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Analysis of Clad Bead Width Response on Mild Steel Metal Geometry Using Statistics

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The research showed the statistical analysis of clad bead width on mild steel metal geometry. The statistical analysis was performed using response surface method of statistics. The analysis of variance (ANOVA) shows that the Model F-value of 8.95 which implies that the model is significant. There is only a 0.23% chance that an F-value this large could occur due to noise. Probability values of less than 0.0500 indicate model terms are significant. The lack of fit for F-value of 1.05 implies the lack of fit is not significant relative to the pure error. There is a 51.67% chance that a Lack of Fit for F-value this large could occur due to noise. Non-significant lack of fit is good and makes the model more fit. The coefficient of determination of the parameters (R-squared) is 0.9249. The predicted R-Squared of 0.9249 is close to the adjusted R-Squared of 0.8215; however, the difference is not more than 0.2 which is of reasonable agreement. Adequate Precision measures the signal to noise ratio of 10.757, which indicates an adequate signal in the data. The fraction of design space plot, perturbation plot, normal probability plot and the cook's distance plot show less residuals and more fitness of the data which is good in making the

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parameters very efficient and more effective in modeling the process. The research achieved reasonable and appropriate statistical results which portray the parameters in the system. Finally, the results are recommended for understanding the influence of the parameters in clad height of reinforcement on mild steel cladding weld metals geometry.

Keywords: Cladding; bead width; significant; response surface method; statistical analysis; analysis of variance; mild steel.

1. INTRODUCTION

Amandeep et al [1], Weld cladding is a process for producing surfaces with good corrosion resistant properties by means of laying of stainless steels on low-carbon steel components with an objective of achieving maximum economy and enhanced life. The aim of the work presented here was to investigate the effect of auxiliary preheating of the solid filler wire in mechanized gas metal arc welding (GMAW) process (by using a specially designed torch to preheat the filler wire independently, before its emergence from the torch) on the quality of the as-welded single layer stainless steel overlays. External preheating of the filler wire resulted in greater contribution of arc energy by resistive heating due to which significant drop in the main welding current values and hence low dilution levels were observed. Metallurgical aspects of the as welded overlays such as chemistry, ferrite content, and modes of solidification were studied to evaluate their suitability for service and it was found that claddings obtained through the preheating arrangement, besides higher ferrite content, possessed higher content of chromium, nickel, and molybdenum and lower content of carbon as compared to conventional GMAW claddings, thereby giving overlays with superior mechanical and corrosion resistance properties. The findings of this study not only establish the technical superiority of the new process, but also, owing to its productivity-enhanced features, justify its use for low-cost surfacing applications Palani & Murugan [2] discussed the influence of welding process parameters on the content of delta ferrite in the claddings of AISI 317L, deposited onto IS: 2062 structural steel plate by the flux cored arc welding (FCAW) process. Measurement of delta ferrite within the cladding often gives important insight into the future mechanical and corrosion resistant behavior of the clad structures. To predict and control the amount of residual ferrite, regression models were developed in terms of process parameters, using the data obtained from experiments. The experiments were conducted by using a central composite rotatable design of experiments. The study revealed that the cladding process parameters have influence over the formation of delta ferrite. Shirmohammadi et al [3], presents an age based nonlinear optimization model to determine the optimal preventive maintenance schedule for a single component system. Sreeraj, and Kannan [4], improve the corrosion-resistant properties of carbon steel, usually cladding process is used. It is a process of depositing a thick layer of corrosion-resistant material over carbon steel plate. Most of the engineering applications require high strength and corrosion resistant materials for long-term reliability and performance. Cladding these properties can be achieved with minimum cost. The main problem faced in cladding is the selection of optimum combinations of process parameters for achieving quality clad and hence good clad bead geometry. This paper highlights an experimental study to predict various input process parameters to get optimum dilution in stainless steel cladding of low carbon structural steel plates using Gas Metal Arc Welding (GMAW). Experiments were conducted based on central composite rotatable design with full replication technique, and mathematical models were developed using multiple regression method. The developed models have been checked for adequacy and significance. Using Artificial Neural Network (ANN) the parameters were predicted, and percentage of error was calculated between predicted and actual values. The direct and interaction effects of process parameters on clad bead geometry are presented in graphical form. Sreeraj et al [5], shows that cladding is a surface modification process in which a specially designed alloy is surface welded in order to enhance corrosion resistant properties. Common cladding techniques include Gas Tungsten Arc Welding (GTAW), submerged arc welding (SAW) and gas metal arc welding (GMAW). Because of high reliability, easiness in operation, high penetration good surface finish and high productivity gas metal arc welding became a natural choice for fabrication industries. This paper presents central composite rotatable design with full replication techniques to predict four critical dimensions of bead geometry. The second order regression method was developed to study the correlations. The developed models have been checked for adequacy and significance. The main and interaction effects of process variables and bead geometry were presented in graphical form. Using fmincon function the process parameters were optimized.

2. REVIEW OF LITERATURE

Most of the solids used are technical materials consisting of crystalline solids in which the atoms or ions are arranged in a repetitive geometric pattern called a lattice structure. The only exception is glass materials that combine super cooled liquid and polymers that are aggregates of large organic molecules Cary and Helzer, [6]. The use of compressed gases and flames in many welding processes poses a risk of explosion and fire. Some common precautions include limiting the amount of oxygen in the air and keeping combustible materials away from the workplace James and John, [7]. Tungsten electrodes are often used in lighting, but they do not bind to quartz glass, so tungsten is often moistened with molten borosilicate glass, which binds to tungsten and quartz. However, care must be taken to ensure that all materials have similar thermal expansion coefficients to prevent cracking when the object cools and when it is heated again. Frequently, special alloys are used for this purpose, ensuring that the coefficients of expansion coincide and, sometimes, fine metallic coatings are applied to a metal to create a good bond with the glass Bernard, [8]; David et al, [9].

2.1 Statistics Analysis

Statistics is the study of the collection, organization, analysis, interpretation and presentation of data Dodge, [10]. It deals with all aspects of the data, including the planning of data collection in terms of the design of surveys and experiments Dodge, [10]. The word statistical, when referring to scientific discipline, is unique, as in statistics is an art (Statistics, 2016). This should not be confused with the word statistical, referring to an amount calculated from a set of data (Statistics, 2016). 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, 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 Moses, [11] or as a branch of mathematics Hays, [12] related to the collection and interpretation of data. Due to their empirical roots and their focus on applications, statistics are generally considered a different mathematical science and not a branch of mathematics Moore, [13]; Chance, [14]. Some tasks that a statistician may involve are less mathematical; For example, 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. The 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, [15]. 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.

Gladys et al [16] expressed that in many mixed process experiments, restricted randomization occurs and split plot designs are commonly used to handle these situations. The study used the optimization criteria to compare the efficiency of the designs constructed and the fraction of the spatial design plots were used to evaluate the prediction properties of the two designs. The optimal I-design of divided plots was preferred since it had the capacity of better prediction properties and precision in the measurement of the coefficients. Shamsad and Saeid [17], 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. Liem [18] shows that the factors in a mixing experiment are the ingredients or components of a mixture, and the response is a function of the proportion of each ingredient. These proportional amounts of each ingredient are typically measured by weight, volume or molar ratio. The design, execution and analysis of mixed experiments require different approaches to those used for factorial experiments. Eutimio et al [19] shows that most of the statistical tools currently applied in the area of bioprocesses were discussed and classified. The three main categories were: fair comparison of results, mathematical models for poorly studied systems and taking advantage of a large volume of data to improve robustness and efficiency. For each statistical technique, an example of the literature was discussed to demonstrate its usefulness in bioprocess problems. However, a graph was constructed to guide researchers to select the correct statistical technique according to the specific problem of bioprocessing. Achebo [20], investigating the forces responsible for the detachment of molten metal droplets formed at the tip of an electrode, which imminently and eventually fall into the welding bath during the welding process.

3. METHODOLOGY

The method adopted is the application of statistical tool to portray the data and to understand the behavior of the data statistically. Twenty (20) experimental runs were conducted to ascertain the design and to explore the system more effectively. The application of response surface method with the use of central composite design tool was adopted to statistically analyze the data. The design model developed for the system is a cubic polynomial nonlinear model. The result shows that the data is fit and good for analysis and to model.

4. CLAD BEAD WIDTH MODELING, ANALYSIS AND PREDICTION

The application of response surface method using central composite design was made to understand the need and influence of the welding process factors in the system.

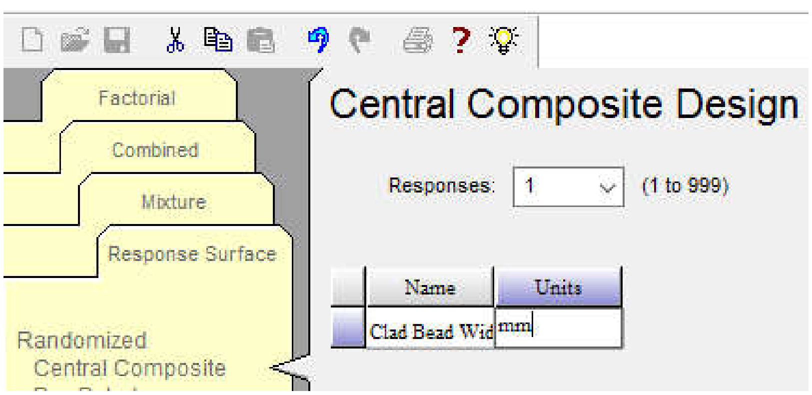

Fig. 1. Clad bead width modeling

3. RESULTS AND DISCUSSION

The Table 1 shows the design summary for the welding process factors and its statistical influence in the system. It shows the minimum and the maximum values used for the experiment. It reveals the mean and the standard deviation of the choose values.

Table two (2) shows the design summary for the response variable and its statistical influence in the system. It shows the minimum and the maximum values for the experiment. It reveals the mean and the standard deviation of the experimental results gotten from the experiment. The model developed for the response is a cubic polynomial model.

The Table 3 represents the analysis of variance (ANOVA) for the model and the factors in the system. The Model F-value of 8.95 implies the model is significant. There is only a 0.23% chance that an F-value this large could occur due to noise. Values of Probability less than 0.0500 indicate model terms are significant. In this case A, B, C, D, A^2, CD^2 are 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 your model. The analysis of variance revealed the significant of the model developed with the significant value of 0.0023. The "Lack of Fit F-value" of 1.05 implies the Lack of Fit is not significant relative to the pure error. There is a 51.67% chance that a lack of fit F-value this large could occur due to noise. Non-significant lack of fit is good and it makes the model to be fit and more appropriate. However, the residuals in the model have insignificant lack of fit with a value of 0.5167. The pure error in the system shows a mean square of 1.29, this means that the error in the system is very minimal and can be significant to the modeling of the system.

Table 4 above shows the model summary of the statistical model developed. The standard deviation and mean of the model is 1.16 and 10.93 respectively. The confidence value around the mean is 10.58 percent. The table shows the standard deviation, mean, confident value, probability error sum of square, R-Square, adjusted R-Square, Predicted R-Square, adequate R-Square, Bayesian information criterion and Akaike information criterion. The predicted R-Squared of 0.9249 is not as close to the adjusted R-Squared of 0.8215 as one might normally expect; that's the difference is more than 0.2. This may indicate a large block effect or a possible problem with your model and/or data. Things to consider are model reduction, response transformation, outliers, etc. All empirical models should be tested by doing confirmation runs. Adequate Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. Your ratio of 10.757 indicates an adequate signal. This model can be used to navigate the design space. The higher the BIC and AICc the better the model; from the model summary table, the BIC and AICc values are 80.17 and 112.79 respectively, which represent that the model is fit and adequate. However, BIC and AICc that is greater than 10 are fit and adequate.

The Table 5 shows the coefficient estimation of the welding input process factors which expressed that the model developed is a nonlinear model. The table also revealed the standard error in the coefficient. In addition it expressed the confidence intervals in the coefficient estimation. The standard errors of the estimated coefficients hovers towards the zero mean. This shows that the error in the estimated coefficient is negligible. Furthermore, it conforms to insignificant of the errors lack of fit in the model. The results of the confidence interval show that the lower and the upper levels for confidence interval is ninety five percent (95%) estimate of the coefficient for the model.

Final Equation in Terms of Coded Factors:

$$\text{Clad Bead Width} = +9.37 - 1.77*A - 1.82*B - 4.27*C + 1.38*D + 1.19*BC + 0.45*BD - 0.63*CD + 3.36*A^2 - 0.66*D^2 + 1.45*BCD + 4.86*CD^2$$

The equation in terms of coded factors can be used to make predictions about the response for given 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. The coded factors A, B, C and D represents gas flow rate, welding speed, welding voltage and welding current respectively. The model can be applied to predict the response variable.

Table 1. Design summary for the factors

Factor	Name	Units	Type	Subtype	Minimum	Maximum	Coded	Values	Mean	Std. Dev.
A	Gas Flow Rate	mm/s	Numeric	Continuous	10	16	-1.000=10	1.000=16	13	2.38416
B	Welding Speed	m/s	Numeric	Continuous	90	145	-1.000=90	1.000=145	116.125	22.7034
C	Welding Voltage	V	Numeric	Continuous	18	24	-1.000=18	1.000=24	20.7	2.55672
D	Welding Current	Amp	Numeric	Continuous	180	240	-1.000=180	1.000=240	208.5	24.7673

Table 2. Design summary for the response variable

Response	Name	Units	Obs	Analysis	Minimum	Maximum	Mean	Std. Dev.	Ratio	Trans	Model
R1	Clad Bead Width	mm	20	Polynomial	5.8	16.2	10.926	2.73539	2.7931	None	RCubic

Table 3. ANOVA for clad bead width response surface reduced to cubic model

Source	Sum of Squares	df	Mean Square	F- Value	p-value (Prob > F)	
Model	131.48	11	11.95	8.95	0.0023	significant
A-Gas Flow Rate	*15.42*	*1*	*15.42*	*11.55*	*0.0094*	
B-Welding Speed	*13.40*	*1*	*13.40*	*10.04*	*0.0132*	
C-Welding VOltage	*30.95*	*1*	*30.95*	*23.18*	*0.0013*	
D-Welding Current	*12.19*	*1*	*12.19*	*9.13*	*0.0165*	
BC	*3.98*	*1*	*3.98*	*2.98*	*0.1226*	
BD	*0.67*	*1*	*0.67*	*0.50*	*0.4991*	
CD	*1.68*	*1*	*1.68*	*1.25*	*0.2951*	
A^2	*17.41*	*1*	*17.41*	*13.04*	*0.0069*	
D^2	*0.92*	*1*	*0.92*	*0.69*	*0.4308*	
BCD	*4.75*	*1*	*4.75*	*3.56*	*0.0959*	
CD^2	*22.21*	*1*	*22.21*	*16.63*	*0.0035*	
Residual	10.68	8	1.34			
Lack of Fit	*6.80*	*5*	*1.36*	*1.05*	*0.5167*	*not significant*
Pure Error	*3.88*	*3*	*1.29*			
Cor Total	142.16	19				

Table 4. Model summary

Std. Dev.	1.16	**R-Squared**	0.9249
Mean	10.93	**Adj R-Squared**	0.8215
C.V. %	10.58	**Pred R-Squared**	0.0952
PRESS	128.63	**Adeq Precision**	10.757
-2 Log Likelihood	44.22	**BIC**	80.17
		AICc	112.79

Table 5. Coefficient estimation table

Factor	Coefficient Estimate	df	Standard Error	95% CI Low	95% CI High	VIF
Intercept	9.37	1	0.93	7.22	11.52	
A-Gas Flow Rate	-1.77	1	0.52	-2.97	-0.57	2.43
B-Welding Speed	-1.82	1	0.57	-3.15	-0.50	3.21
C-Welding Voltage	-4.27	1	0.89	-6.32	-2.22	8.13
D-Welding Current	1.38	1	0.46	0.33	2.44	2.03
BC	1.19	1	0.69	-0.40	2.78	3.20
BD	0.45	1	0.64	-1.02	1.92	2.73
CD	-0.63	1	0.56	-1.93	0.67	2.13
A^2	3.36	1	0.93	1.21	5.50	3.11
D^2	-0.66	1	0.80	-2.50	1.18	2.17
BCD	1.45	1	0.77	-0.32	3.22	2.30
CD^2	4.86	1	1.19	2.11	7.60	9.50

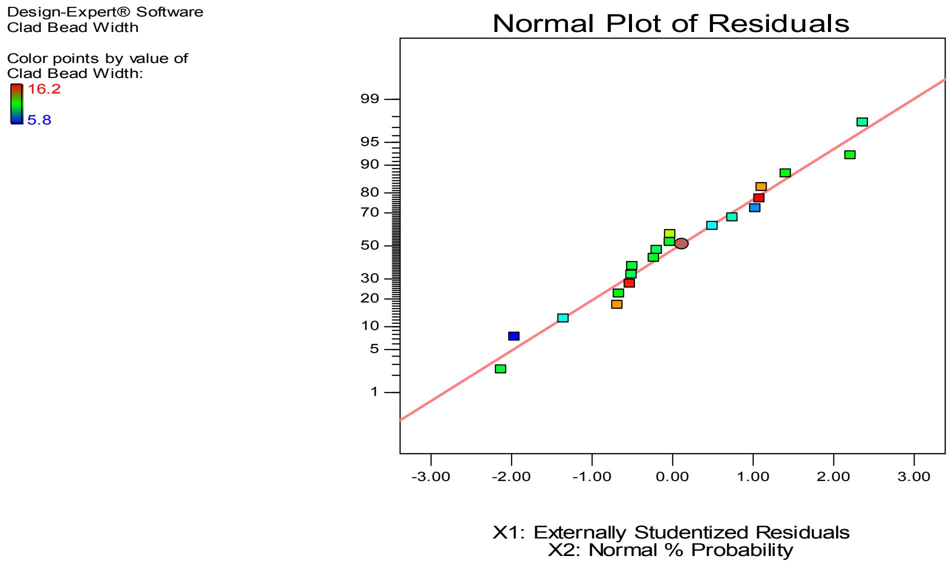

Fig. 2. Normal probability plot

Normal probability plot of the studentized residuals is to check for normality of residuals in the data used to model the system. The plot shows that the number of experimental runs around the mean tends towards zero error in the experiment conducted. This shows that the results are achievable with less error in the system.

The fraction of design space of the welding input process factors are desirable especially towards the pick of the factors used in the system. The graph is within the design limits needed for effective desirability. The design space of the model and its diagnostic plot is adequate to model the system.

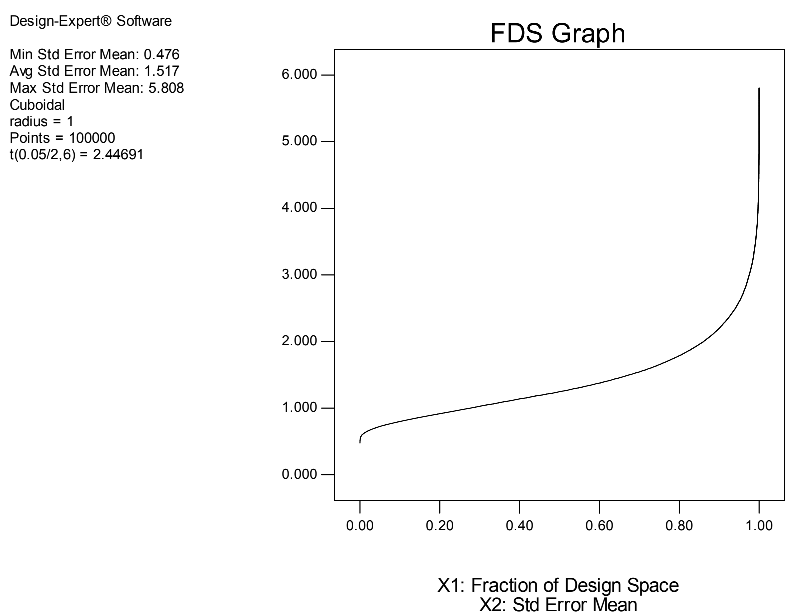

Fig. 3. Fraction of design space graph

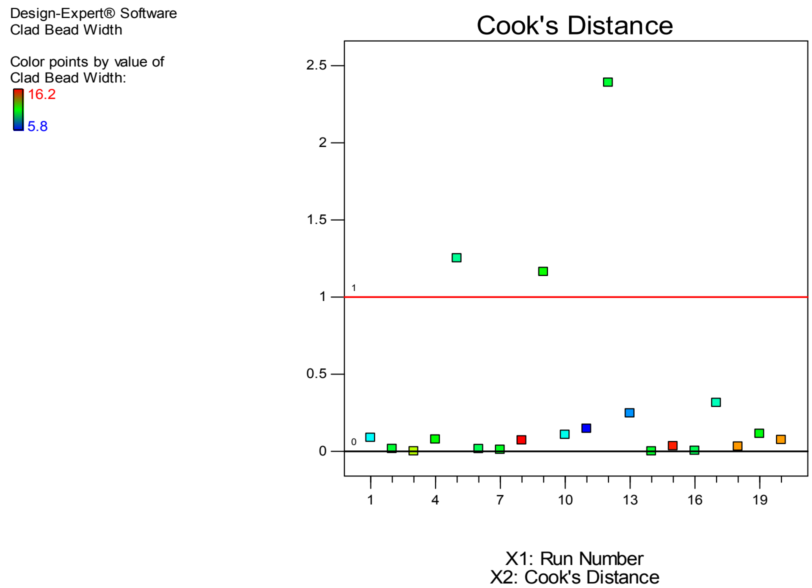

Fig. 4. Cook distance plot

Cook's distance plot looks for outliers that are influential values among the experimental trials in the system. The outliers are values that are above 1 or below 0. The numbers of outliers in the system are negligible and the levels of influence of the outliers are not strong but insignificance.

The perturbation plot shows the influence of the welding input process factors used in the system. It expressed the negative and the positive influence of the process factors in the system. The plot shows that gas flow rate (that's factor A) is more influential both negative and positive influence.

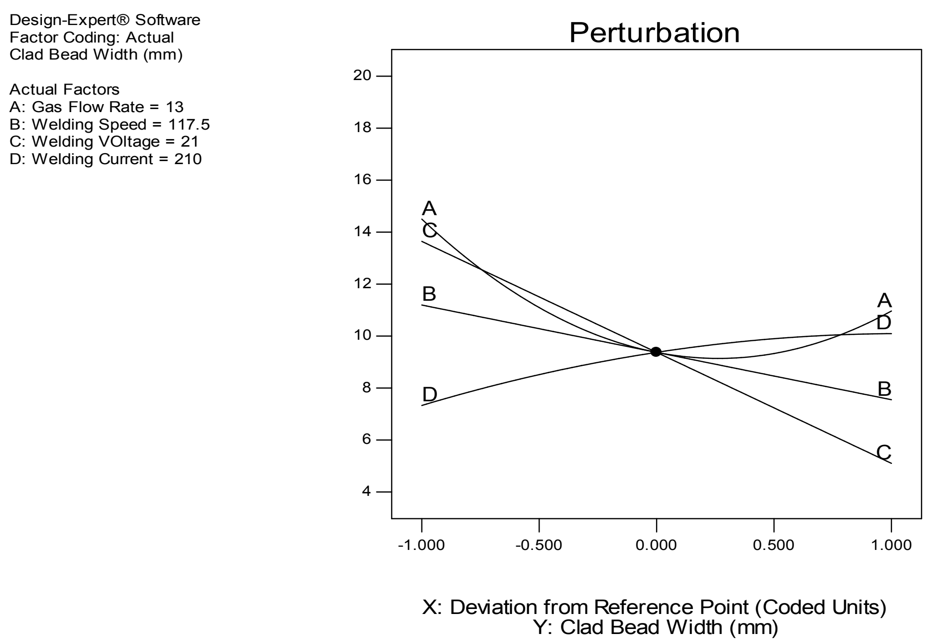

Fig. 5. Perturbation plot

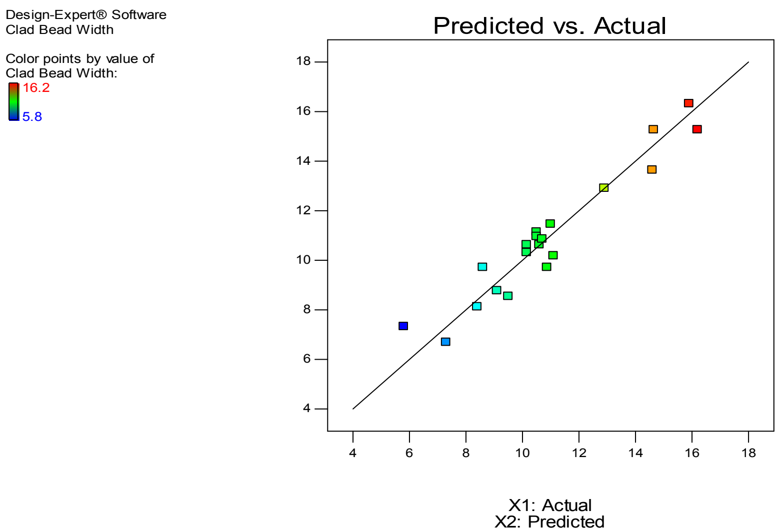

Fig. 6. Actual versus predicted values plot

The actual values versus predicted values plot is to check for errors in the values and to understand the rate at which the error occurs. The result shows that there's less error between the predicted and the actual values in the experimental trials.

5. CONCLUSION

The research expressed the statistical goodness of fit and the adequacy of the experimental data used for the trials. The application of various statistical tools like descriptive statistics, analysis of Variance, coefficient estimation analysis, model summary, normality plot, perturbation plot and cook's distance were implored to evaluate and to explore the experimental data statistically. The statistical results show that the experimental data are fit to model and to analyze. It further expressed that there's less error in the experimental trials and the model developed is significant. The results portray the data statistically to understand the data and the experimental trials conducted for the system.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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