STATISTICAL EVALUATION OF THE EFFECT OF PROCESS PARAMETERS ON THE DEPTH OF PENETRATION OF TUNGSTEN INERT GAS ARC CLADDING WELD IN MILD STEEL

Abstract

The study expressed the statistical investigation in depth of penetration on mild steel cladding weld geometry. The use of analytical tools and analysis of variance (ANOVA) were use to investigate the statistical influence of the mild steel cladding weld process parameters that gives rise to the geometry of the mild steel material. The results portray and express the statistical effects, variations and models of the process parameters and the response parameter in the system the parameters used are significant, while the model developed has a significance value of 0.48%.Finally, the need for this research has shown the essence of statistical investigation and mathematical modeling for depth of penetration on mild steel cladding weld metal geometry which give solutions to the system and more appropriate suggestions that will influence the decision making on mild steel metal utilization.

Key words: analysis of variance; welding; statistics; mild steel; depth of penetration; cladding

1. INTRODUCTION

Statistical analysis is the study of the collection, organization, analysis, interpretation and presentation of data (Dodge, 2006). It deals with all aspects of the data, including the planning of data collection in terms of the design of surveys and experiments (Dodge, 2006). The word statistical when referring to scientific discipline is unique. This should not be confused with the word statistical, referring to an amount calculated from a set of data. A higher probability density is found the closer the expected average value approaches in a normal distribution. The statistics used in the evaluation of standardized tests are shown. Scales include standard deviations, cumulative percentages, percentile equivalents, Z scores, T scores, standard nines, correlation, missing value analysis, descriptive, frequency analysis and percentages in standard nines.

Statistics are alternatively described as a mathematical body of science that pertains to the collection, analysis, interpretation or explanation and presentation of data or as a branch of mathematics related to the collection and interpretation of data (Dodge, 2006). Due to their empirical roots and their focus on applications, statistics are generally considered a different mathematical science and not a branch of mathematics (Chance, 2005). Some tasks that a statistician may involve are less mathematical; For instance, make sure that the data collection is done in a way that generates valid conclusions, codifies the data or reports the results in a comprehensible way for those who should use them. Statisticians improve the quality of data by developing specific experiment designs and sample surveys. T

he statistics themselves also provide tools for the prediction and forecasting of the use of data and statistical models. The statistics apply to a wide variety of academic disciplines, including natural and social sciences, government and business. Statistical consultants can help organizations and companies that do not have relevant internal expertise for their particular questions. Statistical methods can summarize or describe a data collection. This is called descriptive statistics. This is particularly useful for communicating the results of experiments and investigations. In addition, the data patterns can be modeled in a way that takes into account the randomness and uncertainty in the observations. These models can be used to extract inferences about the process or population under study, a practice called inferential statistics. Inference is a vital element of scientific advance, since it provides a way to draw conclusions from data that are subject to random variations. To test the propositions that are being investigated further, the conclusions are also tested, as part of the scientific method.

The descriptive statistics and the analysis of new data tend to provide more information about the truth of the proposition. The statistics applied include descriptive statistics and the application of inferential statistics (Anderson, 1994). Theoretical statistics refer both to the logical arguments that underlie the justification of statistical inference approaches and to mathematical statistics. Mathematical statistics includes not only the manipulation of the probability distributions necessary to obtain results related to estimation and inference methods, but also several aspects of computational statistics and the design of experiments. The statistics are closely related to the theory of probability, with which they are often grouped. The difference is approximately, that the theory of probability begins from the given parameters of a total population to deduce the probabilities that belong to the samples. However, the statistical inference moves in the opposite direction by inductively inferring the samples to the parameters of a larger or total population. Statistics have many links to machine learning and data mining.

2. CLADDING

The act or process of bonding together of dissimilar metal to another, usually to protect the inner metal from corrosion is known as cladding (Bralla, 2007). Cladding can also be express as something that covers or overlays; specifically: metal coating bonded to a metal core. It is dissimilar from fusion welding or gluing as a technique to zip the metals as one. Cladding is often achieved by extruding two metals all the way through a die in addition to pressing or rolling sheets as one in elevated pressure.

2.1 Laser cladding

Study by Toyserkani et al. (2004) reported that Laser cladding is a method of depositing material for melting and consolidating a powder or wire feedstock material with a laser to cover part of a substrate. It is often used to improve mechanical properties or corrosion resistance, repair worn parts (Brandt et al., 2009) and to manufacture metal matrix composites (Yakovlev et al., 2004).

2.2 Explosive Welding

In explosive welding, the pressure to bind the two layers is provided by the detonation of a sheet of chemical explosive. No heat affected zone is produced in the bond between the metals. The explosion propagates through the sheet, tending to remove impurities and oxides as soon as the leaves are connected. Pieces up to 4 x 16 meters could be manufactured. This method is useful for coating plates with a corrosion resistant layer (Bralla, 2007).

2.3 Empirical Review

The statistical tools currently applied in the area of bioprocesses were discussed and the three main categories were: fair comparison of results, mathematical models for poorly studied systems and advantage of a large volume of data to improve robustness and efficiency. A graph was constructed to guide researchers on how to select the correct statistical technique according to the specific problem of bioprocess methods (Eutimio et al., 2013). Shamsad and Saeid (2014), proposed a step-by-step statistical approach that can be used to obtain an optimal dosage of concrete mixtures using the data obtained through a statistically planned experimental program. The statistical model developed was used to show how the optimization of concrete mixtures can be carried out with different possible options.

3. MATERIALS AND METHOD

The material used for the experiment is a mild steel (HA 250 grade) material. The material was cut into twenty (20) pieces. Each of the materials cut has 60mm length, 40mm width and 10mm thickness. The material was cut 2mm deep at the centre of its length which was coated with cladding weld using tungsten inert gas (TIG) welding method. The coated environment was statistically analyzed and modeled to investigate the best results of the penetration depth on the used material. The research method applied is the use of analytical tools and analysis of variance tool which are statistical tools in response surface method in design expert version 10.0.1. These statistical tools were applied to evaluate what the experimental data portrays, to investigate the effects and to model the parameters. This will reveal the influence of the experimental data, its residuals and the summary of fitness in the parameters that was utilized in the system.

TABLE 1 Results of Experimental Parameters

S/N	Control Factors				Responses
Runs	Gas Flow Rate	Welding Speed	Welding Voltage	Current	Depth of Penetration (P)
1	10	80	18	180	2.85
2	10	80	21	210	2.62
3	10	112.5	21	210	1.4
4	10	112.5	24	180	1.13
5	10	145	21	240	1.2
6	10	145	24	240	2.9
7	10	145	24	180	1.97
8	16	80	24	210	2.25
9	16	80	24	210	2.71
10	13	80	24	210	2.5
11	13	80	21	210	2.25
12	13	145	24	240	1.85
13	10	145	24	180	3.05
14	13	112.5	18	210	2.9
15	13	112.5	18	210	0.7
16	13	112.5	18	240	1.65
17	13	112.5	21	180	2.61
18	13	112.5	24	180	2.5
19	13	80	24	240	2.85
20	13	80	21	240	2.6

4. ANALYSIS, MODELING AND OPTIMIZATION

Design Summary

File Version	10.0.1.0				
Study Type	Response Surface	**Subtype**	Randomized		
Design Type	Central Composite	**Runs**	20		
Design Mode	Quadratic	**Blocks**	No Blocks	**Build Time (**	15.00

Factor	Name	Units	Type	Subtype	Minimum	Maximum	Coded	Values	Mean	Std. Dev.
A	Gas Flow Rate		Numeric	Continuous	10	16	-1.000=10	1.000=16	13.15	2.47673
B	Welding Speed		Numeric	Continuous	90	145	-1.000=90	1.000=145	116.125	22.7034
C	Welding VOlta		Numeric	Continuous	18	24	-1.000=18	1.000=24	20.7	2.55672
D	Welding Curre		Numeric	Continuous	180	240	-1.000=180	1.000=240	208.5	24.7673

Response	Name	Units	Obs	Analysis	Minimum	Maximum	Mean	Std. Dev.	Ratio	Trans	Model
R1	Depth of pene	mm	20	Polynomial	0.7	3.05	2.219	0.691405	4.35714	None	2FI

FIG 1 Design Summary of the Parameters

Fig. 1 shows the statistical evaluation of the parameters in the experimental data. The response parameter revealed that the type of model developed in the analysis is two factorial interactions (2FI) of polynomial analysis. The figure also observed the minimum, maximum, mean and standard deviation in the experimental data.

TABLE 2 Analysis of variance for Response Surface 2FI model

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob> F)	
Model	7.08	10	0.71	3.19	0.0048	significant
A-Gas Flow Rate	*4.606E-003*	*1*	*4.606E-003*	*0.021*	*0.8887*	
B-Welding Speed	*0.096*	*1*	*0.096*	*0.43*	*0.5282*	
C-Welding VOltage	*0.068*	*1*	*0.068*	*0.31*	*0.5928*	
D-Welding Current	*9.914E-003*	*1*	*9.914E-003*	*0.045*	*0.8374*	
AB	*0.46*	*1*	*0.46*	*2.08*	*0.1830*	
AC	*0.071*	*1*	*0.071*	*0.32*	*0.5856*	
AD	*0.044*	*1*	*0.044*	*0.20*	*0.6654*	
BC	*0.76*	*1*	*0.76*	*3.40*	*0.0982*	
BD	*0.062*	*1*	*0.062*	*0.28*	*0.6113*	
CD	*0.18*	*1*	*0.18*	*0.83*	*0.3860*	
Residual	2.00	9	0.22			
Lack of Fit	*1.89*	*5*	*0.38*	*14.22*	*0.0418*	*significant*
Pure Error	*0.11*	*4*	*0.027*			
Cor Total	9.08	19				

As shown in Table 2 the Model F-value of 3.19 is significant. There is only a 0.48% chance that an F-value this large could occur due to noise. Values of "Prob> F" less than 0.0500 indicate model terms are significant. In this case there are no significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms, model reduction may improve the model. The "Lack of Fit F-value" of 14.22 implies the Lack of Fit is significant. There is only a4.18% chance that a "Lack of Fit F-value" this large could occur due to noise.

TABLE 3 Model Summary of the Parameters

Std. Dev.	0.47	R-Squared	0.7798
Mean	2.22	Adj R-Squared	0.5352
C.V. %	21.24	Pred R-Squared	-0.7543
PRESS	15.93	Adeq Precision	6.473
-2 Log Likelihood	10.70	BIC	43.66
		AICc	65.70

In Table 3, a negative predicted R-Squared implies that the overall mean may be a better predictor of your response than the current model. Adequate precision measures the signal to noise ratio. A ratio greater than 4 is desirable. However, a ratio of 6.473 indicates an adequate signal. This model can be used to navigate the design space.

TABLE 4Model Coefficient and its residuals

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	2.20	1	0.11	1.95	2.44	
A-Gas Flow Rate	0.036	1	0.25	-0.54	0.61	3.72
B-Welding Speed	0.34	1	0.52	-0.83	1.51	15.55
C-Welding Voltage	0.13	1	0.23	-0.39	0.64	3.20
D-Welding Current	0.053	1	0.25	-0.52	0.63	3.72
AB	-0.96	1	0.67	-2.48	0.55	18.02
AC	0.19	1	0.33	-0.57	0.94	4.50
AD	-0.34	1	0.75	-2.05	1.37	22.95
BC	-0.71	1	0.38	-1.58	0.16	5.97
BD	0.35	1	0.67	-1.16	1.86	18.02
CD	0.30	1	0.33	-0.45	1.06	4.50

Table 4 shows that the coefficient of the process parameters will predict the response parameters. Table 4 also lists the standard errors on the coefficient of the variables. The low or high confidence interval of the error with ninety five percent (95%) confidence interval was established. The variance impact factor (VIF) of the coefficient was also established.

TABLE 5 Final Equation in Terms of Coded Factors

Depth of penetration =	
+2.20	
+0.036	* A
+0.34	* B
+0.13	* C
+0.053	* D
-0.96	* AB
+0.19	* AC
-0.34	* AD
-0.71	* BC
+0.35	* BD
+0.30	* CD

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

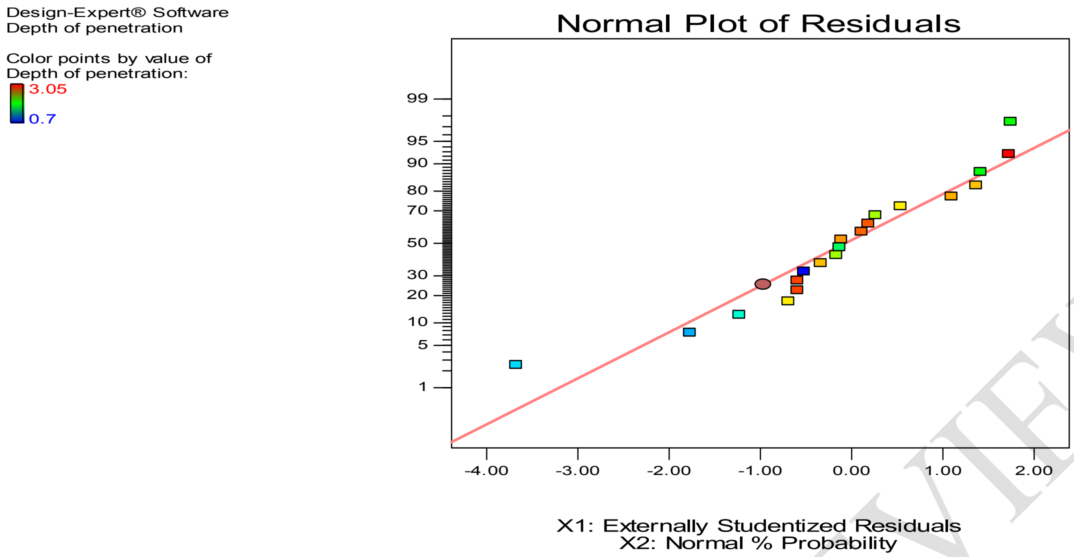

FIG. 2 Normal Percentage Probability Plot of Residuals

Fig. 2 shows the predicted and the actual errors of the data in percentage. It reveals the linear fitness and its normality of the errors.

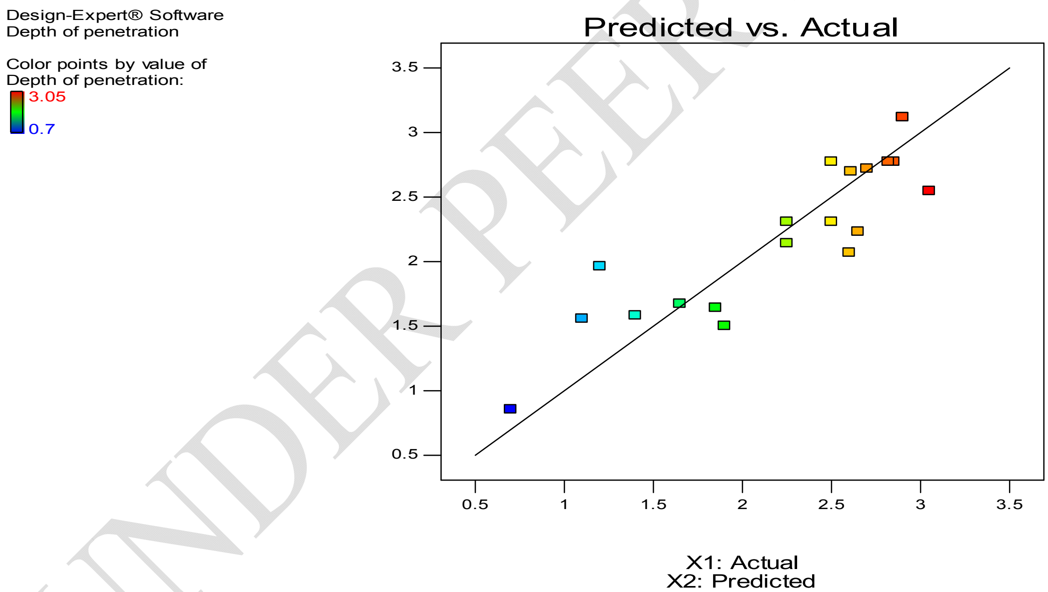

FIG. 3 Errors in Predicted and Actual experimental Data

Fig. 3 shows the fitness of the predicted response and the actual response parameter in the experimental data.

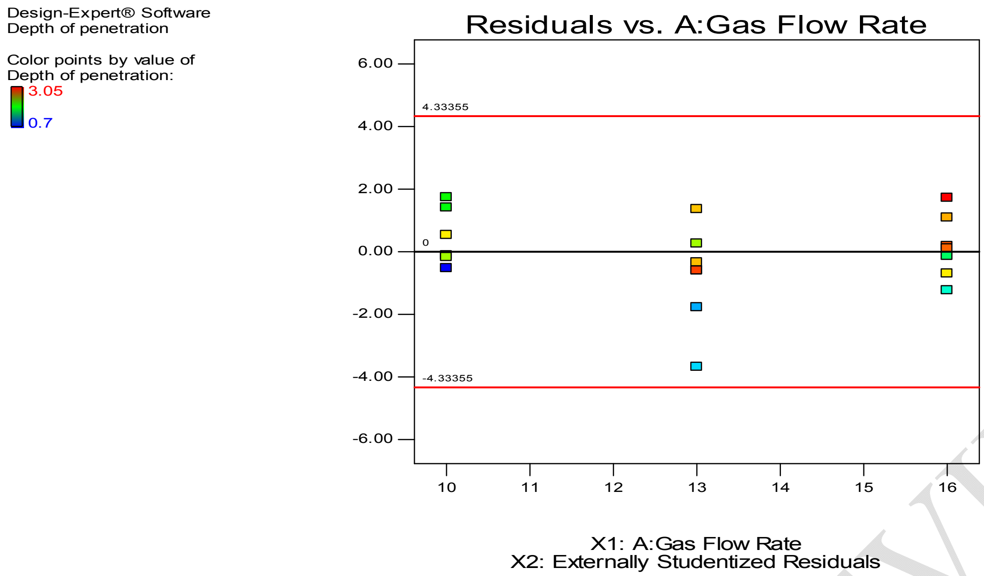

FIG. 4 External Residuals-versus-the Gas Flow Rate

Figure 4 shows the external residual of the response parameter and the gas flow rate parameters. The residual errors show that the predicted errors in the response parameter between ±4.00. However, there is no too much error in the predicted residual on the response parameter.

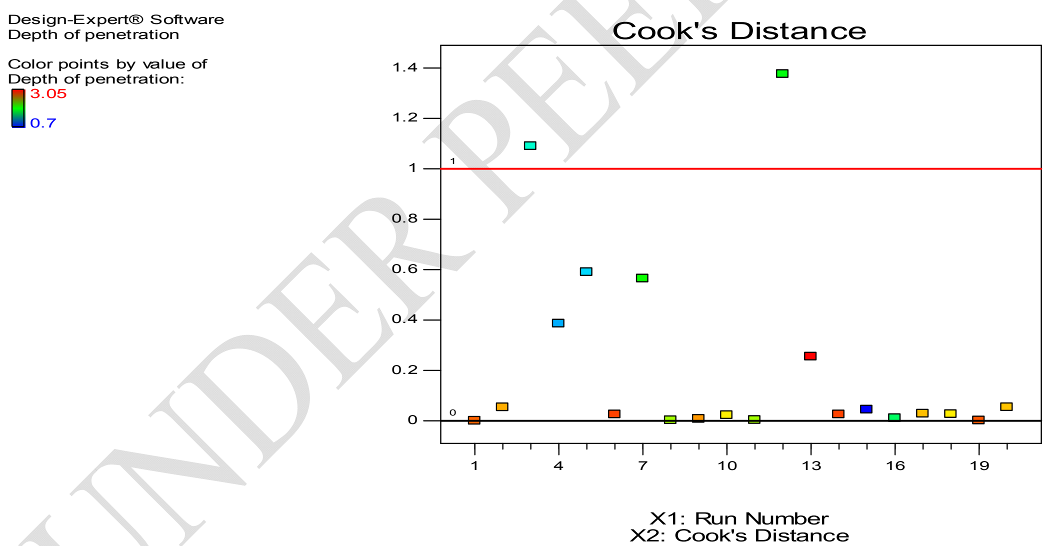

FIG 5 Cook's Distance Statistical Analysis

Fig. 5 describes the statistical analysis using cook's distance technique. In cook's distance, as the errors tend to zero the better, but between zero and one is good but above one is not significance and there is a need to verify the data. Such data always lead to insignificance in the statistical modeling of the experimental data.

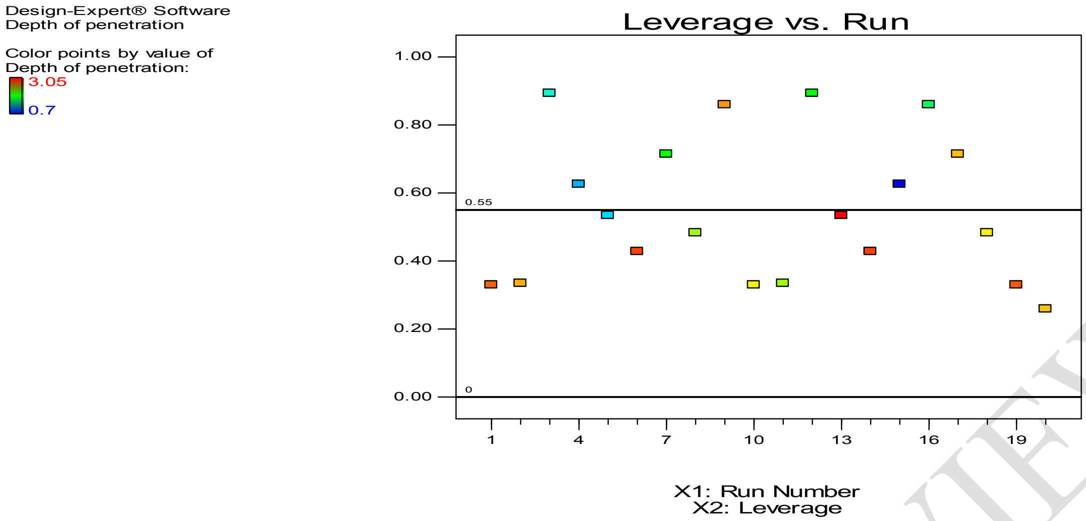

FIG 6 Analysis of Leverage and Experimental Design run

Figure 6 shows the plot of leverage in the data and the experimental design runs. If the leverage is above one, the statistical analysis will have nil predicted R-squared value.

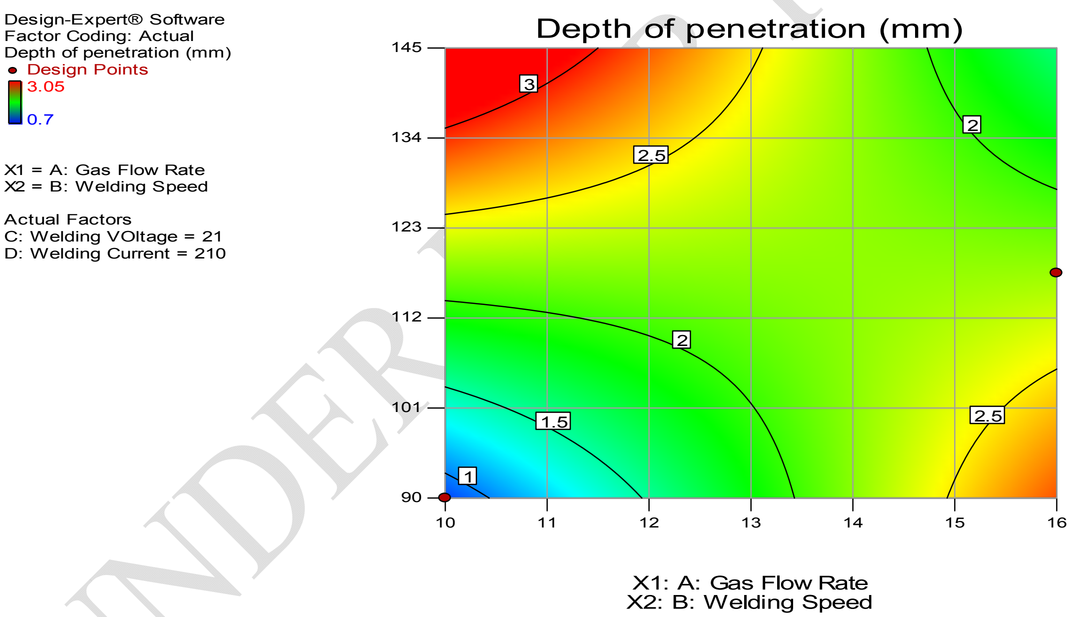

FIG 7 Contour Plot Analysis for Gas Flow Rate and Welding Speed

Fig. 7 shows the contour plot of the gas flow rate parameter and welding speed parameter. The result shows that increase in gas flow rate and welding speed increase the depth of penetration on mild steel cladding weld and vice-versa

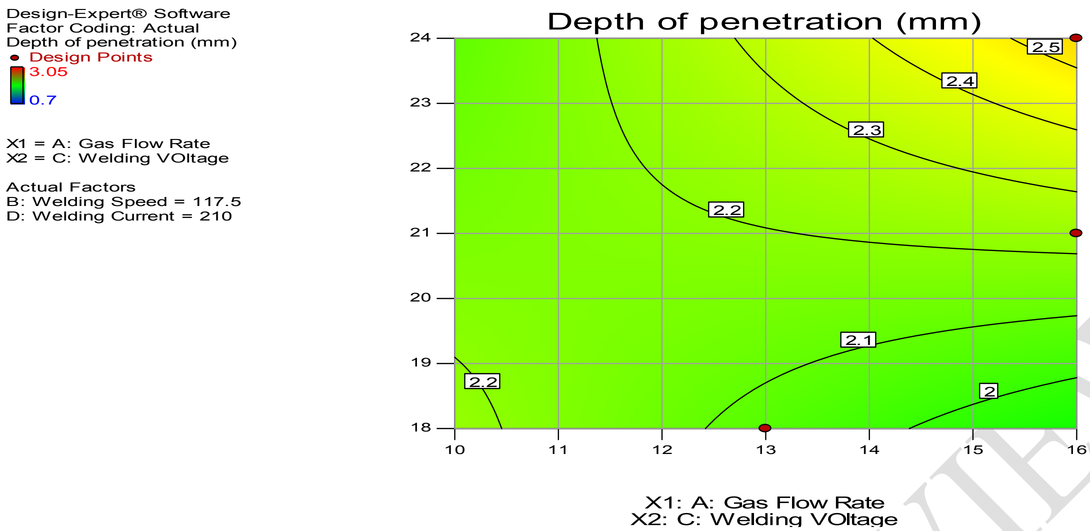

FIG 8 Contour Plot Analysis for Gas Flow Rate and Welding Voltage

Fig. 8 shows the contour plot of the gas flow rate parameter and welding voltage parameter. The result shows that increase in gas flow rate and welding voltage increase the depth of penetration on mild steel cladding weld, while decrease in gas flow rate and welding current decrease the depth of penetration on mild steel cladding weld.

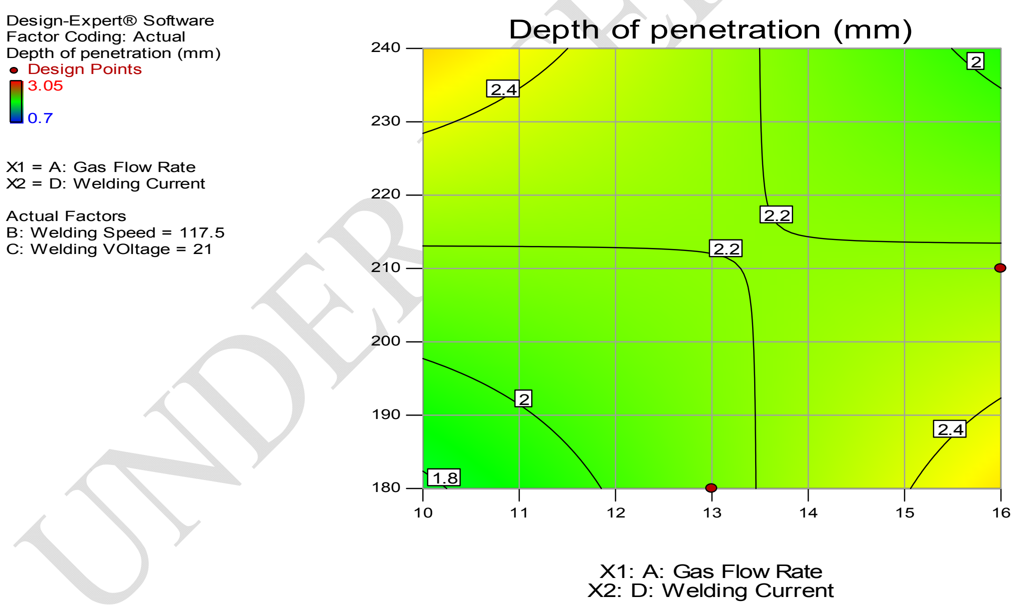

FIG 9 Contour Plot Analysis for Gas Flow Rate and Welding Current

Fig. 9 shows the contour plot of the gas flow rate parameter and welding current parameter. The result shows that increase in gas flow rate and welding current increase the depth of penetration on mild steel cladding weld, while decrease in gas flow rate and welding current decrease the depth of penetration on mild steel cladding weld.

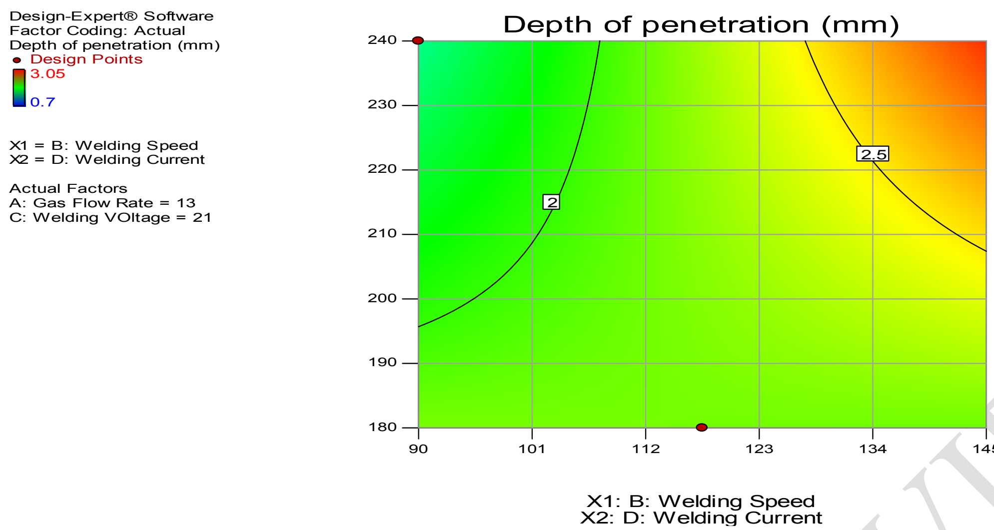

FIG 10 Contour Plot Analysis for Welding Speed and Welding Current

Figure 10 shows the contour plot of the welding current parameter and welding speed parameter. The result shows that increase in welding current and welding speed increase the depth of penetration on mild steel cladding weld, while decrease in welding speed and welding current decrease the depth of penetration on mild steel cladding weld.

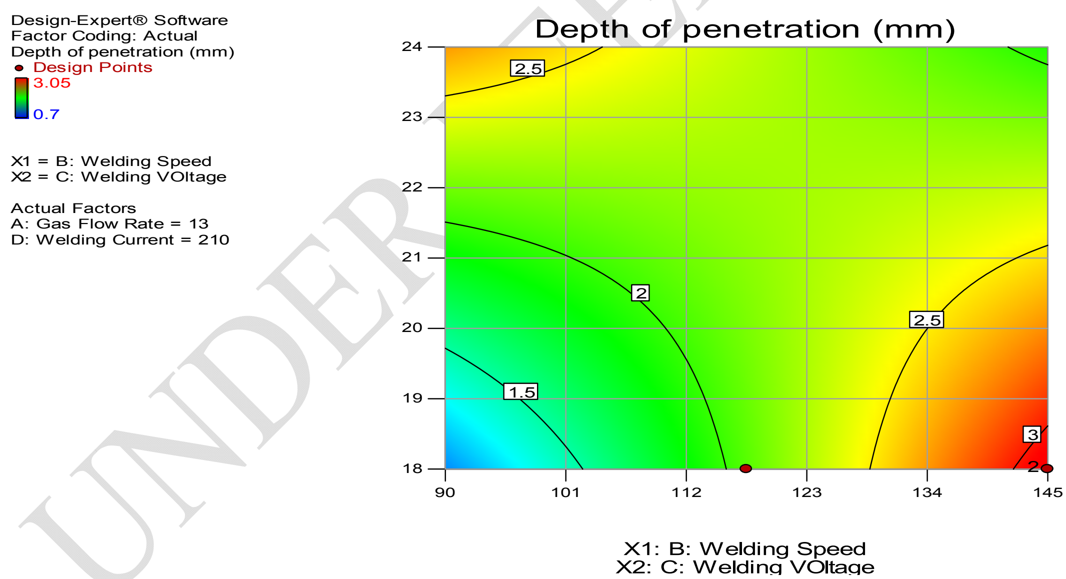

FIG. 11 Contour Plot Analysis for Welding Speed and Welding Voltage

Fig. 11 observed the contour plot of the welding speed and welding voltage parameter. The result shows that increase in welding speed and welding voltage increase the depth of penetration on mild steel cladding weld, while decrease in welding speed and welding voltage decrease the depth of penetration on mild steel cladding weld.

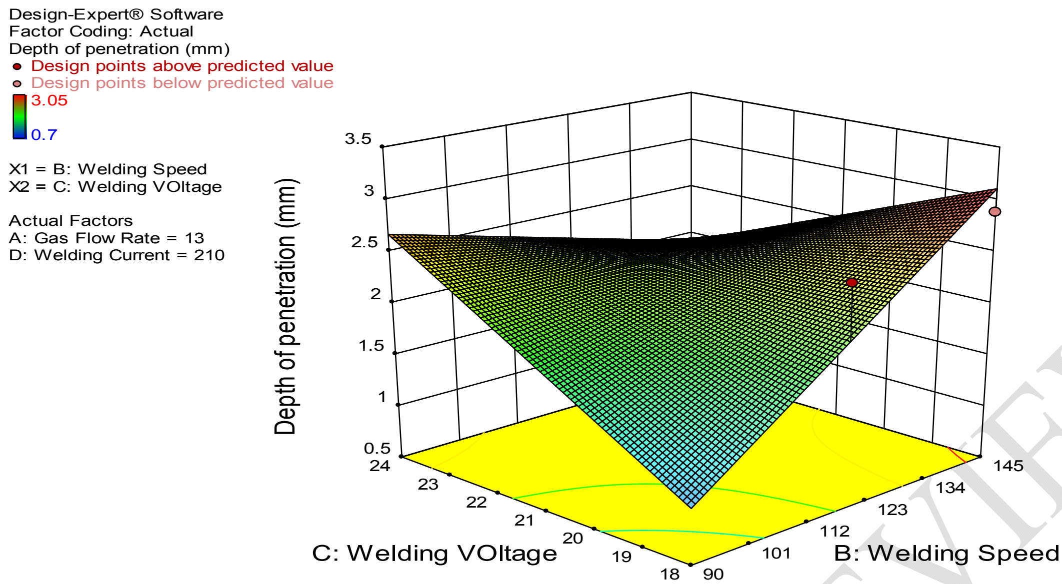

FIG 12 Surface Plot Analysis for Welding Speed and Welding Voltage

Fig. 12 shows that as the welding speed and welding voltage increase the depth of penetration on the mild steel also increases and vice versa.

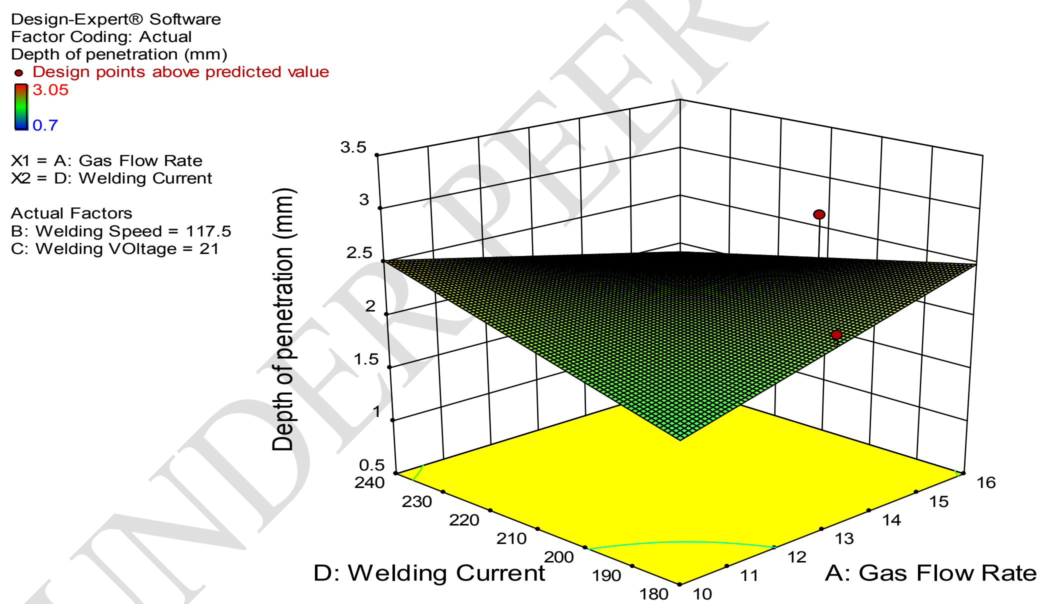

FIG. 13 Surface Plot Analysis for Gas Flow Rate and Welding Current

Fig. 13 shows that as the welding current and gas flow rate increases the depth of penetration on the mild steel also increases and vice versa.

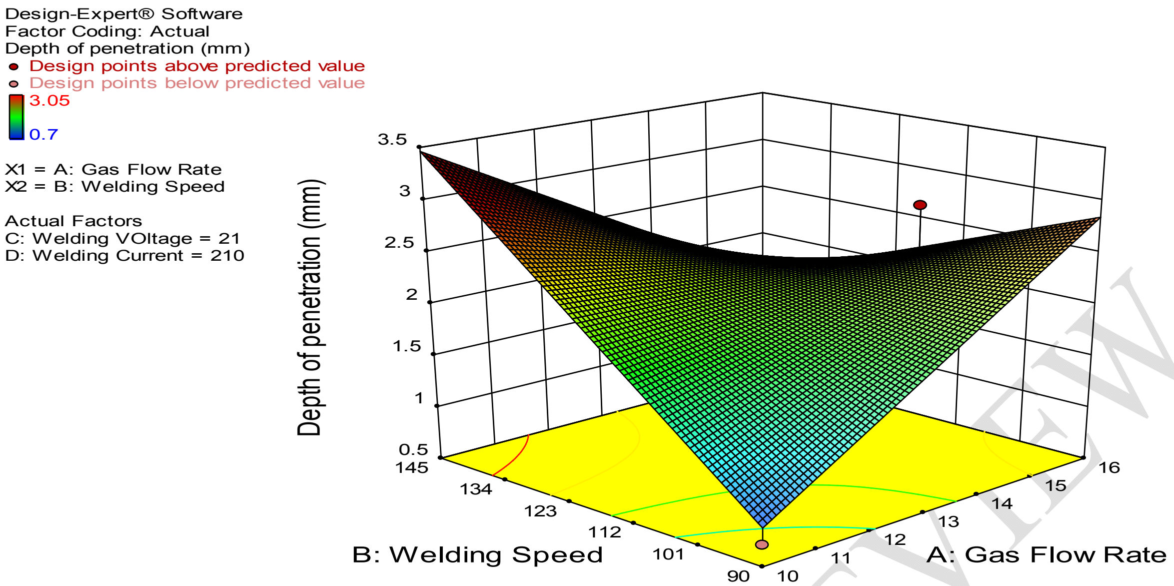

FIG. 14 Surface Plot Analysis for Gas Flow Rate and Welding Speed

In figure 14, the surface plot shows that as the welding speed and gas flow rate increases the depth of penetration on the mild steel also increases and vice versa.

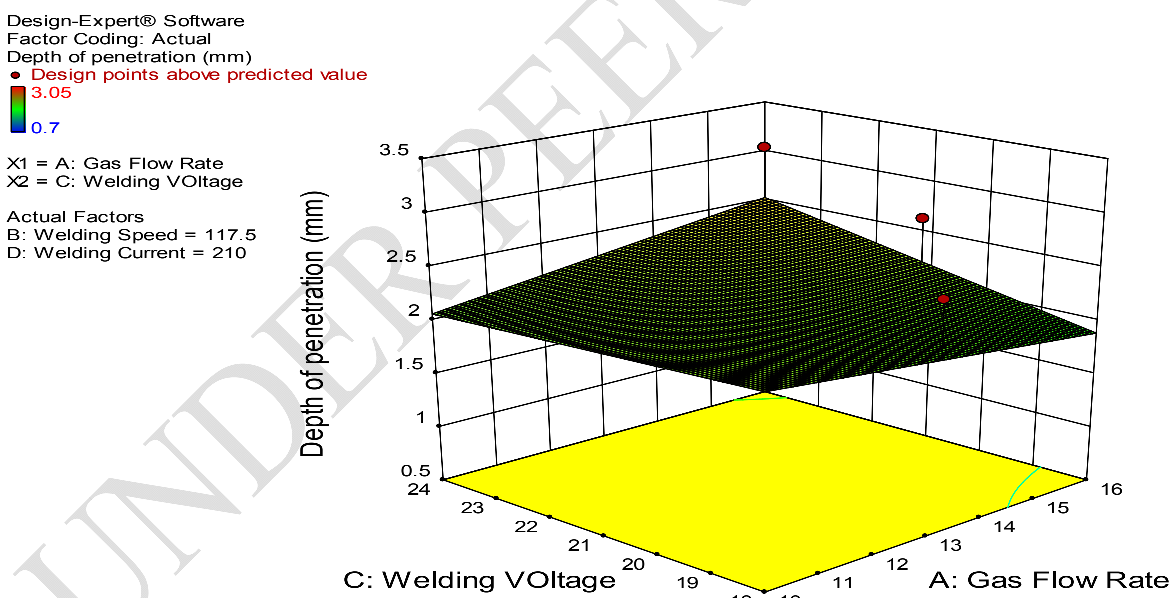

FIG. 15 Surface Plot Analysis for Gas Flow Rate and Welding Voltage

Fig. 15 shows that as the welding voltage and gas flow rate increases the depth of penetration on the mild steel also increases and vice versa.

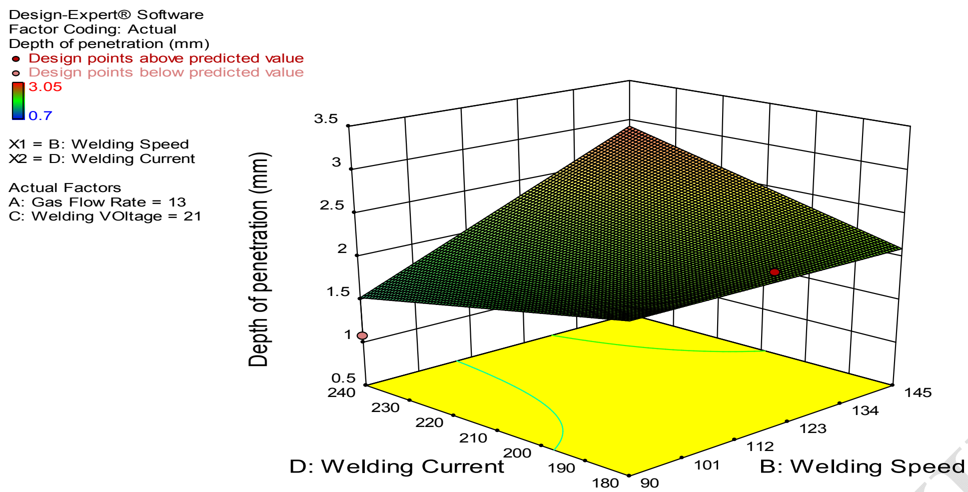

FIG. 16 Surface Plot Analysis for Welding Current and Welding Speed

Fig. 16 shows that as the welding current and welding speed increase the depth of penetration on the mild steel also increases and vice-versa.

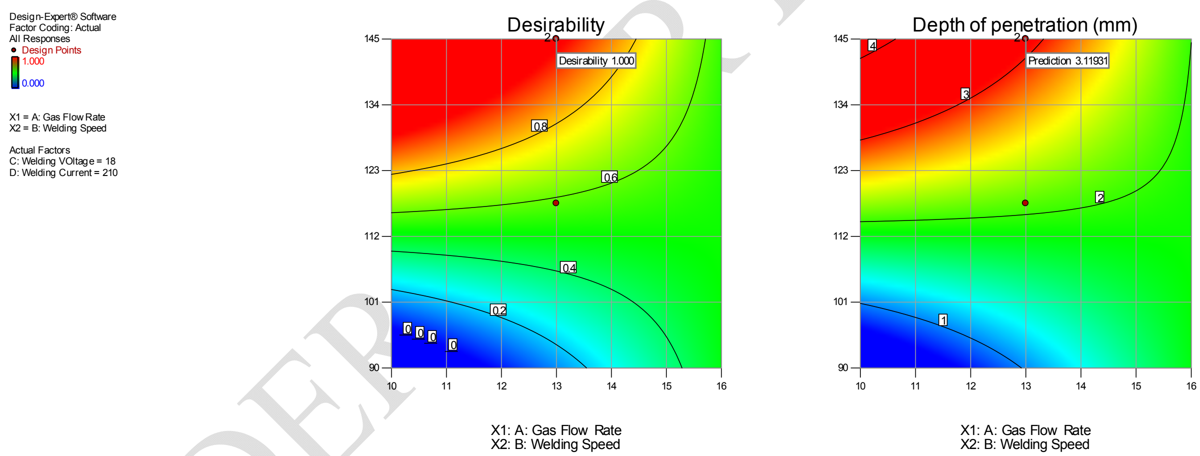

FIG. 17 Optimal Solutions and Desirability Plots

Fig. 17 shows the optimal solution plot and desirability plot of the optimization result. It reveals that the optimal solution of the response is 3.12mm approximately. However, the desirability of achieving the optimal solution is 100%, and the optimal solution occurs at high penetration depth.

5. DISCUSSION OF RESULTS

The results were discussed based on the charts, tables, statistical investigation results and modeling analyses. Table 1 shows the process parameters and their levels in the system. Figure 1 shows the statistical mean, minimum, maximum, standard deviations in the parameters used in the experiment. It also revealed that the model selected for the statistical analysis is two Factorial interactions (2FI) by polynomial analysis. Table 2 observed the probability value of 0.0048 which shows that the model developed is significance. Table 3 shows the model summary of the parameters which observed that the coefficient of determination (R-Squared) is 0.7798. The adjusted R-Squared of the parameters is 0.5352, while the predicted R-Squared is -0.7543. However, the adequate precision of the model is 6.473. The adequate precision shows that there is adequacy to signal. Figure 2 shows the predicted and the actual errors of the data in percentage. It reveals the linear fitness and its normality of the errors. Figure 3 observed the fitness plot of the predicted response and the actual response parameter in the experimental data.

Fig. 4 shows the externally studentized residual plot of the response parameter and the gas flow rate parameters. The residual errors show that the predicted errors in the response parameter between ±4.00. However, there is no too much error in the predicted residual on the response parameter. Figure 5 shows the cook's distance plot, it shows the outliers that is the influential factors of the parameters. Fig. 6 shows the plot of leverage in the data and the experimental design runs. It expressed that if the leverage is above one, the statistical analysis will have nil predicted R-squared value. The contour and surface plots show that increase in depth of penetration will increase the gas flow rate, welding speed, welding voltage and welding current on mild steel cladding weld. Figure 17 shows the optimal solution plot and desirability plot of the optimization result. It reveals that the optimal solution of the response is 3.12mm approximately. However, the desirability of achieving the optimal solution is 100%, and the optimal solution occurs at high penetration depth.

6. CONCLUSIONS

The analysis revealed the statistical evaluation of the depth of penetration on mild steel cladding weld metals. The plots, tables, and charts express the statistical investigation of the experimental parameters. The statistical analysis was performed using statistical tools of response surface method in design expert software. The analysis of variance shows that the model is fit and significance with negligible errors in the system. The normal probability plot and cook's distance reveal the influential values in the experimental data are good. The result shows that the model has 0.48% significance value. This shows that the model can predict the results and there is only 0.48% signal to noise in the model. Furthermore, the contour and surface plots reveal that increase in process parameters increase the response parameters. The optimal solution plot and desirability plot expressed that the optimal solution of the response is 3.12mm approximately. However, the desirability of achieving the optimal solution is 100%, and the optimal solution occurs at high penetration depth. The statistical evaluation and its results show the significance of the experimental data and it's optimal solution in the system. The model developed shows its goodness of fit and significance. Finally, the statistical evaluation portrays the results of the experimental data.

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