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PREDICTIVE MODELLING OF TIG WELDING PROCESS PARAMETERS: A COMPARATIVE STUDY OF TAGUCHI, FUZZY LOGIC, AND RESPONSE SURFACE METHODOLOGY

AUTHORS:
M. A. Afabor[1,*], E. Emozino[2], I. D. Friday[3], O. O. David[4] and A. S. Abella[5]

AFFILIATIONS:
[1,4,5]Department of Materials and Metallurgical Engineering, Delta State University of Science and Technology, Ozoro, Nigeria.
[2]Department of Mechanical Engineering, Delta State University of Science and Technology, Ozoro, Nigeria.
[3]Department of Agricultural Engineering, Delta State University of Science and Technology, Ozoro, Nigeria.

***CORRESPONDING AUTHOR:**
Email: afabormartins2@gmail.com

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Abstract

The optimisation design approach has garnered significant attention in experimental design due to its ability to develop unique designs that align with specific experimental objectives. Welding has been a unique joining process applied across various engineering fields. Optimisation of the welding process can significantly affect the quality of the welded joint. However, the choice of which optimisation technique to deploy for an experimental process is often a random decision taken by researchers. The aim of this study, therefore, is to perform a comparative study of the Taguchi, fuzzy, and response surface methodology optimisation techniques in the optimisation of tungsten inert gas welding parameters of current, voltage, and gas flow rate of mild steel. Results obtained from the analytical and statistical analyses, with MATLAB used for fuzzy logic modelling, Minitab used for ANOVA and main effect analyses, and Design Expert used for chart analysis, revealed that all three optimisation techniques are effective, but fuzzy logic (with a % error range of 1.8–5.4) as against RSM (with a % error range of 0.72–12.3) and Taguchi (with a % error range of 0.79–33.54) was the more robust and effective model, as its results were closer to actual experimental results than the other two traditional techniques.

1.0 INTRODUCTION

The creation of tools for statistics is an ever-growing trend, and its continual deployment in industrial research, science, and engineering cannot be overemphasised. According to [1], the optimal design technique has drawn a lot of interest in experimental design lately since it can produce customised designs that support particular experimental objectivees. Process parameters are one of the most important elements affecting the quality of welding. The operator has direct or indirect control over some factors that affect the microstructure and mechanical characteristics of the joints. To create weld microstructures with superior mechanical qualities and improve weldment performance throughout service, it is essential to choose the right process parameters for welding operations. According to [2], incorrect welding parameter selection is to blame for a large number of welded component failures that occur during service. Therefore, it is crucial to screen the various candidate process parameters to ascertain their impact on weld qualities to prevent unwanted microstructures with poor mechanical properties, which could be harmful to the safety and integrity of

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welded structures in service. Research has indicated that, despite the vast range of statistical and modelling instruments available, Taguchi, response surface methodology, and fuzzy logic techniques are among the often employed predictive and optimisation strategies in literature [3-6].

Taguchi's process modelling has shown to be a useful method by utilising minimal experimental runs, thereby reducing material wastage, enhancing process efficiency and potential cost savings; it utilises the mathematical design of experiments based on orthogonal arrays and not only saves costs and energy but also gives the required information about the primary and interaction outcomes [7]. [8] deployed the Taguchi technique to maximise tensile strength for dissimilar welds of AISI 4340 steel and 304 austenitic stainless steel. They investigated the influence of welding settings on surface roughness experimentally. In their investigation, they used 308L filler material and TIG welding to examine the effects of welding parameters on the micro-hardness, tensile strength, and surface roughness of AISI 316L stainless steel welded joints. [9], utilising the Taguchi optimisation technique, reported that minimum surface roughness was achieved at the parametric combination of current 125 A, voltage 18 V, and gas flow rate 12 L/min. and concluded that arc current was the most influential factor. The Taguchi technique was utilised by [10] to optimise the input factors for tungsten inert gas welding of mild steel.

RSM is a statistical and mathematical technique used to develop empirical models and optimise processes in which a response variable of interest is influenced by multiple parameters by fitting approximating models to the experimental data obtained in a designed experiment [11]. RSM was used by [12], to predict and optimise the welding parameters for tungsten inert welding of mild steel plates. [13], optimised output responses for TIG-welded low carbon by utilising an artificial neural network and the central composite design of trials of RSM. Using RSM, [11] optimised the welding and heat treatment parameters for improved mechanical performance in micro-alloyed steel components. They found that RSM-predicted outcomes could be obtained with minimal variations from experimental results of 0.67%.

Zadeh's [14] set theory serves as the foundation for the idea of fuzzy theory. Fuzzy set theory is a very appealing technique to extract information from data for controller design, and it may be used to model the amount of ambiguity or uncertainty owing to parameter inaccuracy and unmodelled dynamics. A new approach to welding parameter optimisation is provided via fuzzy logic modelling. The components of fuzzy logic are the fuzzy inference system, membership functions, rule base, fuzzy inference system, and defuzzifier (Figures 1 - 4). Fuzzifier expresses the input variables in the form of fuzzy membership values based on various membership functions. Rules based on linguistic form are formulated based on experimental observations. The fuzzy logic method was applied for the optimisation of spot welding parameters of stainless steel (AISI 304) by [15]. [16], optimised the process parameters of friction stud welding on the joining of AA 6063 and AISI 1030 steel, using Taguchi L9 orthogonal array method. In that work, they considered process parameters such as Rotational speed, friction time, and friction pressure as the influential input process parameters. They analysed the impact strength, axial shortening, and microhardness across the weld interface. [17], investigated the optimisation of the MIG Arc weld-brazing process on aluminium and steel lap-joint welds using the intrgrated grey relational analysis and Taguchi method, and reported that the wettability and tensile strength of the Al-steel lap-joint specimens were improved simultaneously by using the proposed approach.

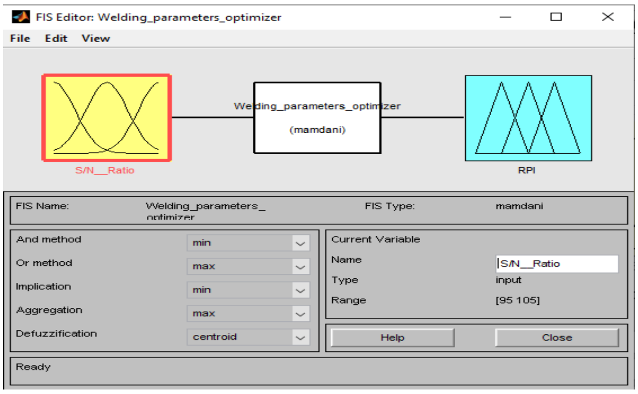

Figure 1: Fuzzy logic toolbox

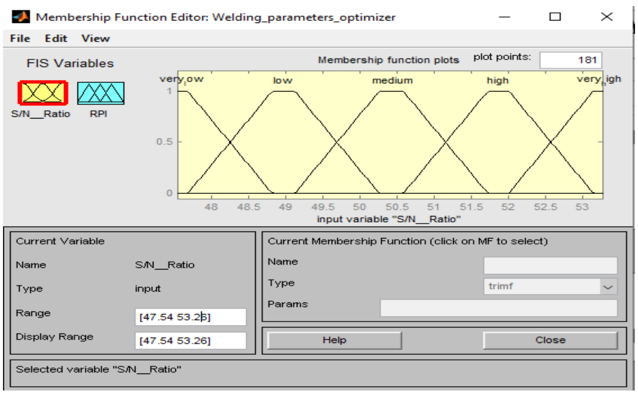

Figure 2: Membership function editor

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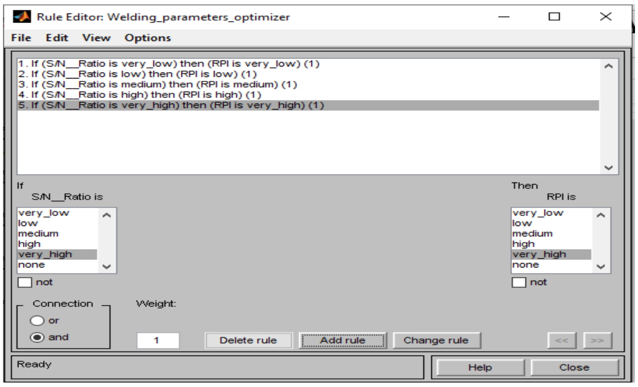

Figure 3: Fuzzy rule editor

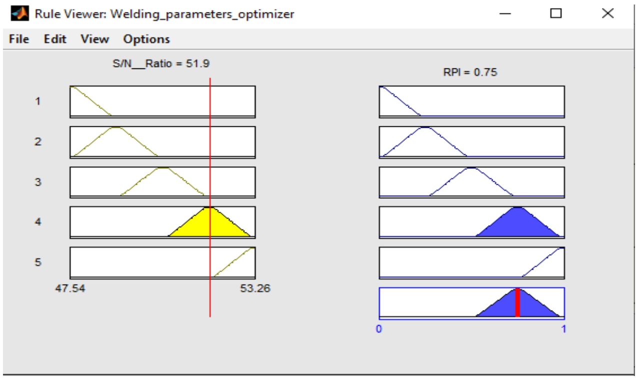

Figure 4: Fuzzy rule viewer

A review of the various literature [8-13, 15-17] highlighted in this paper reveals that optimisation techniques have been extensively employed in research to determine suitable welding parameters for producing welds with optimal mechanical properties, thereby enhancing performance in critical service applications. However, the choice of which optimisation cum predictive model to deploy for an experimental process to achieve consistent, reliable, and accurate results is often a random decision taken by researchers [18-21]. Therefore, the optimisation of TIG welding process parameters, and its effect on structural steel's tensile strength; and the comparative analysis of Taguchi, fuzzy logic, and RSM predictive models are the main focus of this work.

2.0 MATERIALS AND METHODS

2.1 Materials and Equipment

The mild steel samples utilised in this investigation had the chemical makeup shown in Table 1. The dimensions of the samples were 80 mm by 80 mm by 6 mm. Argon was used as the shielding gas and electrode ER70S-6 for the welding process, which was performed with a tungsten inert gas (TIG) Miller welding machine. Table 2 displays the filler material's chemical composition. For this investigation, the ultimate tensile strength of the welded steel samples at different welding parameter settings was determined using a universal tensile test machine.

2.2 Methods

2.2.1 Welding procedure

The weld joint's edges were ground away to eliminate surface contamination prior to welding. Additionally, the parts that needed to be joined were meticulously cleaned to remove any paint, dirt, oil, or grease. The bead-on-plate approach was used in the welding process, in which weld beads were placed longitudinally in the centre of each plate in a straight line. The preset parameter settings for the welding operation are outlined in Tables 3 and 4.

2.2.2 Statistical analyses

The signal-to-noise ratio (S/N) for the Taguchi analysis was computed using the larger-the-better option for tensile strength according to equation (1). The main effects analyses of fuzzy logic via the single multi response performance index (MRPI) and that of Taguchi, using signal-to-noise ratio with the option of larger-the-better, were achieved with the aid of MINITAB computer software, and the results obtained are illustrated in Tables 5–6 and Figure 5, respectively. The optimisation of the welding process output response by fuzzy logic was accomplished with the instrumentality of MATLAB computer software, using the fuzzy logic-Mamdani toolbox.

$$Larger - is - better: S/N = -10 \log \left(\sum_{i=1}^{n} \frac{y_i^{-2}}{n} \right) \quad (1)$$

The full quadratic model developed and the subsequent regression analysis of RSM was performed for the optimisation of tensile strength for mild steel were performed with the use of Design Expert computer software. Also, the determination of the statistical significance of the welding parameters employed in this study was carried out using analysis of variance (ANOVA), and the results are displayed in Table 7. The fit statistics results are exhibited in Table 8.

Table 1: Chemical composition of the mild steel

Element	C	Si	Mn	P	S	Cu	Ni	Cr	Mo	Al	N	Fe
%Wt.	0.17	0.31	0.78	0.03	0.03	0.51	0.09	0.05	0.008	0.047	0.007	Bal.

Table 2: Chemical composition of the filler material (ER70S-6)

Element	C	Mn	Si	P	S	Ni	Cr	Mo	V	Cu
%Wt.	0.15	1.60	1.1	0.025	0.035	0.1	0.12	0.13	0.03	0.50

Table 3: Welding parameters and their levels

Parameters	Unit	Level 1 (Low)	Level 2 (Medium)	Level 3 (High)
Current	Ampere (A)	95	100	105
Voltage	Volt (V)	23	25	27
Gas flow rate	Litre per minute (L/min.)	10	15	20

3.0 RESULTS AND DISCUSSION

3.1 Analysis of Taguchi

Results for the Taguchi analysis are displayed both in Table 5 and Table 6, respectively. Predicted Taguchi tensile strength is obtained based on Equation (2) according to [22].

$$\mathrm{T} = \mathrm{T_m} + \sum_1^n (T_o - \mathrm{T_m}) \quad (2)$$

Where, T is the calculated or predicted S/N; $\mathrm{T_m}$ is the mean of the total of the S/N of all the runs; T_o is the mean of the S/N at the particular level of the process parameter, and n is the relevant welding process parameter for the S/N.

The experiments were conducted based on RSM central composite design of experiment of 20 runs (Table 4), and the results obtained were all subjected to the Taguchi, RSM and fuzzy logic optimisation techniques (Table 5) respectively. The purpose of this comparative study of the aforementioned optimisation techniques, was to determine the predictive modelling accuracy of each optimisation technique as compared with actual experimental results obtained. The deviations of predicted results from actual experimental results were calculated via percentage error computations; and the values so obtained formed the bases for comparisons. From Table 6, among the 20 experimental runs conducted, trial run three has the maximum experimental test tensile strength of 460.3 MPa, signal-to-noise ratio of 53.26 dB, and a predicted tensile strength of 387.7 MPa, from a parametric combination of $X_2Y_2Z_3$; While experimental run 8 has the least tensile strength of 238.2 MPa, S/N of 47.54 dB and a predicted tensile strength of 318.1MPa, from a parametric combination of current 100 A, voltage of 27 and gas flow rate of 15 L/min. According to Taguchi, the optimum condition (of the welding process) is obtained from the analysis of the main effects of the factors. Since the higher-the-better is desired for the tensile strength, Table 9 and Figure 5, demonstrate that the optimal combination of welding parameters is $X_3Y_2Z_1$, that is, a current of 105 A, a voltage of 25 V, and a gas flowrate of 10 L/min. The percentage error for the Taguchi predicted tensile strength for the experimental runs ranges from 0.79 to 33.54 %. Only 30 % of the data produced percentage errors above 10 %, indicating that the Taguchi predictive model is reliable.

3.2 Fuzzy Logic

The results obtained from the analysis of the fuzzy logic toolbox using MATLAB computer software are illustrated in Table 5 and Table 6, respectively. The fuzzy predicted tensile strength of 454 MPa was the maximum for order run 3 with the corresponding test tensile strength of 460.3 MPa at the same parametric combination of current at 100 A, voltage at 25 V and gas flow rate 20 L/min. Table 10 and the main effects plot for MRPI in Figure 5, developed by MINITAB computer software, also highlighted the optimum welding process parameters of current of 105 A, a voltage of 25 V, and a gas flowrate of 10 L/min. The fuzzy logic model recorded a maximum % error of 5.4 and a minimum % error of 1.8 respectively. 100% of the fuzzy data exhibited a percentage error of less than 10%, demonstrating that it is a very robust and reliable predictive model.

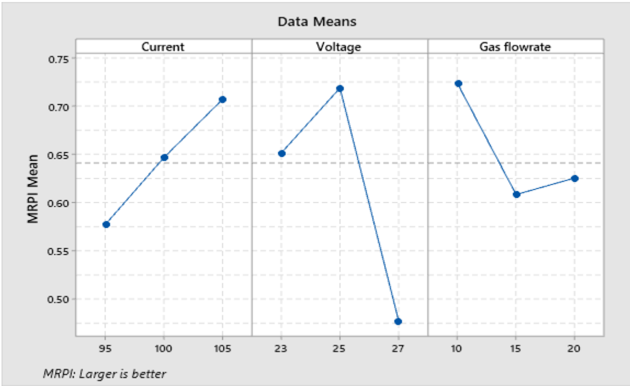

Figure 5: Main effects plot for single MRPI

3.3 Statistical Analysis of the Response Surface Methodology Quadratic Model

Analysis of variance (ANOVA) was used in the statistical testing of the quadratic model with the aid of Design Expert computer software and the results are presented in Table 7. The significance of the quadratic model was analysed via the Fisher's value (F-value). The full quadratic model as presented in Table 7 for tensile strength with an F-value of 5.12 and a P-value of 0.0088 (less than 0.0500) implies the model and its terms are significant. The experimental data acquired is well-fitted to the second-order quadratic model developed. The final equation in terms of actual factors is given in equation (3).

$$Tensile\ strength = 382.67364 - 8.31X - 1.26Y - 16.96Z - 20.4XY + 41.95XZ + 46.8YZ + 15.79091X^2 - 22.05909Y^2 - 14.25909Z^2 \quad (3)$$

As depicted in Table 8, the standard deviation value of 30.08 was achieved from the model. A coefficient of determination (R^2) value of 0.8216 was obtained for the model indicating that there is an actual correlation among the parameters selected in the experiment. It showed that only 17.84 % of the total variation in the tensile strength of structural cannot be accounted for by the experimentally studied variables. Adequate precision measures the signal-to-noise ratio. A ratio greater than 4 is desirable. A sufficient signal of 9.941 was obtained, indicating a satisfactory precision was achieved. As a result, the model can be used to traverse the design space.

Figures 6 - 8 show generated 3D surface response graphs from the RSM quadratic model analysis. According to Figure 6, tensile strength decreases as voltage falls but it increases as current increases. This suggests that high tensile strength may be attained at moderate heat input, which is supported by [23]. The impact of voltage and gas flow rate on tensile strength is shown in Figure 7. Tensile strength increases with decreasing gas flow rate and lowers with increasing voltage. The impact of gas flow rate and current on the tensile strength of structural steel is emphasised in Figure 8. It is noted that higher tensile strength values are obtained at lower current and gas flowrate levels; this provides additional evidence that; moderate heat is required for high tensile strength. A plot of predicted versus actual tensile strength values is presented in Figure 9.

Table 5 shows that the RSM predicted tensile strength of 457.0 MPa was the highest for order run 3 with the corresponding test tensile strength of 460.3 MPa at the same parametric combination of $X_2Y_2Z_3$. The maximum settings predicted from the quadratic second-order polynomial equation were $X_3Y_3Z_3$ corresponding to the maximum Tensile strength of 403.97 MPa. The RSM quadratic model recorded a maximum of 12.3 % error and a minimum of 0.72 % error respectively. 90 % of the RSM data exhibited a percentage error of less than 10 %, demonstrating that it is a robust and reliable predictive model.

Apart from Taguchi, whose optimal combination of $X_2Y_2Z_3$ welding parameters did not occur in the 20 experimental runs, fuzzy logic with an optimal combination that occurs in run 3 estimated a higher tensile strength of 452 MPa compared to RSM with an optimal combination of $X_3Y_3Z_3$ that did not occur in the 20 experimental runs with an estimated tensile strength of 403.97 MPa.

Table 4: Design of experiment using central composite design of RSM

Std. order	Run order	Current (A)	Voltage (V)	Gas flowrate (L/min.)	Tensile Strength (MPa)	S/N	MRPI
11	1	0	-1	0	368.9	51.34	0.660
6	2	1	-1	1	336.8	50.55	0.500
1	3	-1	-1	-1	460.3	53.26	0.927
17	4	0	0	0	347.0	50.81	0.559
10	5	1	0	0	395.9	51.95	0.750
20	6	0	0	0	357.7	51.07	0.610
7	7	-1	1	1	360.0	51.13	0.621
5	8	-1	-1	1	238.2	47.54	0.0728
3	9	-1	1	-1	415.1	52.36	0.768
4	10	1	1	-1	264.3	48.44	0.230
12	11	0	1	0	366.3	51.28	0.649
19	12	0	0	0	392.0	51.87	0.750
18	13	0	0	0	354.4	50.99	0.596
13	14	0	0	-1	350.8	50.90	0.578
9	15	-1	0	0	415.0	52.36	0.768
16	16	0	0	0	401.9	52.08	0.752
14	17	0	0	1	400.0	52.04	0.751
15	18	0	0	0	415.1	52.36	0.768
2	19	1	-1	-1	411.3	52.28	0.763
8	20	1	1	1	397.2	51.98	0.750

Table 5: Tensile test results and their predicted values

Run order	Levels of Parameters			Test Tensile strength (MPa)	Predicted Taguchi (MPa)	Predicted RSM (MPa)	Predicted Fuzzy logic (MPa)
	Current (A)	Voltage (V)	Gas flowrate (L/min.)				
1	95	23	20	368.9	351.1	361.9	385
2	100	23	15	336.8	370.4	353.3	354
3	100	25	20	460.3	387.8	457.0	452
4	105	23	20	347.0	389.9	382.7	365
5	105	27	20	395.9	334.8	390.2	408
6	100	25	15	357.7	385.6	382.7	377
7	100	25	15	360.0	385.6	377.5	377
8	100	27	15	238.2	318.1	245.6	247
9	100	25	15	415.1	385.6	401.7	428
10	95	27	20	264.3	301.5	260.3	273

11	95	25	15	366.3	363.4	359.4	383
12	100	25	15	392.0	385.6	382.7	405
13	100	25	15	354.4	385.6	382.7	374
14	95	27	10	350.8	329.7	385.4	369
15	95	23	10	415.0	383.9	406.8	426
16	100	25	10	401.9	424.0	382.7	414
17	100	25	15	400.0	385.6	351.5	413
18	105	23	10	415.1	426.3	382.7	426
19	100	25	15	411.3	385.6	397.3	422
20	105	27	10	366.1	322.7	404.0	410

Table 6: Tensile test results and their deviations

Run order	Test Tensile strength (MPa)	Taguchi Predicted (MPa)	% Error	Fuzzy logic Predicted (MPa)	% Error	RSM Predicted (MPa)	% Error
1	368.9	351.1	4.83	385	4.36	361.9	1.90
2	336.8	370.4	9.98	354	5.12	353.3	4.90
3	460.3	387.8	15.75	452	1.80	457.0	0.72
4	347.0	389.9	12.36	365	5.19	382.7	10.29
5	395.9	334.8	15.43	408	3.06	390.2	1.44
6	357.7	385.6	7.80	377	5.40	382.7	6.99
7	360.0	385.6	7.11	377	4.72	377.5	4.86
8	238.2	318.1	33.54	247	3.69	245.6	3.11
9	415.1	385.6	7.11	428	3.11	401.7	3.23
10	264.3	301.5	14.07	273	3.29	260.3	1.51
11	366.3	363.4	0.79	383	4.56	359.4	1.88
12	392.0	385.6	1.63	405	3.32	382.7	2.37
13	354.4	385.6	8.80	374	5.53	382.7	7.99
14	350.8	329.7	6.01	369	5.19	385.4	9.86
15	415.0	383.9	7.49	426	2.65	406.8	1.98
16	401.9	424.0	5.50	414	3.01	382.7	4.78
17	400.0	385.6	3.60	413	3.25	351.5	12.13
18	415.1	426.3	2.70	426	2.63	382.7	7.81
19	411.3	385.6	6.25	422	2.60	397.3	3.40
20	397.2	322.7	18.76	410	3.22	404.0	1.71

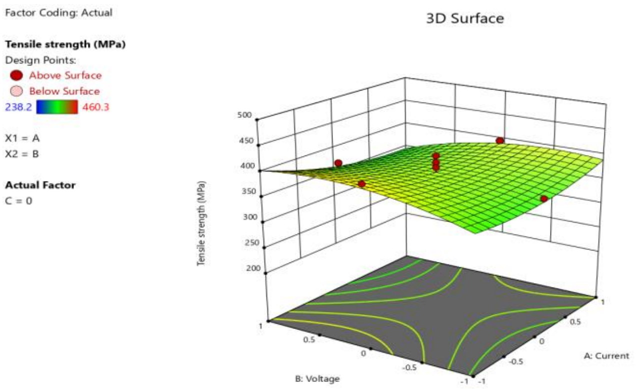

Figure 6: Plot of current, voltage vs TS

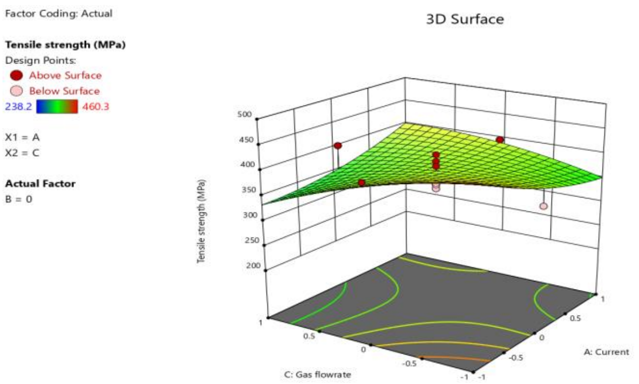

Figure 7: Plot of current, gas flowrate vs TS

Table 7: ANOVA for quadratic model

Source	Sum of Squares	DF	Mean Square	F-value	p-value	
Model	41655.14	9	4628.35	5.12	0.0088	Significant
X-Current	690.56	1	690.56	0.7633	0.4028	
Y-Voltage	15.88	1	15.88	0.0175	0.8972	
Z-Gas flowrate	2876.42	1	2876.42	3.18	0.1049	
XY	3329.28	1	3329.28	3.68	0.0840	
XZ	14078.42	1	14078.42	15.56	0.0028	
YZ	17521.92	1	17521.92	19.37	0.0013	
X^2	685.72	1	685.72	0.7580	0.4044	
Y^2	1338.16	1	1338.16	1.48	0.2518	
Z^2	559.13	1	559.13	0.6180	0.4500	
Residual	9046.92	10	904.69			
Lack of Fit	4973.25	5	994.65	1.22	0.4160	not significant
Pure Error	4073.67	5	814.73			
Cor Total	50702.06	19				

Table 8: Fit statistics

Std. Dev.	30.08
R^2	0.8216
Adjusted R^2	0.6610
Adequate Precision	9.9406

Table 9: Signal-to-noise ratio mean response values **(higher is better)**

Parameter	Mean S/N			Maximum
	Level 1	Level 2	Level 3	
Current	50.864	51.379	51.775	51.775
Voltage	51.484	51.833	50.162	51.833
Gas flowrate	51.936	51.111	51.160	51.936
Mean of the total of S/N = 51.300 dB				

Table 10: MRPI mean response values

Parameter	MRPI Mean			Maximum
	Level 1	Level 2	Level 3	
Current	0.577	0.646	0.707	0.707
Voltage	0.650	0.719	0.476	0.719
Gas flowrate	0.723	0.608	0.625	0.723
Mean of the total of MRPIs = 0.637				

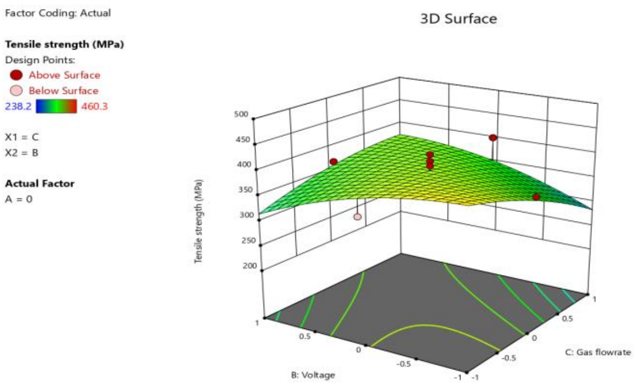

Figure 8: Plot of voltage, gas flowrate vs TS

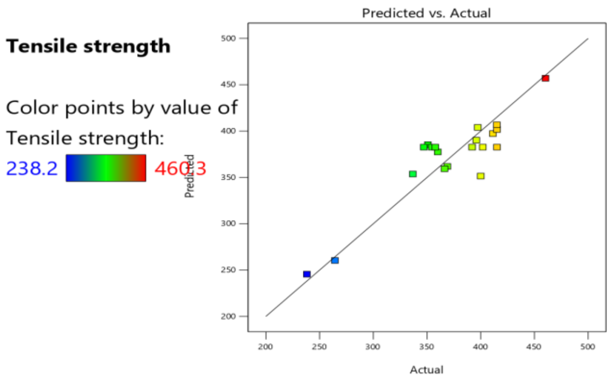

Figure 9: Plot of predicted vs actual TS values

3.4 Validation Evaluation

An experimental validation of the various predictive modelling of welding process parameters for mild steel was carried out. The value of the calculated or predicted single MRPI as per tensile strength for Taguchi method, using the maximum levels of the welding process parameters is derived from Equation (2)

Table 11: Validation experiment results

Run order	Test Tensile strength (MPa)	Predicted Taguchi	% Error	Predicted Fuzzy logic	% Error	Predicted RSM	% Error
1	389.9	443.8	13.8	404	3.62	361.9	7.18

A validation experiment was performed based on the optimal levels of the TIG welding parameters obtained and from Equation (2), the tensile strength was calculated or predicted, to verify and validate the comparative performances of the selected modelling techniques employed in this study. Results obtained from the validation experiment are displayed in Table 11 showing the predicted and actual tensile strength values, as well as the percentage error for each modelling technique used. From the results, it is clear that from the three modelling techniques utilised in this study, fuzzy logic optimisation technique, with a percentage error of 3.26 % is the preferred modelling technique for welding process parameters for structural steel.

4.0 CONCLUSIONS

This study focused on the comparative analyses of the output responses of tensile strength from the input of welding parameters using the Taguchi, Fuzzy logic, and regression analysis of RSM. The study's findings show that the three methods are reliable, but fuzzy logic (with a % error range of 1.8 – 5.4) as against RSM (with a % error range of 0.72 – 12.3) and Taguchi (with a % error range of 0.79 – 33.54), is more reliable and robust model than the other two models as its results are much closer to the actual experimental results. However, it must be noted, that the use of different software in this study may raise fair comparison, result interpretation and consistency concerns. This perhaps may form a basis for future research.

5.0 COMPETING INTERESTS

The authors declare that they have no competing interests

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