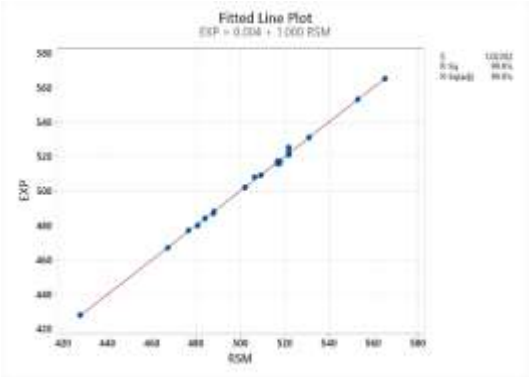


Figure 3: **Line plot of Exp and RSM**

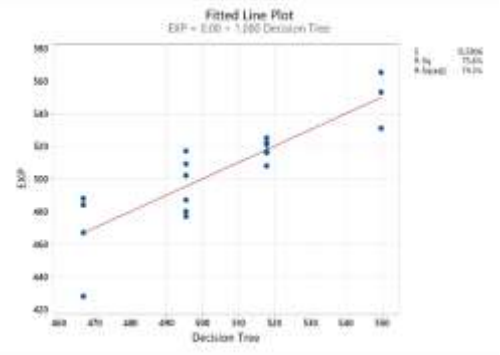


Figure 4: **Line plot of Exp and DT**

The Line Plot of Exp, RSM, for Tensile Strength in Figure 3 illustrates the relationship between the experimental (EXP) values and the predictions made by the Response Surface Methodology (RSM) while Figure 4 illustrates the relationship between the experimental (EXP) values and the predictions made by the Decision Tree model. The plot shows a linear trend with the fitted line equation

Discussion

This research investigates the relationships between input factors (Current, Voltage, Gas Flow Rate, and Ambient Temperature) and the response: Tensile Strength. The experimental results in Table 2. provides a comprehensive dataset, showing significant variability in response across different combinations of input parameters. For example, Tensile Strength ranges from 428 MPa to 565 MPa. These variations highlight the sensitivity of material properties to changes in process conditions.

The ANOVA results for the response, summarized in Tables 5. provides insight into the significance of individual factors and their interactions. For instance, Voltage and Current consistently emerge as dominant factors influencing the response, with significant main effects and interactions observed. The high F-values and low p-values (<0.0001 for many terms) confirm the robustness of the models, with R^2 values exceeding 0.99 for most responses, demonstrating excellent goodness-of-fit.

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Response Surface Methodology (RSM) demonstrates superior predictive accuracy compared to the Decision Tree model, as evidenced by the fit statistics in Tables 3 and 4. High R^2 values (>0.99 for most responses) indicate that RSM captures complex nonlinear relationships effectively

In contrast, the Decision Tree model, while capable of identifying broad trends, tends to oversimplify finer details, leading to lower predictive accuracy. The Decision Tree struggles to capture rapid changes or subtle variations observed in the experimental data. Despite its limitations, the Decision Tree model offers interpretability and simplicity, making it a valuable tool for preliminary analyses or situations where computational resources are limited. The time series and line plots comparing experimental, RSM, and Decision Tree predictions reveal that while the Decision Tree captures overall trends, it often smooths out fluctuations and fails to align closely with experimental data during periods of rapid change.

Conclusion

In conclusion, this study highlights the complementary strengths of RSM and Decision Tree models in analyzing and optimizing material responses. While RSM is better suited for capturing intricate relationships and performing multi-objective optimization, the Decision Tree provides a simpler, interpretable framework for understanding general trends. The findings emphasize the importance of selecting the appropriate modeling approach based on the specific requirements of the analysis. Future work could explore hybrid models that combine the strengths of both approaches, leveraging RSM's precision for detailed predictions and the Decision Tree's interpretability for broader insights. Such an integrated strategy could enhance the robustness and applicability of predictive models in materials science and related fields.

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