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Comparative analysis and optimization of quenched heat affected zones on mild steel weldment using artificial neural network

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Abstract:

This study explores the comparative analysis and optimization of quenched heat-affected zones (HAZ) in mild steel weldments using coconut oil as an eco-friendly quenching medium. A sheet of mild steel was cut into 40 samples of size 60x40x10 and then cut into two equal halves before it was welded. The effects of coconut oil on the microstructure and mechanical performance of TIG welded HAZ were examined through controlled quenching experiments. The strength of the welded joint tested for mechanical properties like yield strength, tensile strength, elastic modulus, elongation and flexural strength. 30 experimental runs was carried out on the welded samples and the results showed average tensile strength, yield strength, flexural strength, elastic modulus and elongation of 471.89 MPa, 377.49 MPa, 731.06 MPa, 3009.53 MPa, and 21.82%, respectively. The findings indicate an increased tensile strength, a moderate hardening, improved flexural resistance and preserved ductility signifying that coconut oil provides balanced mechanical properties through its moderate cooling rate. Comparative literature supports these results, showing that vegetable oil quenchants (coconut oil) can achieve desirable mechanical performance with reduced distortion and favorable cooling behavior. This research reinforces the viability of bio-based oils as sustainable alternatives to conventional quenchants. Additionally, the integration of Artificial Neural Networks (ANNs) is highlighted as an effective approach for predicting and optimizing welding parameters and mechanical outcomes, offering enhanced accuracy over traditional statistical methods.

Keywords: Mild Steel, Heat Affected Zone, Coconut Oil, Mechanical Properties, Artificial Neural Network.

1. Introduction

Steel remains fundamental to industrialization, construction, and infrastructure due to its superior strength, micro structural stability, versatility and cost effectiveness (Singh & Singh, 2020). Its malleability and weldability make it ideal for various fabrication and structural applications with both low and high carbon steels commonly employed to meet diverse performance demands (Sivakumar et al., 2022). Among modern welding techniques, Tungsten Inert Gas (TIG) welding stands out for its precision and quality; however, its performance is highly dependent on parameters such as current, voltage, travel speed, root gap and gas flow rate. Studies have shown that these parameters critically influence bead geometry, heat distribution and mechanical strength (Kumar et al., 2020; Srinivasan et al., 2022; Rahman et al., 2023).

To enhance weld quality, contemporary optimization methods like Design of Experiments (DoE) and computational intelligence approaches are increasingly applied. DoE enables systematic evaluation of process response relationships (Costa et al., 2011) while Artificial Neural Networks (ANNs) provide robust predictive capabilities for tensile strength, hardness and other mechanical properties based on process inputs (Okoroafor et al., 2024). Moreover, hybrid models integrating ANN with evolutionary algorithms, such as Genetic Algorithms, further improve predictive accuracy and process optimization (Pal & Chakraborty, 2009). Post weld heat treatment or controlled cooling techniques such as quenching are often employed to modify the mechanical properties of steel. Quenching techniques involves the rapid cooling from above the critical temperature to achieve desired transformations. In mild steel, welding processes like TIG typically generate heterogeneous microstructural regions

within the weldment, including the fusion zone, HAZ, and unaffected base metal. These zones often display different mechanical behaviors, making weld quality highly dependent on welding parameters (Singh & Kumar, 2020; Ahmed et al., 2019). Poor parameter selection may result in low tensile strength, reduced ductility, residual stresses or premature failure (Ravindra et al., 2021). Response Surface methodology which is an optimization techniques have been applied to improve welding processes (Patel & Sharma, 2020), limited research has focused specifically on optimizing TIG welded mild steel to simultaneously enhance yield strength, elongation and tensile strength. The absence of such targeted optimization contributes to inconsistent weld performance, reduced structural reliability and higher maintenance costs (Olawale et al., 2018). The research looks into the use of alternative cooling media such as coconut oil for quenching and the parameter optimization which is necessary to improve the mechanical performance and durability of mild steel weldments. Overall, these advancements underscore the importance of integrating experimental design and computational modeling to optimize TIG weldments for superior structural performance.

2. Materials and Methods

2.1 Collection of Material and Preparation

This study focuses on the experimental investigation of mild steel welds using a scientific approach that integrates design of experiments (DoE), expert systems and statistical and mathematical modeling to evaluate mechanical properties. Mild steel sheets were sectioned into forty (40) specimens, each measuring approximately 60 × 40 × 10 mm, and the cut edges were filed smooth. Each specimen was then divided into two halves of 30 × 20 × 10 mm, with varying root gaps prepared for different samples. Welding was carried out under controlled conditions with systematically varied parameters, including weld bead size, welding time, current and weld depth. After welding, the joints were quenched in coconut oil with different cooling durations for each sample. Detailed data were recorded for all welding operations, corresponding to the specific process parameters applied. The welded samples were subsequently tested for key mechanical properties which includes tensile strength, yield strength, elongation and Young's modulus thereafter the effects of process parameters and quenching conditions on weld performance will be evaluated.

Table 1 Welding Parameters Specification

MATERIAL	SPECIFICATION
Material thickness	10mm
Filler material	ER 70 5-6
Joint type	Butt
Welding current	DCEP
Welding current range	150-250
Welding voltage range	5-25
Welding speed range	80-120
Welding gas flow rate range	7 – 21
Root gap	0.5 – 3.0
Filler Wire	1.5-3.5
Filler rod angle	150
Welding torch angle	450
Fixed frequency	60Hz
Torch type	PTA -9
Tungsten size	3/1326 ‘’
Tungsten type	gThoriated
Tungsten shape	Pointed
Shielding gas	Argon
Grade of steel	HA 250
Experimental run	20



Fig 1 Uncut Mild Steel Sheet



Fig 1.2 Cut Mild Steel Samples



Fig1. 3. Extracted coconut oil



Fig 1.4. Welded Mild Steel Sample



Fig 1.5. Mild Steel Sample after Testing

2.1.1 Method of Data Collection

A Central Composite Design (CCD) matrix was generated using Design Expert software, resulting in a total of 30 experimental runs. The experimental matrix comprised both input and output parameters, with the measured responses from the welded samples serving as the dataset for analysis. Table 2.1 presents the Central Composite Design matrix used in this study. It should be noted that the coded value (-1,0,1) represents Minimum value, Neutral/No value and Maximum value respectively for the input parameters.

Table 2.1: Central Composite Design Matrix (CCD)

S/N	Gas Flow Rate	Quenching Period	Welding Time	Current	Root Gap	Responses
1	-1	-1	-1	-1	-1	
2	-1	0	0	0	0	
3	-1	1	1	1	1	
4	0	-1	0	1	0	
5	0	0	1	-1	0	
6	0	1	-1	0	0	
7	1	-1	1	0	0	
8	1	0	-1	1	0	
9	1	1	0	-1	0	
10	-1	-1	-1	-1	1	
11	0	0	0	-1	1	
12	1	1	1	-1	1	
13	-1	0	1	0	0	
14	0	1	-1	0	1	
15	1	-1	0	0	1	
16	-1	1	0	1	0	
17	0	-1	1	1	0	
18	1	0	-1	1	0	
19	-1	-1	-1	-1	-1	
20	0	0	-1	0	1	
21	0	0	0	1	1	
22	1	0	1	0	1	
23	1	1	1	0	0	
24	1	0	0	0	1	
25	1	1	1	1	1	
26	-1	-1	0	0	0	
27	-1	1	-1	-1	1	
28	-1	-1	-1	0	-1	
29	0	0	1	-1	0	
30	-1	-1	-1	0	0	

2.1.2 Artificial Neural Network (ANN) MODEL DEVELOPMENT

For ANN, the multi-input-single-output (MISO) architectural neural fitting design in Figure3.1 was adopted to model the performance of the process variables and predict the optimal mechanical properties. The multi-input variables are root gap, gas flow rate, welding time, quenching period and current while tensile strength, yield strength, elastic modulus, flexural strength, and elongation are the output. The variables were chosen to investigate the combined influence of input variables on the output variable. The MISO architectural neural network in Figure3.1 was duplicated and the number of neurons was adjusted to prevent overtraining and over fitting. Consequently, thirty (30) sets of data were utilized for the experiment and the data was analyzed using the Levenberg-Marquardt training algorithm transfer function. As noted, the network was train with 75 % of the data representing 22 samples, validate 15 % of the variables, and test 15 % representing 4 samples each using Levenberg-Marquardt training algorithm. This algorithm takes more memory and less time to run various neurons in the hidden layer. The random data were processed with different number of artificial neurons (10, 12, 15, 19 & 23) in the hidden layer and were trained on the algorithm network. The neuron with the least mean square error (MSE) was taken to be the best performing algorithm network and the interactive effect of the process variable on the output was significant and maximized at data processed with the number of neurons. The best algorithm network was adopted to predict the optimal mechanical properties. This was done on a feed forward back propagation network. The mean square error (MSE) is represented in Equation (1). The correlation coefficient (R^2) was also determined.

$$\text{MSE} = \left(\sum_{i=1}^{n} \frac{\{Predicted\ value - Experimental\ value\}^2}{n}\right) \quad (1)$$

Where, n = number of datasets used to train the network

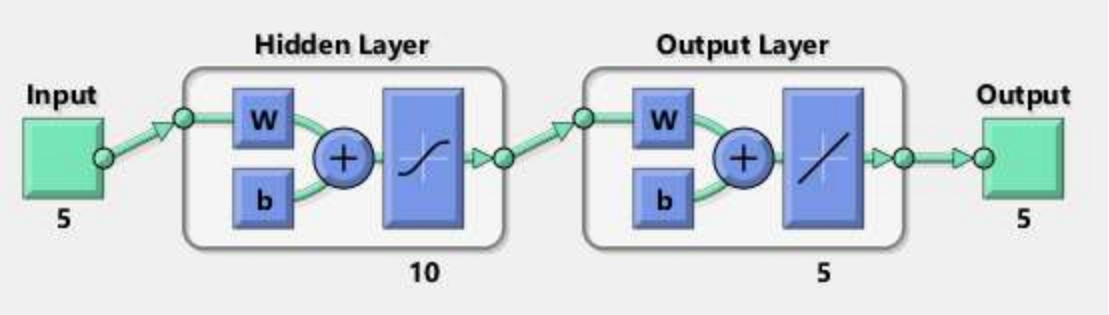

Figure 2.1 ANN Structure.

The ANN-based model was developed based on the feed-forward, back-propagation (B.P.) algorithms. Table 3 shows the Levenberg-Marquardt training algorithm was the best to predict the tensile strength, yield strength, elastic modulus, flexural strength, and elongation. The optimal model design had 5 neurons in the input layer, 10 in the hidden layer and 5 in the output layer.

3. Result and Discussion

Table 3.1: Experiment Data and Results for Responses

	Factors								Responses				
Run	Root Gap	Gas Flow Rate	Welding Time	Quenching Period	Current	Depth of Penetration Mm	Height of Reinforcement Mm	Width of Weld Mm	Tensile Strength MPa	Yield Strength MPa	Elastic Modulus MPa	Flexural Strength MPa	Elongation %
1	2.5	10	10	30	120	9.2	14	15	414	336.8	1989.55	636.384	22.78
2	0.5	5	14	10	120	7.6	12	12	469.33	374.4	4216.87	713.814	21.78
3	1.5	7.5	8	20	130	9.81	12	12	521.2	387.8	4615.38	668.458	25.26
4	2.5	5	10	30	140	14.05	12.5	13	456.8	365.2	1964.8	641.767	22.79
5	0.5	10	10	30	140	10.1	11	20	446.4	421.2	2334.49	807.307	20.68
6	3.5	7.5	12	20	130	15.2	13	17	422.26	392.68	1754.25	686.384	27.26
7	1.5	7.5	12	40	130	10.1	12	15	508.62	374.14	2103.27	845.726	16.95
8	0.5	5	10	30	120	6.9	12	14	507.83	302.38	4619.23	638.246	20.14
9	0.5	10	14	10	140	10.2	12.3	18	496.61	345.42	1916.84	669.854	25.86
10	0.5	10	14	30	120	9.5	12	20	406.43	403.22	2153.34	797.936	21.04
11	1.5	7.5	12	20	130	9.07	13	14	498.23	398.2	2389.35	706.249	19.54
12	0.5	5	10	10	140	10.1	13	13	496.44	389.22	4556.58	820.125	19.72
13	1.5	7.5	12	20	130	10.5	14	12	467.35	408.17	2654.21	769.246	20.56
14	2.5	5	14	10	140	12.05	13	13	528.26	402.21	4313.25	771.854	24.1
15	1.5	7.5	12	20	130	10.17	12	19	477.3	409.54	2089.33	710.321	21.58
16	1.5	12.5	12	20	130	11.4	15	15	445.23	355.56	1810.32	838.325	22.12
17	1.5	7.5	12	20	150	13.1	13	12	439.42	384.23	3054.29	623.143	17.96
18	0.5	5	14	30	140	10.47	12	15	498.35	394.2	4195.84	659.396	20.24
19	2.5	5	14	30	120	11.9	12	11	413.21	356.64	3703.71	743.746	21.26
20	2.5	10	14	10	120	9.71	11	20	466.63	330.1	2254.56	835.256	22.25
21	1.5	7.5	12	20	110	8.15	14	15	386.23	328.59	3020.2	635.366	19.2
22	0.5	10	10	10	120	9.59	13	15	477.65	308.98	3302.21	716.824	21.21
23	1.5	7.5	16	20	130	14.1	12.5	14	518.33	425.22	4398.97	668.468	22.75
24	2.5	10	14	30	140	12.25	11	14	489.85	413.31	2923.23	649.764	20.66
25	1.5	7.5	12	20	130	11.77	11	20	472.56	397.98	2054.56	802.325	20.21
26	-0.5	7.5	12	20	130	7.9	14	20	425.15	369.25	2602.36	674.344	25.12
27	1.5	2.5	12	20	130	10.4	12	15	501.27	375.55	3995.89	813.824	20.15
28	2.5	10	10	10	140	12.1	12	18	494.28	356.58	4015.26	798.514	23.25
29	1.5	7.5	12	10	130	13.5	13	13	512.2	387.84	2749.62	831.476	22.06
30	2.5	5	10	10	120	11.2	12	20	499.22	430.2	2534.03	757.302	26.24

Table 3.1 presents the results of a Design of Experiments (DOE) study for a welding process. The experiment systematically varies several input parameters /factors to observe their effect on the resulting weld quality and mechanical properties (responses). There are 30 experimental runs, each representing a unique combination of factor

settings. These are the five input variables that were intentionally changed during the experiment: Root Gap, Gas Flow Rate, Welding Time, Quenching Period and Current. The eight output variables that were measured after each weld to assess its quality are Weld Geometry: Depth of Penetration, Height of Reinforcement, and Width of Weld, Mechanical Properties: Tensile Strength, Yield Strength, Elastic Modulus, Flexural Strength and Elongation %. Table 3.1 is a comprehensive dataset from a structured experiment designed to understand and optimize a welding process by analyzing the relationship between the controlled "Factors" and the measured "Responses," engineers can develop a predictive model to improve the quality, strength and consistency of the welds.

3.1 Statistical Modeling

The generalized fitting PRS model is a reduced cubic function which can be expanded as follows:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_{1,2} X_1 X_2 + \beta_{1,3} X_1 X_3 + \beta_{1,4} X_1 X_4 + \beta_{1,5} X_1 X_5 + \beta_{2,3} X_2 X_3 + \beta_{2,4} X_2 X_4 + \beta_{2,5} X_2 X_5 + \beta_{3,4} X_3 X_4 + \beta_{3,5} X_3 X_5 + \beta_{4,5} X_4 X_5 + \beta_{1,1} X_1^2 + \beta_{2,2} X_2^2 + \beta_{3,3} X_3^2 + \beta_{4,4} X_4^2 + \beta_{5,5} X_5^2 + \beta_{1,1,1} X_1^3 + \beta_{2,2,2} X_2^3 + \beta_{3,3,3} X_3^3 + \beta_{4,4,4} X_4^3 + \beta_{5,5,5} X_5^3 \quad (2)$$

The above mathematical equation (2) is best suited for polynomial equations with many variables hence it was chosen. Levenberg-Marquardt training algorithm with ten neurons is indicated in the correlation coefficient while the values of the R-square indicate very high correlation coefficients for the training, testing and validation sets, ranging from 0.99544, 0.98556, and 0.9878 respectively and the overall R-square was 0.99269 for the process. This is shown in figure 2.2. The unknown coefficient terms were evaluated by multiple regression analysis and the results are presented in Table 3.2

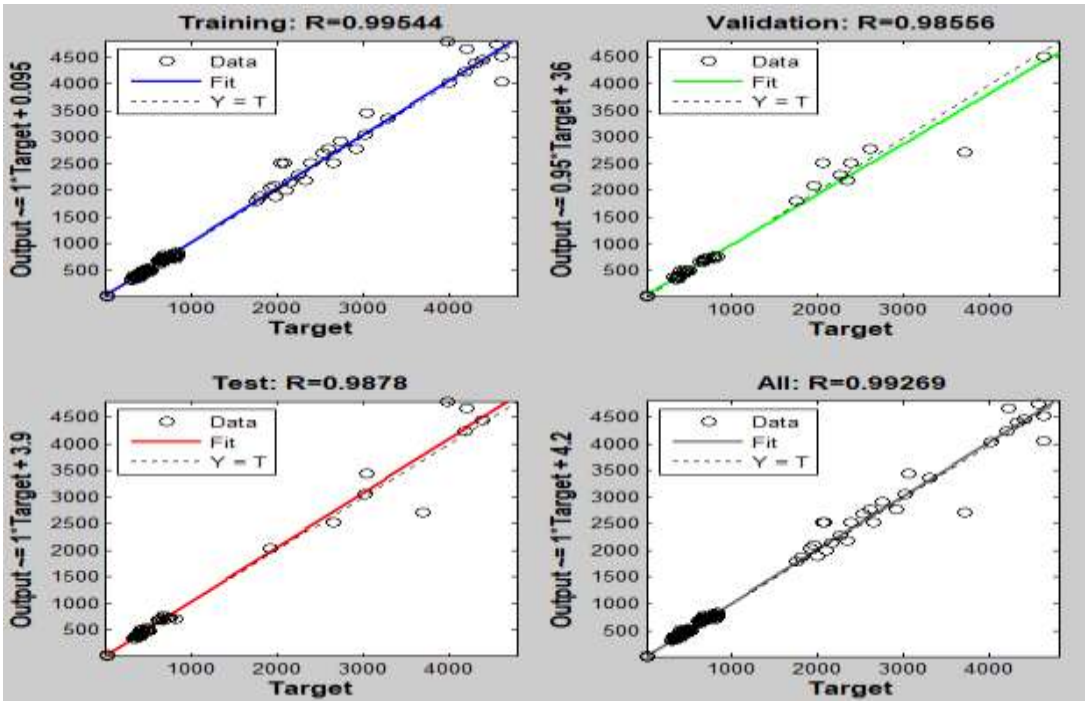

Figure 3.1. Mechanical Properties of Mild Steel weld for ANN Regression plot.

Table 3.2 above displays the regression coefficients for a set of mathematical models. Each column y1 through y8 represents a separate model predicting one of the eight response variables from the welding experiment e.g., y1 could be the model for Depth of Penetration, y2 for Height of Reinforcement, and so on. Each number in the table is a coefficient. These coefficients are the weights that determine the specific impact of the input factors like Root Gap, Current, etc and their interactions on the final predicted response.

Table 3.2: PRS Model Coefficient Terms

Coeff.	y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8
β_0	13.27	12.44	12.52	478.97	402.41	2332.53	752.18	20.62
β_1	1.36	-0.9400	-0.9583	-1.77	4.12	-220.55	1.47	0.7058
β_2	0.1162	0.9325	0.6250	-12.07	-5.78	-566.08	8.94	0.2250
β_3	0.2029	-0.0317	0.0417	-1.24	7.66	-2.97	1.05	-0.1933
β_4	-0.4148	-0.8482	-0.8683	-18.21	3.46	-212.46	-31.34	-1.00
β_5	1.13	-0.0592	-0.7917	14.96	14.83	63.12	-1.89	-0.0783
$\beta_{1,2}$	-0.8469	0.0763	-1.06	7.01	-8.50	409.28	-9.69	-0.7725
$\beta_{1,3}$	-0.6481	-0.2400	-0.4375	5.70	-5.12	313.80	19.26	-0.8725
$\beta_{1,4}$	0.7019	0.4650	-1.19	-8.34	-9.38	-115.39	-29.60	-0.1175
$\beta_{1,5}$	-0.0469	-0.9800	-0.3125	6.22	-4.84	251.41	-12.54	-0.2537
$\beta_{2,3}$	0.6994	-0.9362	1.19	4.90	1.75	-321.79	-2.35	0.2125
$\beta_{2,4}$	-0.1931	0.8738	1.19	-3.84	25.69	-59.44	15.68	0.0000
$\beta_{2,5}$	-0.9344	0.1162	-0.1875	4.51	4.39	95.85	-6.31	0.3588
$\beta_{3,4}$	0.0431	0.0525	-0.6875	-0.6519	10.92	235.91	14.32	-0.4225
$\beta_{3,5}$	0.1669	0.2825	0.4375	16.39	-3.94	37.16	-41.18	0.5288
$\beta_{4,5}$	-0.7106	-0.3200	0.1875	2.95	9.07	-221.36	-5.95	-0.1437
$\beta_{1,1}$	-0.7090	-0.0681	1.61	-13.97	-5.08	-42.03	-19.48	1.39
$\beta_{2,2}$	-0.6415	0.3194	-0.3906	-1.59	-8.93	139.17	16.95	0.1306
$\beta_{3,3}$	0.0348	-0.0806	-0.1406	10.04	1.31	540.18	-22.45	0.8481
$\beta_{4,4}$	-0.4931	-0.7323	2.24	16.14	-8.41	51.53	36.72	-0.3625
$\beta_{5,5}$	-0.5252	0.3756	-0.0156	-16.69	-11.22	172.70	-32.25	-0.5081

Table 3.3: Performance of different ANN membership function in Estimation of Mild Steel Weld

Algorithm	Function	MSE	R^2
Levenberg-Marquardt	Trainlm	0.42943	0.99269
Bayesian regularization	Trainscgp	0.872774	0.91457
Scaled Conjugate Gradient	Trainscgp	0.98307	0.90559
Resilient back propagation (Rprop)	Trainrcgp	422.0911	0.03796
Fletcher–Reeves conjugate gradient	Traincgf	6.7541	0.99219
Polak–Ribi´ere conjugate gradient	Traincgp	19.7238	0.99830

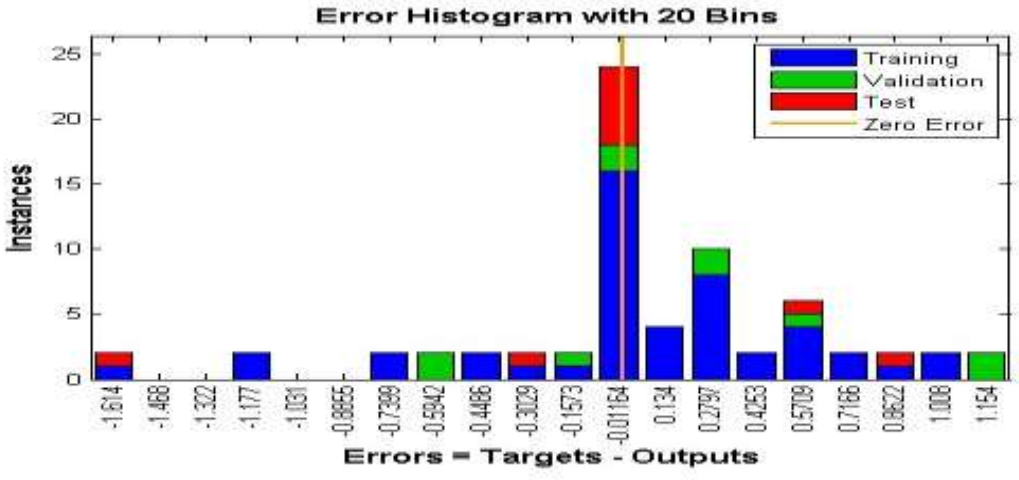

Figure 3.2: Histogram showing error distribution of experimented data and predicted data for the mechanical properties of mild steel weld

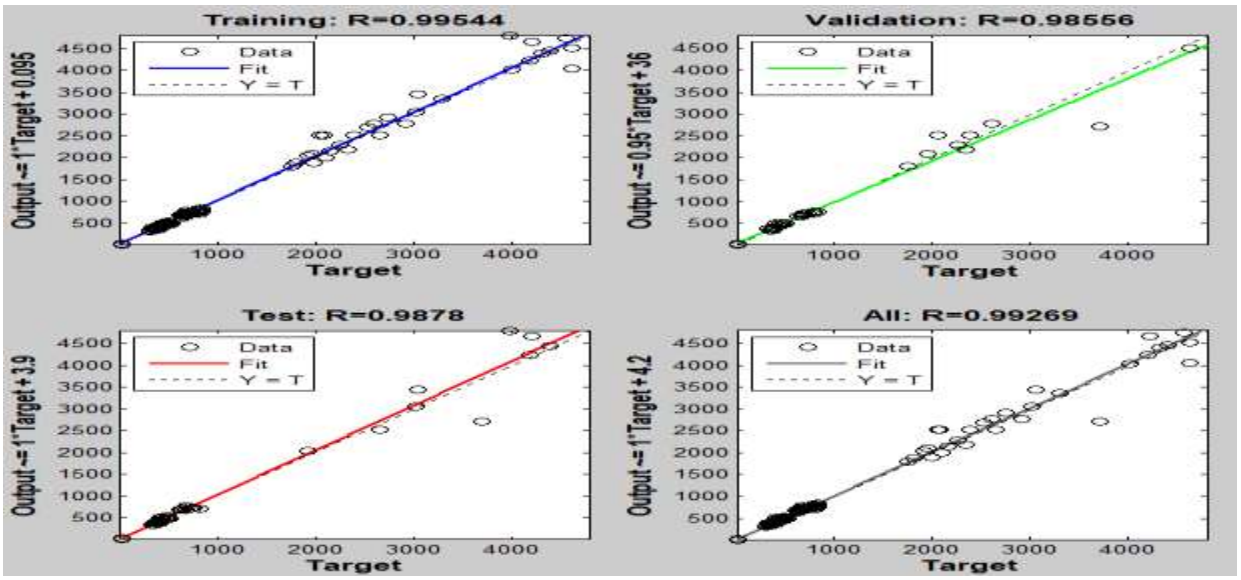

Figure 3.3. ANN Regression plot for the mechanical properties of mild steel weld

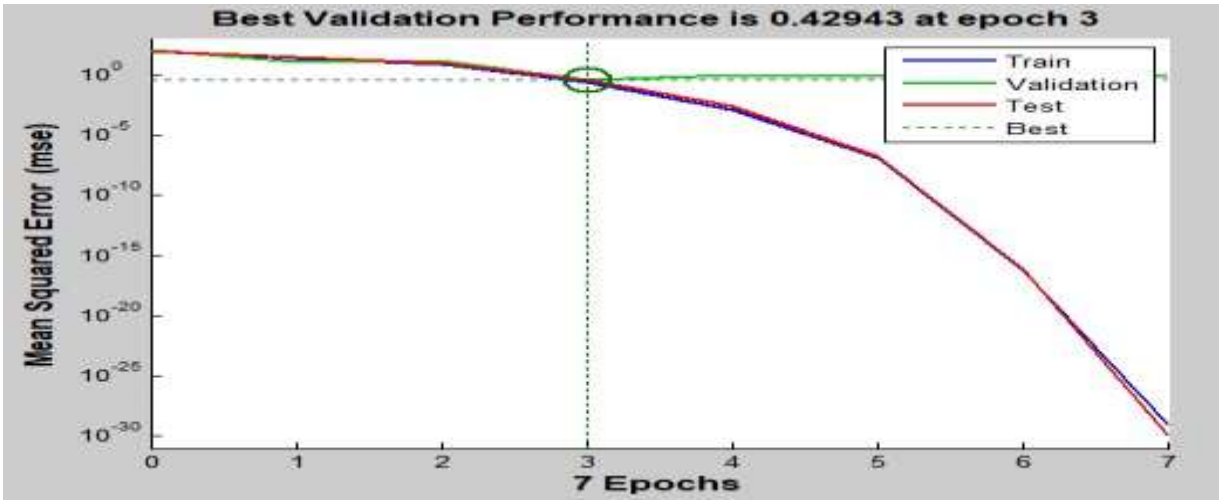

Figure 3.4. ANN training error curve for the mechanical properties of mild steel weld

The Figures 3.1, 3.2, and 3.3 represent the error histogram, plots of regression analysis, and training error curve performance plot respectively of the ten activating neurons. Figure 3.1 shows the network model's error histogram for the process, which shows that the errors were within the range of -0.01164 to -0.1573 (zero region), indicating good performance. This is in agreement with the prior report of Singh*et al*. (2020) on Application of ANN to analyze and predict tensile strength and hardness of shielded metal arc welded joints under an external magnetic field and Caio*et al*. (2021) on Mild Steel GMA Welds Microstructural Analysis and Estimation Using Sensor Fusion and Neural Network Modeling.

Figure 3.2 shows the best fit between the target data and the output data. The correlation coefficient indicates that the best training, testing, and validation were carried out using the Levenberg-Marquardt training algorithm with ten neurons. R-square values indicate extremely high correlation coefficients for the training, validation, and testing sets, ranging from 0.99544, 0.98556, and 0.9878 respectively and the overall R-square was 0.99269 for the processas shown in Figure 3.3 suggesting that the model performs exceptionally well and exhibits strong predictive accuracy across different data sets. The values being close to 1 indicate a nearly perfect linear relationship between the predicted and actual values, underscoring the reliability and consistency of the model across various evaluation scenarios. This is in line with the report of Ogbeide*et al*. (2024), Shukla*et al*. (2015).

At epoch 3, the MSE dropped from 100 to 0.42943 as shown in Figure 2.4. The maximum number of epochs for performing the best validation was 7 and the training and testing of process variables were significantly achieved at epoch 3 at the best performance validation. The lower MSE values suggest that the model accurately predicted outcomes. This compared well with Majid*et al*. (2021).

Table 4: Predictive ANN Model Adequacy for 30 Experimental Run.

ANN PREDICTED VALUES					
Experimental Run	**Tensile strength**	**Yield strength**	**Elastic Modulus**	**Flexural Strength**	**Elongation**
1	400.12	363.24	1877.92	659.91	20.79
2	466.16	350.70	4158.88	728.29	25.92
3	501.74	374.44	4386.16	729.85	19.12
4	453.09	394.40	2220.49	649.34	23.09
5	479.79	397.03	2281.88	829.03	18.74
6	455.98	379.43	1812.63	696.49	23.9
7	401.8	378.64	2678.72	687.23	23.54
8	459.43	312.80	4558.33	647.32	27.17
9	469.86	376.02	2038.41	690.78	22.32
10	408.08	405.90	2157.45	797.00	19.32
11	471.69	376.06	2294.66	769.35	22.09
12	514.89	385.02	4504.99	813.92	19.35
13	471.69	376.06	2294.66	769.35	22.09
14	520.98	404.33	4504.34	793.82	23.18
15	471.69	376.06	2294.66	769.35	22.09
16	473.7	389.54	2010.65	821.68	20.18
17	471.53	386.75	3186.23	648.02	21.58
18	426.05	398.42	2600.63	771.68	20.72
19	419.73	359.87	3713.21	744.81	23.3
20	469.25	361.31	2230.36	799.2	23.93
21	407.56	324.95	2874.97	640.67	26.17
22	499.54	361.13	3163.46	726.39	22.74
23	457.36	382.85	4378.39	848.55	21.69
24	446.97	368.23	2936.38	669.06	26.86
25	471.69	376.06	2294.66	769.35	22.09
26	450.62	367.84	2563.92	675.47	22.39
27	498.85	384.63	3953.69	786.93	22.99
28	503.91	382.28	3970.07	802.14	19.98
29	497.18	380.00	2818.43	816.38	21.75
30	473.28	389.65	2482.29	755.59	18.39

Table 5: Statistical Evaluation of the model.

Performance Indicator	Predicted RSM	ANN
	Tensile strength	**Tensile strength**
R^2	0.9848	0.99269
MSE	8.53	0.42943
	Yield strength	**Yield strength**
R^2	0.9928	0.99269
MSE	5.10	0.42943
	Elastic Modulus	**Elastic Modulus**
R^2	0.9878	0.99269
MSE	195.38	0.42943
	Flexural Strength	**Flexural Strength**
R^2	0.9534	0.99269
MSE	28.83	0.42943
	Elongation	**Elongation**
R^2	0.9579	0.99269
MSE	16.24	0.42943

Table 5 shows that results obtained using ANN as an effective analytical tool. ANN consistently yields higher predictive accuracy and lower errors across all performance indicators. This observation is consistent with previous studies where ANN models have been shown to out perform other computational tools due to their ability to model highly nonlinear and multi-dimensional relationships in welding processes (Katherasan et al., 2021; Zhang et al., 2022). Similarly, Adedayo et al. (2023) and Uwoghiren & Ozigagun (2023) reported that ANN provides superior generalization in predicting mechanical properties of welded joints, particularly when multiple interacting parameters are involved. Kumar & Singh (2023) also emphasized that ANN's flexibility makes it more suitable than traditional regression-based approaches for optimization tasks in welding and materials engineering. Table 5 shows that ANN is the more reliable tool for predicting weld mechanical properties, offering near perfect R^2 values (~0.993) and minimal error across all responses. This reinforces recent findings that hybrid approaches, where ANN complements RSM for optimization, provide the most accurate and practical solutions in welding research.

4. Conclusion

In this study, the heat affected zone (HAZ) behavior of mild steel was examined using coconut oil as a quenching medium. The primary aim was to optimize welding parameters to achieve an optimal balance between mechanical strength and ductility in welded joints. A systematic, data driven framework integrating experimental design with desirability based multi-response optimization was employed to assess the effects of key process parameters namely root gap, gas flow rate, welding time, quenching duration and welding current on critical mechanical properties which includes tensile strength, yield strength, elastic modulus, flexural strength and elongation. A total of 30 experimental runs were conducted and the resulting mechanical responses were thoroughly analyzed. Among the runs, Experimental Run 1 achieved the highest desirability score of 0.835, corresponding to a tensile strength of 524.18 MPa, yield strength of 417.30 MPa, elastic modulus of 3806.03 MPa, flexural strength of 832.37 MPa and elongation of 24.08%. These results indicate that the selected combination of parameters provides a desirable compromise between strength and ductility, producing welds suitable for demanding service applications. The use of desirability based optimization proved effective for selecting welding process parameters, enhancing process consistency, repeatability and overall weld quality. Based on the optimized results, parameter settings of approximately 2.5 mm root gap, 5.0 L/min gas flow rate, 14secs welding time, 10secs quenching duration and a welding current range of 130–135A were identified as optimal for achieving balanced mechanical performance.

5.0 Recommendation

This study recommends the appropriate application of input parameters within the heat affected zone (HAZ) of mild steel utilizing coconut oil as the quenching medium. The experimental findings and analysis are suggested for broader adoption in the treatment of mild steel HAZ, with potential applications across various industrial sectors. These results can provide valuable insights for engineering fields that work with mild steel, support process optimization in steel manufacturing, and contribute to more structured and data driven decision making in industrial operations. It is also recommended that an investigation of the effects of alternative shielding gases or different welding positions to expand the scope and applicability of the findings.

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