OPEN ACCESS
Saudi Journal of Engineering and Technology
Abbreviated Key Title: Saudi J Eng Technol
ISSN 2415-6272 (Print) | ISSN 2415-6264 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Original Research Article

Application of Central Composite Design, Response Surface Methodology in Predicting the Thermal Expansion of Mild Steel Weldment

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DOI: 10.36348/sjet.2024.v09i02.008 | **Received:** 14.12.2023 | **Accepted:** 19.01.2024 | **Published:** 15.02.2024

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Abstract

The compositional range of materials to be welded, the thickness of the base materials, and current type are the main determining variables in the choice of welding. However, thermal expansion in mild steel weldments occurs when the material expands or contracts when subjected to changes in temperature during welding or subsequent heating and cooling cycles. This expansion and contraction can lead to residual stresses, distortion, and even cracking in the weldment if not properly managed. Mild steel, like many other metals, expands when heated and contracts when cooled. One major challenge occurs when during welding, the high temperatures cause the metal to expand in the heat-affected zone (HAZ) and the weld zone itself, then as the weldment cools down, it contracts, but this contraction might not be uniform due to differences in cooling rates across the weldment. The present study aims to predict the thermal expansion of mild steel weldments in relation to the current, voltage and gas flow rate. The central composite design is used for the design of experiment of 20 experimental runs, while the Response Surface Methodology (RSM) was used for the analysis. The model used in the RSM is Quadratic, while the coefficient of determinant, R-Squared of 0.9642, Adj R-Squared, 0.9319, Pred R-Squared, 0.7133, Adeq Precision 22.307 were obtained. There was no outliner which showed that the model adequately predicted the response. The study establishes that thermal expansion of mild-steel weldment can be adequately predicted by applying expect system such as the Response Surface Methodology.

Keywords: Tungsten inert gas (TIG) welding, central composite design matrix, Response Surface Methodology (RSM), mild steel weldment.

1. INTRODUCTION

Thermal expansion is a fundamental aspect of welding processes, especially in materials like mild steel (Bai *et al*., 2022). The application of Response Surface Methodology is explored as a key strategy for optimizing and predicting thermal expansion in mild steel weldments. Thermal expansion refers to the tendency of materials to change in dimension in response to temperature variations (Cao *et al*., 2021) (Somano, 2022). In the context of mild steel weldments, understanding and controlling thermal expansion is crucial for preventing distortions, ensuring proper fit, and maintaining the overall quality of welded structures. When materials are exposed to temperature fluctuations, a basic physical process known as thermal expansion takes place (Takenaka, 2018) (Ghorbel *et al*., 2021). The propensity of matter to alter its volume, area, and form in reaction to temperature changes is known as thermal expansion. It results from the particles' higher momentum as they absorb heat. The expansion can occur linearly, volumetrically, or in other specific directions depending on the material's properties (Zorzi and Perottoni, 2021) (Liu, 2022) (Chee *et al*., 2019). In welding, especially when working with materials like mild steel, understanding and managing thermal expansion are paramount. As temperatures fluctuate during the welding process, the material expands, and if not controlled, this expansion can lead to distortions, warping, and compromised structural integrity in the welded components (Huyghe *et al*., 2019) (Zahidin *et al*., 2023). Response Surface Methodology, as a statistical and mathematical approach, aids in modeling and optimizing the relationship between welding parameters and thermal expansion. This systematic methodology becomes instrumental in achieving precise control over thermal expansion in mild steel weldments (Sravan *et al*., 2023). The application of theoretical knowledge finds resonance in real-world case studies and practical applications. These examples illustrate the adaptability and success of RSM in diverse welding environments, providing valuable insights into managing thermal expansion effectively. In his work, Lu *et al*., (2023) elucidates the role of Response Surface Methodology as a systematic and statistical approach for modeling and optimizing the complex relationship between welding parameters and thermal expansion. Panicker (2023) delves into the theoretical foundations of RSM, highlighting how this methodology becomes instrumental in achieving optimal thermal expansion in mild steel weldments.

Strategies for optimizing thermal expansion in mild steel weldments are explored, with a specific emphasis on leveraging RSM to fine-tune welding parameters. Real-world applications and case studies exemplify successful optimization strategies in diverse welding scenarios (Azeez and Akinlabi, 2018). Yaseen candidly addresses the challenges associated with accurately predicting thermal expansion, considering factors such as current, voltage and gas flow rate. They provide insights into how RSM serves as a predictive tool, bridging the gap between theoretical modeling and real-world outcomes in the realm of thermal expansion prediction (Yaseen, 2021). In the present study, the optimization and prediction of thermal expansion in mild steel weldments emerge as critical considerations for welding processes. The strategic application of Response Surface Methodology proves instrumental in navigating the complexities associated with thermal expansion, paving the way for enhanced weld integrity and performance.

2. METHODOLOGY

2.1 Design of Experiment

A crucial component of the modern optimization process is experimental design; before, optimization was done one variable or one element at a time. Today for appropriate polynomial selection a design of experiment is employed to collect data. Experimental design works the rules of repetition, randomisation and local control. There are various forms of experimental designs, such as Taguchi, D-optimal, factorial, central composite, and latin hypercube designs. The number of given input parameters determines the type of experimental design; in this investigation, the central composite design was chosen because it can handle three input parameters the best.

2.2 Samples and Sampling Technique

After the edges were machined and bevelled, the plates were welded using the welding tungsten inert gas equipment. Figure 1A depicts the setup for TIG welding while the regulator and shielding gas cylinder are depicted in Figure 1B.

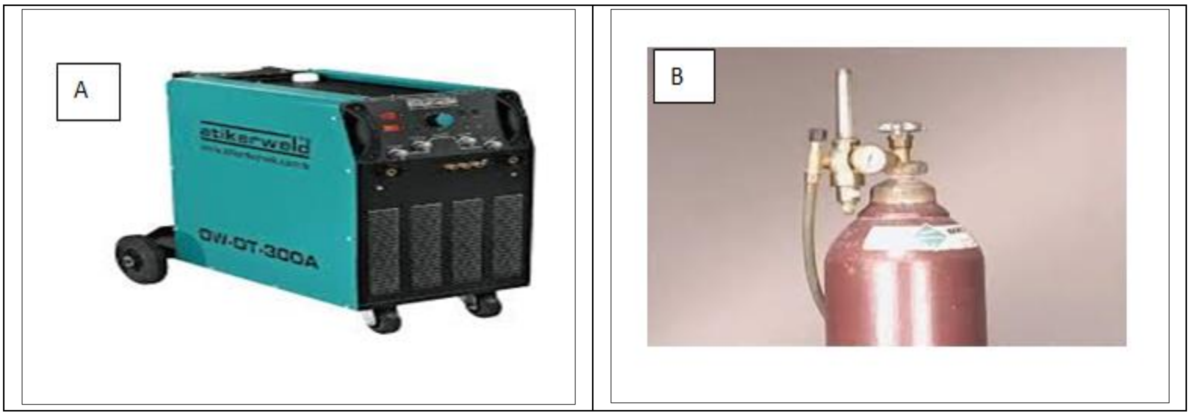

Figure 1A: TIG welding equipment B. The shielding gas cylinder and regulator

To insulate the weld specimen from air contact during the welding process, clean argon gas was employed. To make the weld samples, lightweight steel plate with a width of 10 mm was utilized; the plate was trimmed to size using a power hacksaw. The surfaces were smoothed with emery paper, the attachments were welded, the edges were ground, and the results were evaluated and documented.

2.3. Method of Data Collection

Using the design expert program, the center composite design matrix was created, yielding 20 experimental runs. The reactions noted that the information was derived from the welded tests, while the input and output parameters comprised the outcome of the experiment matrix.

2.3.1 Response Surface Methodology

Response Surface Methodology (RSM) experts are constantly looking for the ideal circumstances to optimize the procedure of focus with a goal to determine the experimental design of the procedure that involves the input variables, that lead to the best possible response. In terms of the procedure's parameters being supplied, the optimal value of a given function may be either minimum or maximum. RSM is one of the optimization methods that is now being used extensively to characterize the welding process' performance and identify the best possible answers to the relevant questions. To optimize the response of interest that is impacted by several input parameters, response surface modeling (RSM) is a collection of math and statistics techniques that are useful for modeling and forecasting this response. An analysis of variance (ANOVA) was used to determine how effective the predictions that were constructed were. The models that were generated were used to assess the variable in the model's regression in finding an ideal match. The sequential F-test, lack-of-fit test, and other adequacy measures (such as R2, Adj-R~, Pred. R2, and Adeq. Precision ratio) were employed. ANOVA can be used to calculate the Prob.>F (also known as the p-value) of the model as well as the Prob. of each term in the model.

3. RESULTS

The Sequential sum of square modeL for the thermal expansion response is determined to confirm that the experimental data can be analyzed using the quadratic formula approach. Table 1 shows the Sequential model sum of square for thermal expansion.

Table 1: Sequential model sum of square for thermal expansion

	Sum of		Mean	F	p-value	
Source	**Squares**	**Df**	**Square**	**Value**	**Prob > F**	
Mean vs Total	2141.74	1	2141.74			
Linear vs Mean	3.424E-003	3	1.141E-003	4.12	0.0241	
2FI vs Linear	3.594E-003	3	1.198E-003	18.61	< 0.0001	
Quadratic vs 2FI	5.553E-004	3	1.851E-004	6.58	0.0099	Suggested
Cubic vs Quadratic	2.336E-004	4	5.840E-005	7.33	0.0171	Aliased
Residual	4.782E-005	6	7.971E-006			
Total	2141.75	20	107.09			

From Table 1, the sequential sum of squares table shows the average enhancement to the model's fits as terms are added. The optimal fit was determined to be a first-order polynomials whereby the extra terms are relevant and the model is not aliased based on the sequential model's computed sum of squares. Also, Table 1 showed that the cubic polynomial was found to be aliased, cannot be used to fit the final model. Furthermore, it is suggested that the quadratic and 2FI models match the data the best, which supports the usage of quadratic polynomials in this analysis.

The lack of fit test for the response is used to ascertain the extent to which the quadratic model accounts for the underlying variation related to the experimental data. Table 2 illustrate the impact of the calculated lack of thermal expansion.

Table 2: Lack of fit test for thermal expansion

	Sum of		Mean	F	p-value	
Source	**Squares**	**Df**	**Square**	**Value**	**Prob > F**	
Linear	4.431E-003	11	4.028E-004	3.39	0.0942	
2FI	8.367E-004	8	1.046E-004	4.10	0.0685	
Quadratic	2.814E-004	5	5.628E-005	0.19	0.9545	Suggested
Cubic	4.782E-005	1	4.782E-005	0.12	0.7469	Aliased
Pure Error	0.000	5	0.000			

The results shown in Table 2 showed that the quadratic polynomial had a non-significant lack of fit and is recommended for the model analysis, whereas the cubic polynomial had a significant lack of fit and is therefore aliased to model analysis.

The model statistics calculated for the model sources on the premise of the thermal expansion reaction is shown in Table 3.

Table 3: Model summary statistics for thermal expansion

	Std.		**Adjusted**	**Predicted**		
Source	Dev.	R-Squared	R-Squared	R-Squared	PRESS	
Linear	0.017	0.4359	0.3302	-0.0405	8.174E-003	
2FI	8.023E-003	0.8935	0.8443	0.6190	2.993E-003	
Quadratic	5.305E-003	0.9642	0.9319	0.7133	2.253E-003	Suggested
Cubic	2.823E-003	0.9939	0.9807	-0.3420	0.011	Aliased

From Table 3, the quadratic polynomial model is suggested while the cubic polynomial model is aliased.

Table 4 presents the analysis of variance (ANOVA) for thermal expansion to evaluate the quadratic model's strength.

Table 4: ANOVA table for thermal expansion

	Sum of		**Mean**	**F**	**p-value**	
Source	Squares	Df	Square	Value	Prob > F	
Model	7.574E-003	9	8.416E-004	29.90	< 0.0001	Significant
A-current	4.075E-005	1	4.075E-005	1.45	0.2566	
B-voltage	3.382E-003	1	3.382E-003	120.19	< 0.0001	
C-gas flow rate	1.311E-006	1	1.311E-006	0.047	0.8334	
AB	1.357E-003	1	1.357E-003	48.23	< 0.0001	
AC	8.694E-004	1	8.694E-004	30.90	0.0002	
BC	1.368E-003	1	1.368E-003	48.60	< 0.0001	
A^2	5.523E-004	1	5.523E-004	19.63	0.0013	
B^2	6.696E-007	1	6.696E-007	0.024	0.8805	
C^2	9.198E-006	1	9.198E-006	0.33	0.5801	
Residual	2.814E-004	10	2.814E-005			
Lack of Fit	2.814E-004	5	5.628E-005	0.19	0.9545	not significant
Pure Error	0.000	5	0.000			
Cor Total	7.856E-003	19				

To evaluate the important effects of every single variable and ascertain whether the mathematical framework is essential, the combined effects, and the exponential impact to every single answer, analysis of variance (ANOVA) was required.

The goodness of fit statistics for the thermal expansion confirms the suitability of the quadratic model as shown in Table 5.

Table 5: GOF statistics for thermal expansion

Std. Dev.	5.305E-003	**R-Squared**	0.9642
Mean	10.35	**Adj R-Squaredrfffd**	0.9319
C.V. %	0.051	**Pred R-Squared**	0.7133
PRESS	2.253E-003	**Adeq Precision**	22.307

From Table 5, there is a reasonable degree of concordance among ‘Adj R-Squared’ value of 0.9319 and the ‘Predicted R-Squared’ value of 0.7133. The signal to noise ratio is measured with sufficient precision. Ideally, the ratio should be higher than 4. The computed ratio of 22.307 from Table 5, shows that the signal is sufficient. With the aid of this model, one can effectively explore the design space and forecast the thermal expansion.

Table 6 shows the diagnostic case statistics report, comparing the measured and predicted thermal expansion rates. The diagnostic case statistics shed light on the suitability of the ideal second-order polynomial equation as well as the strength of the model.

Table 6: Diagnostics case statistics report of observed versus predicted Thermal expansion

Standard	**Actual**	**Predicted**			**Studentized**	**Studentized**	**Fitted Value**	**Cook's**	**Run**
Order	**Value**	**Value**	**Residual**	**Leverage**	**Residual**	**Residual**	**DFFITS**	**Distance**	**Order**
1	10.33	10.33	8.248E-004	0.670	0.271	0.258	0.367	0.015	14
2	10.38	10.38	-7.300E-004	0.670	-0.239	-0.228	-0.324	0.012	2
3	10.35	10.35	-1.800E-003	0.670	-0.590	-0.570	-0.812	0.071	16
4	10.36	10.35	8.845E-003	0.670	2.901	6.92	9.86	1.71	9
5	10.37	10.37	-5.755E-003	0.670	-1.888	-2.233	-3.18	0.723	7
6	10.39	10.38	4.890E-003	0.670	1.604	1.766	2.51	0.522	15
7	10.35	10.34	3.820E-003	0.670	1.253	1.295	1.844	0.318	20
8	10.30	10.30	2.265E-003	0.670	0.743	0.725	1.033	0.112	1
9	10.36	10.36	3.220E-003	0.607	0.969	0.965	1.201	0.145	11
10	10.36	10.36	-7.590E-003	0.607	-2.283	-3.130	-3.89	0.806	6
11	10.37	10.37	1.948E-003	0.607	0.586	0.566	0.703	0.053	3
12	10.31	10.32	-6.317E-003	0.607	-1.900	-2.256	-2.80	0.558	10

Standard	Actual	Predict ed			Studentized	Studentized	Fitted Value	Cook's	Run
Order	Value	Value	Residual	Leverage	Residual	Residual	DFFITS	Distance	Order
13	10.34	10.35	-2.756E-003	0.607	-0.829	-0.815	-1.013	0.106	4
14	10.34	10.35	-1.614E-003	0.607	-0.485	-0.466	-0.580	0.036	8
15	10.34	10.34	1.249E-004	0.166	0.026	0.024	0.011	0.000	5
16	10.34	10.34	1.249E-004	0.166	0.026	0.024	0.011	0.000	19
17	10.34	10.34	1.249E-004	0.166	0.026	0.024	0.011	0.000	18
18	10.34	10.34	1.249E-004	0.166	0.026	0.024	0.011	0.000	13
19	10.34	10.34	1.249E-004	0.166	0.026	0.024	0.011	0.000	12
20	10.34	10.34	1.249E-004	0.166	0.026	0.024	0.011	0.000	17

The suitability of these models must first be confirmed by appropriate statistical research findings. Figure 2 shows the normal probability plots of studentized residuals for Thermal expansion.

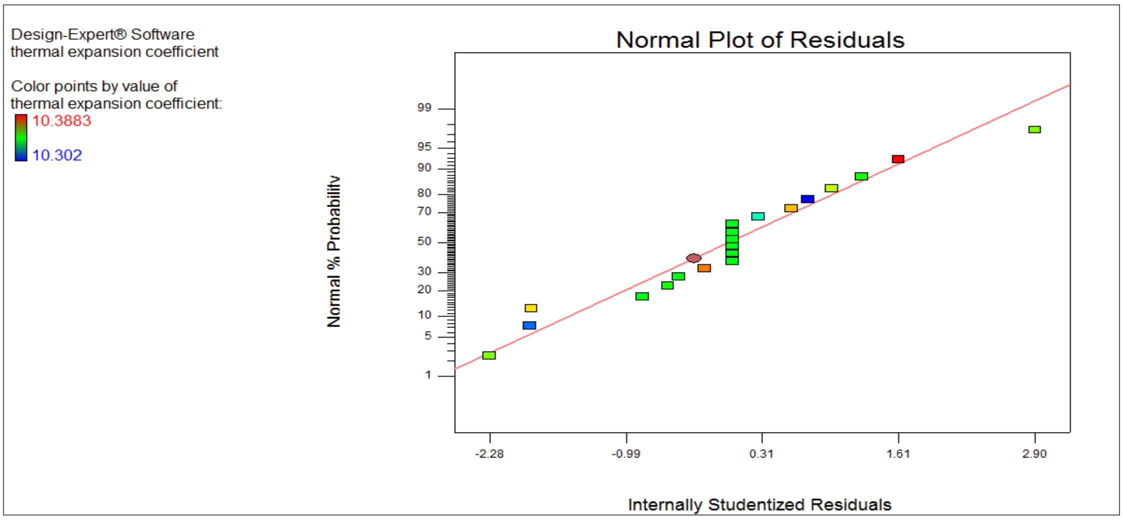

Figure 2: Normal probability plot of studentized residuals for Thermal expansion.

From Figure 2, it is evident that the points follow a straight line. Aside from the linear trend, there is no discernible pattern, such as a ‘s-shaped’ curve. This suggests that the residuals follow a normal distribution, and that further processing of the response data is not necessary.

Figure 3 illustrates the Plot of Residual responses versus the Predicted responses for the thermal expansion.

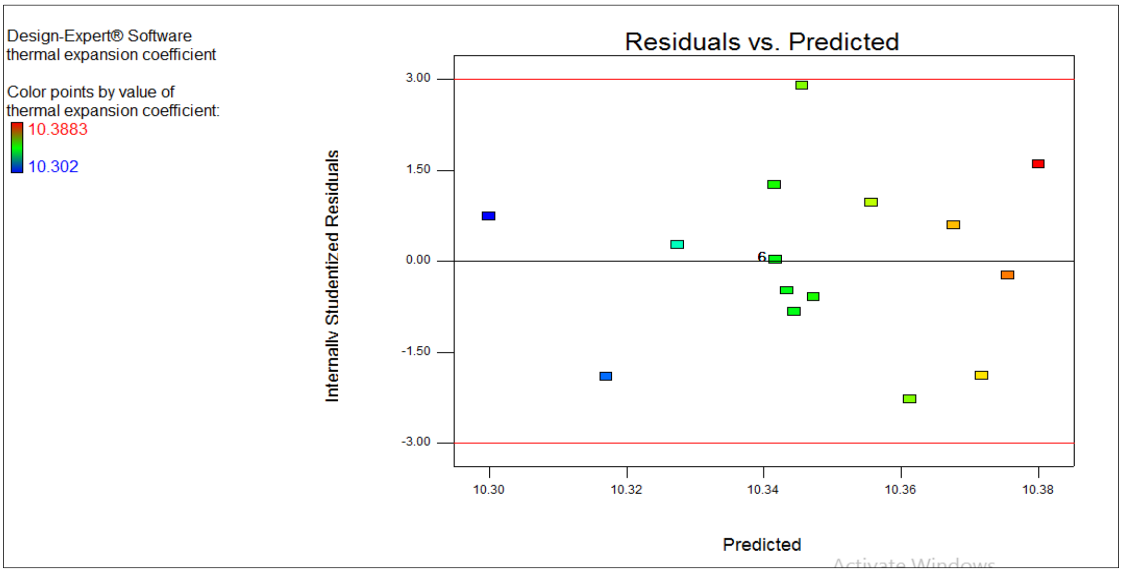

Figure 3: Plot of Residual vs Predicted for Thermal expansion.

From Figure 3, the graph shows the spots are near the line of fit. For the most part, the model can accurately anticipate the data points.

In Figure 4, the predicted values for thermal expansion are compared with the actual values to identify the alignments towards the line of best fits.

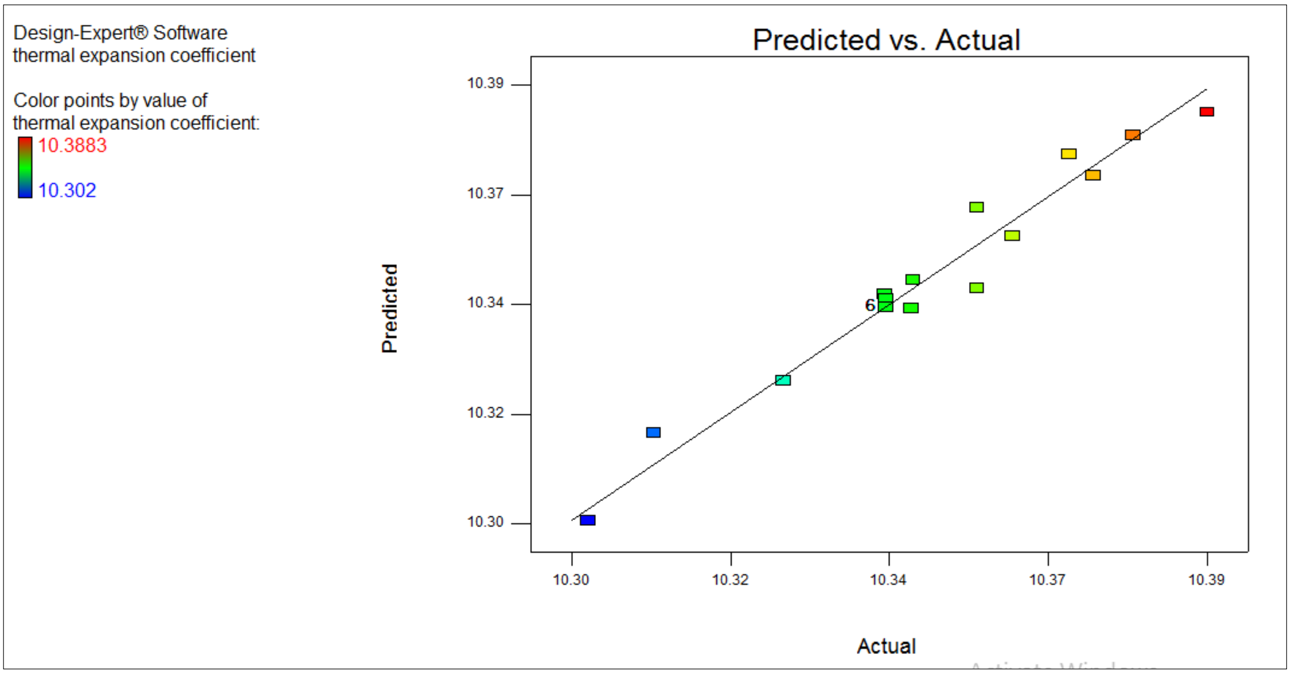

Figure 4: Plot of Predicted Vs Actual for Thermal expansion

Figure 5 illustrates the plot of the leverage and the run for thermal expansion to relate the relationship of the data points on the model fit.

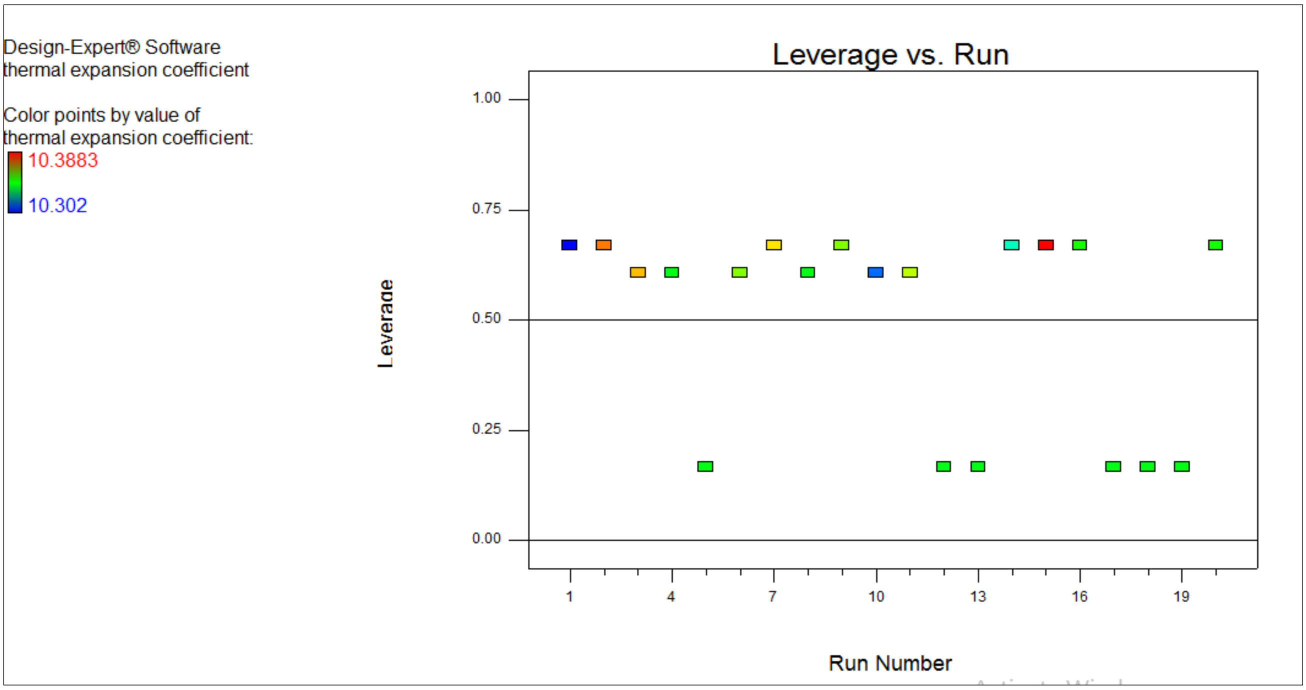

Figure 5: Plot of Leverage Vs Run for Thermal Expansion.

To measure the influence of each data point of thermal expansion on the predicted value, a Plot of DFFITS Vs Run is displayed in Figure 6.

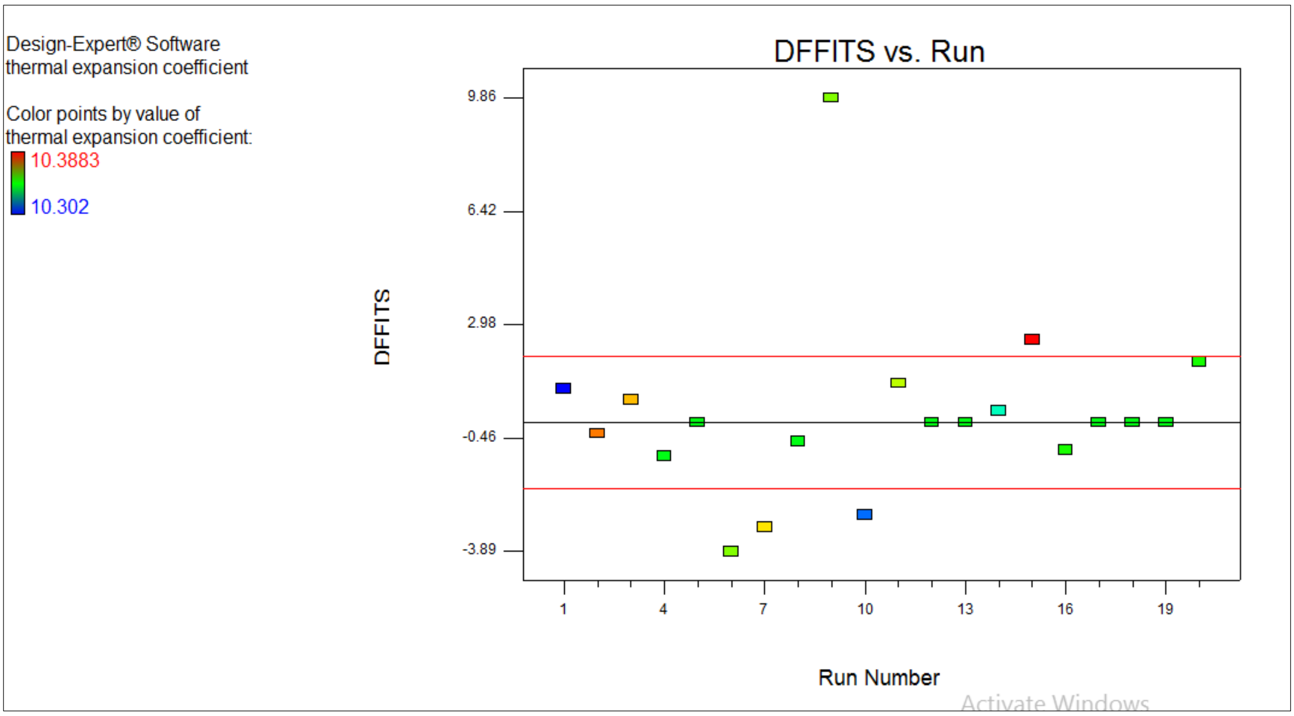

Figure 6: Plot of DFFITS Vs Run Thermal Expansion.

The cook's distance plot ascertains for the response (Thermal Expansion) whether the experimental data contained a potential outlier. The amount that the regression would alter if the outlier were removed from the study is shown by the cook's distance.

The generated cook's distance for the thermal expansion is shown in Figure 7.

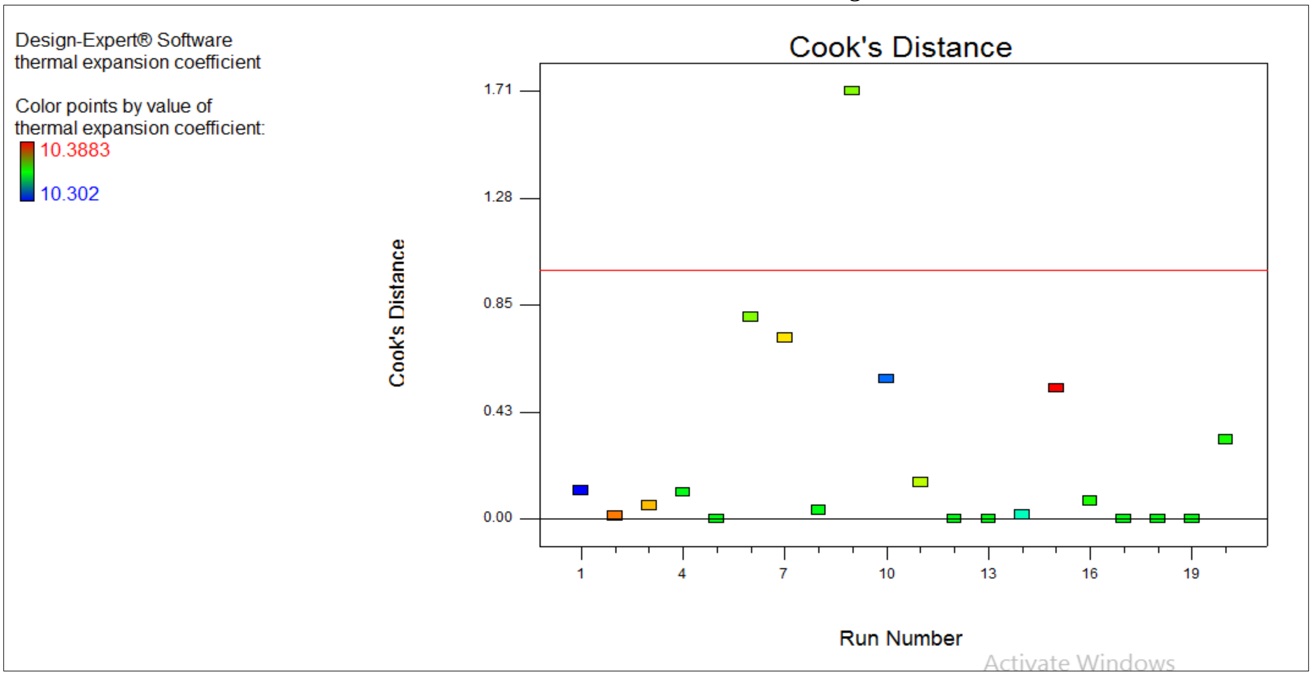

Figure 7: Generated cook's distance for thermal expansion

From Figure 7, the adequacy of the experimental data shows that there are no potential outliers. It can also be observed that the lowest bound of the cook's distance plot is 0.00, and the upper bound is 1.00, thus, Outliers are experimental values that fall outside of the lower or upper boundaries and need to be thoroughly examined.

The 3D surface plot in Figure 8 shows the relationship of two input parameters to responses.

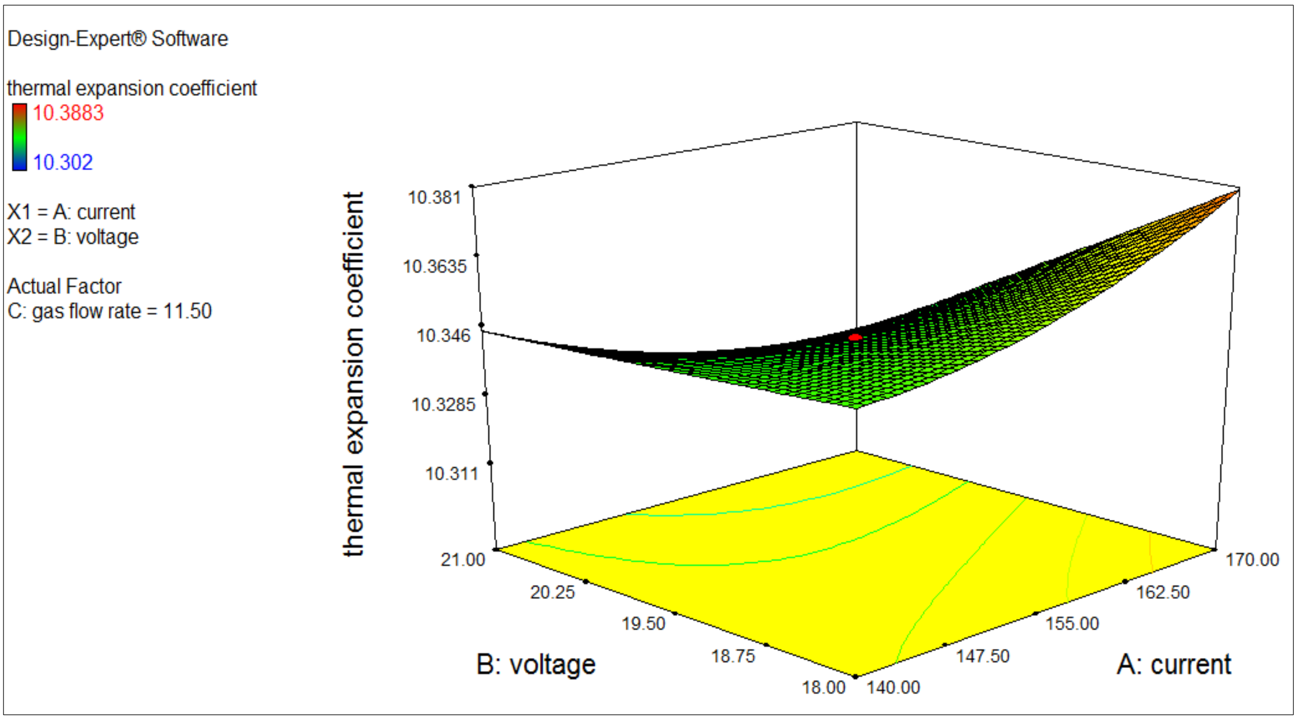

Figure 8: 3D surface plot showing effect of current and voltage on thermal expansion

The 3D surface plot in Figure 9 show the relationship between gas flow rate and current on thermal expansion.

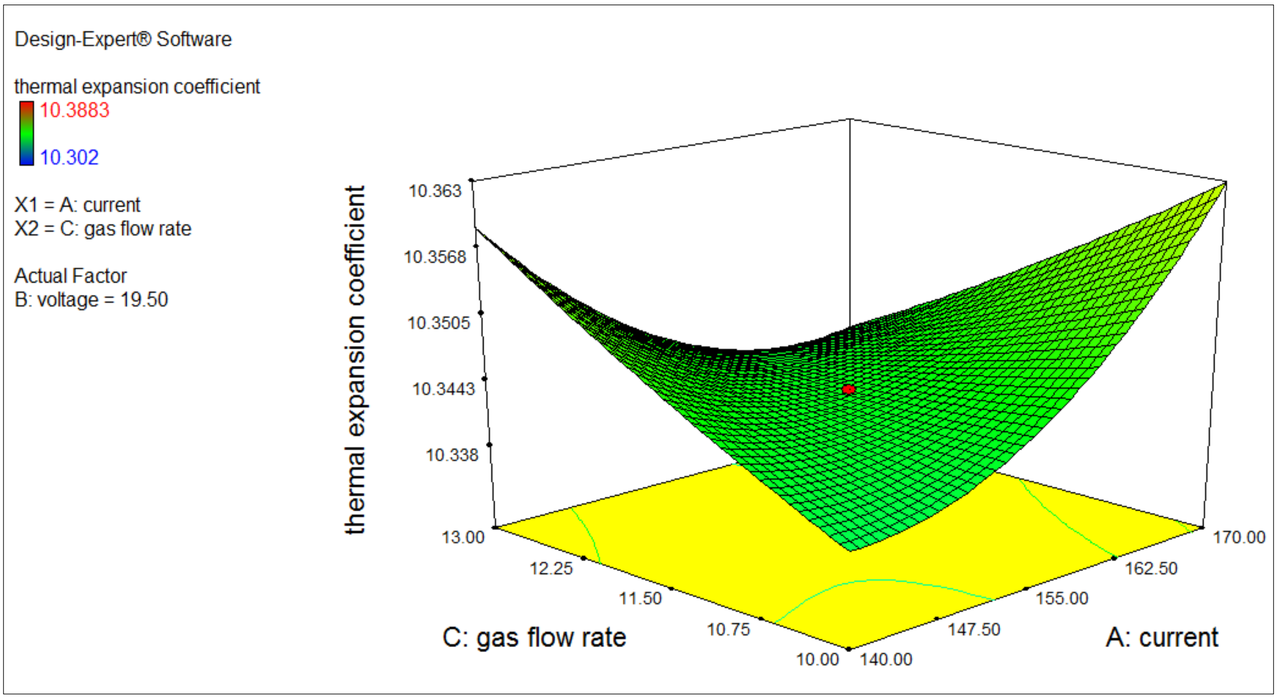

Figure 9: Impact of gas flow rate and current on thermal expansion

The 3D surface plot in Figure 10 shows the Effect of gas flow rate and voltage on thermal expansion.

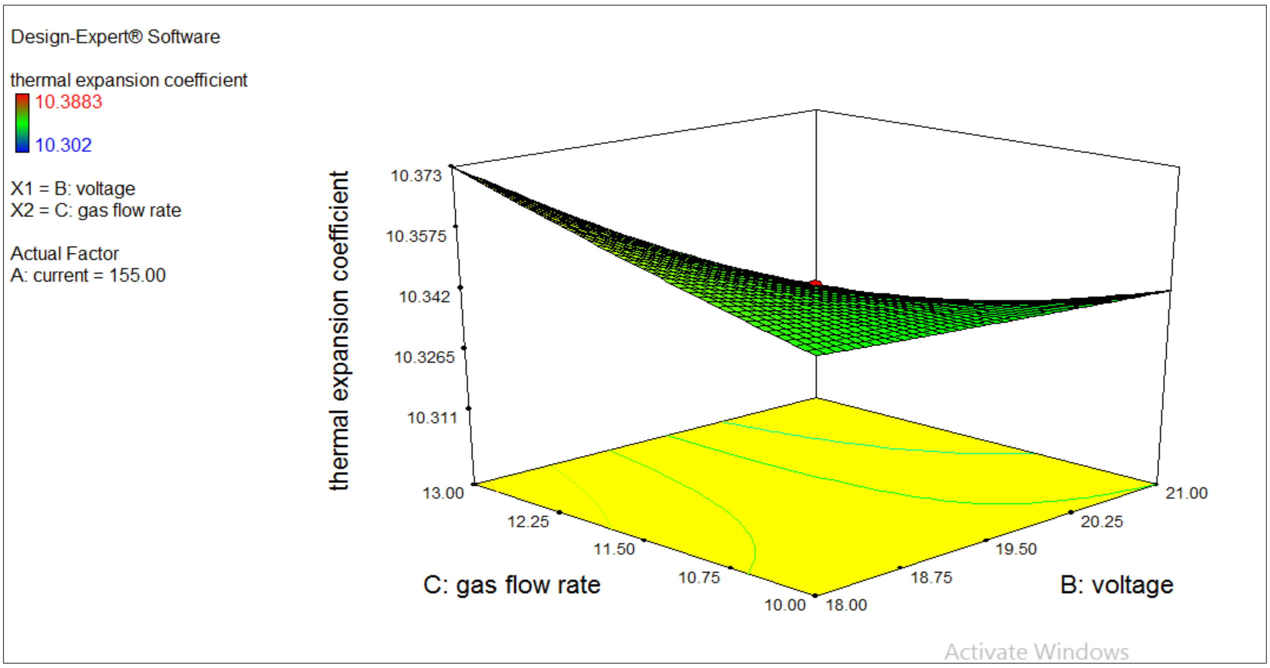

Figure 10: Effect of gas flow rate and voltage on thermal expansion

The 3D surface plots are three-dimensional surface graphics used to visualize the response surface. Though the surface plots have visible x-y-z dimensional planes, the contour plot shows more clearly the dimensional planes of the input parameters in relation to the response.

Figure 11 displays the contour plots of the thermal expansion response variable in relation to the current and voltage.

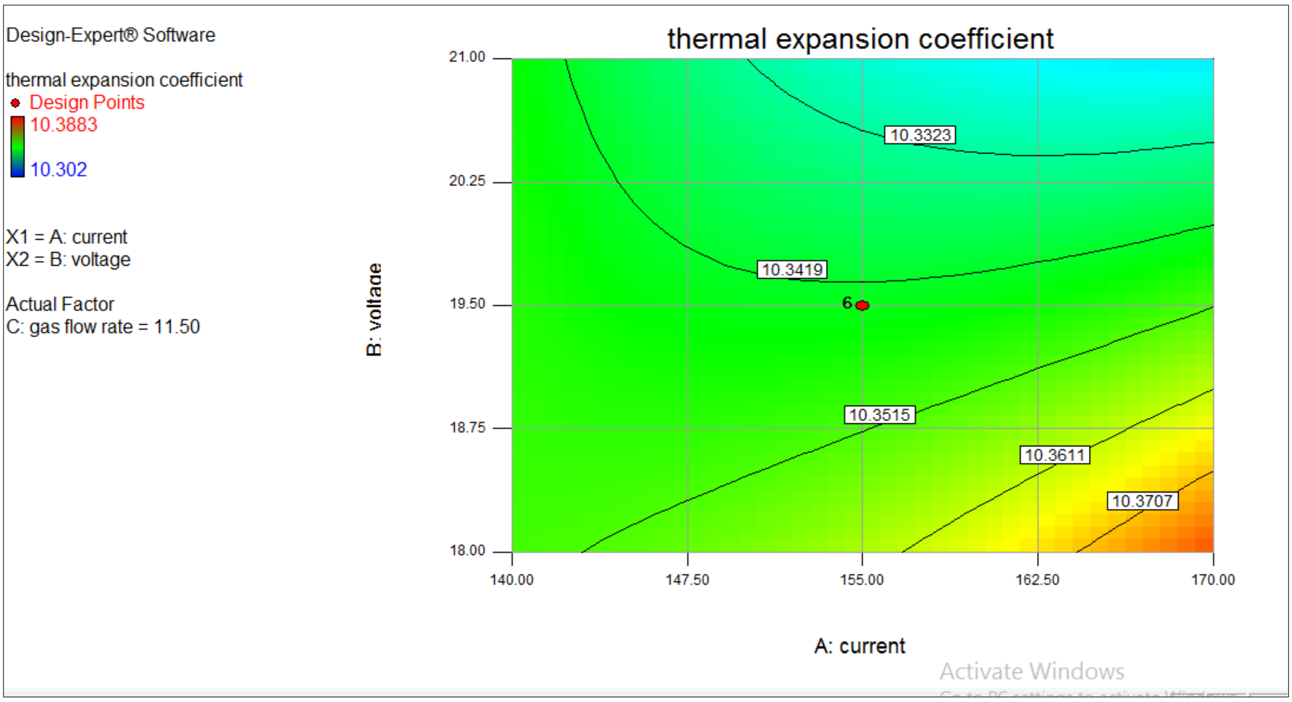

Figure 11: Making thermal expansion predictions with contour plot

Figure 12 displays the contour plots of the thermal expansion response variable versus the gas flow rate and current values.

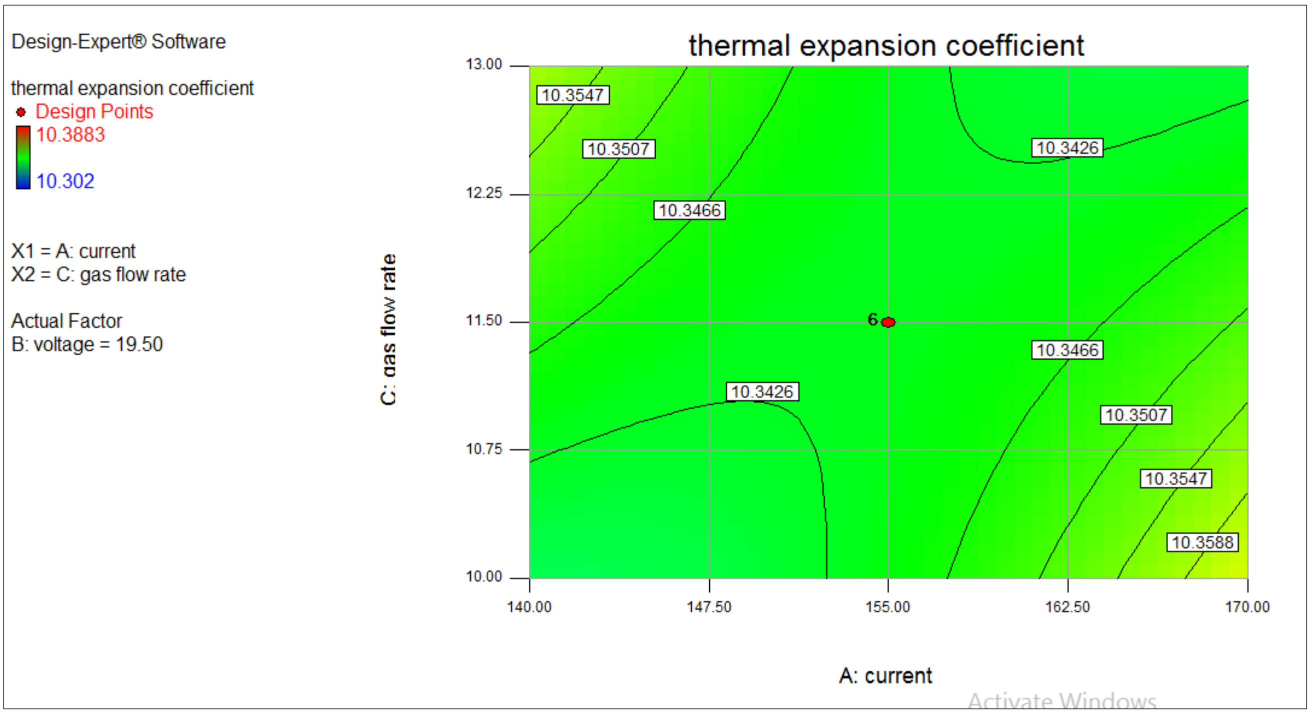

Figure 12: Contour plots of the thermal expansion versus the gas flow rate and current values.

Figure 13 displays the contour plots of the thermal expansion response against the gas flow rate and voltage values.

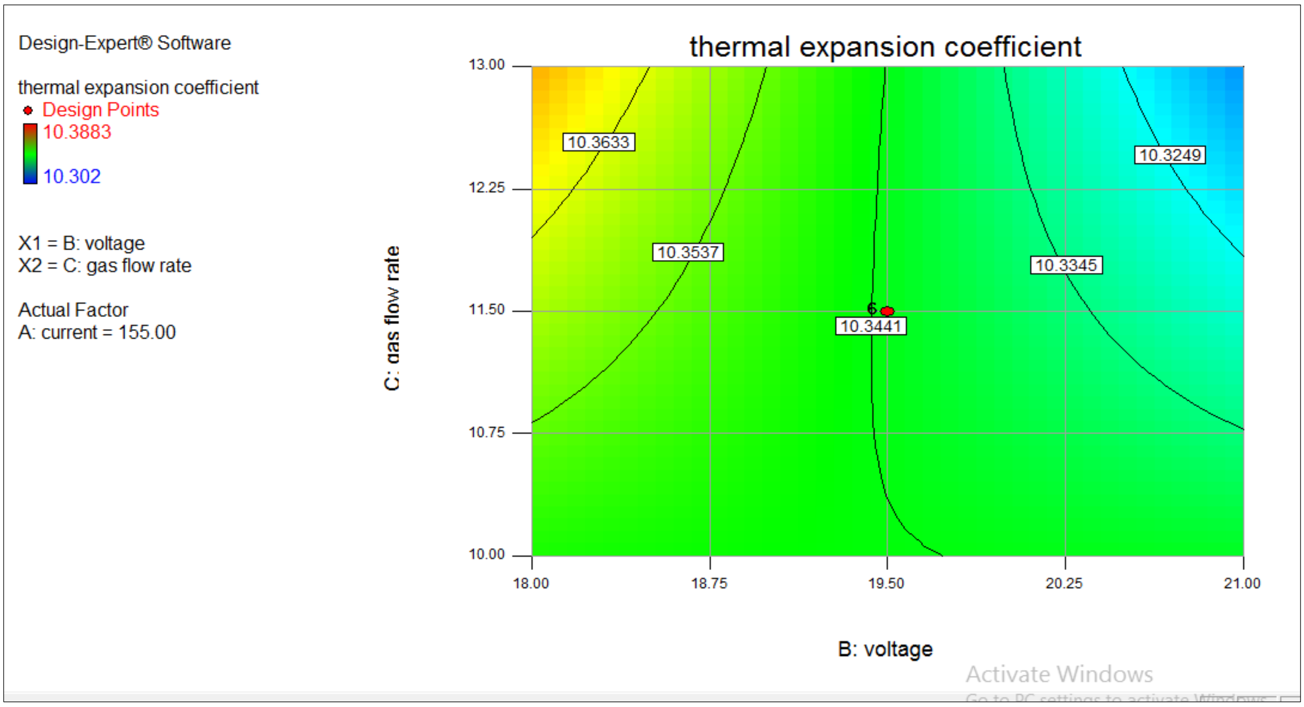

Figure 13: Predicting thermal expansion using contour plot

4. CONCLUSION

The study used the central composite design method and analyzed using the response surface methodology the prediction of the thermal expansion as it affects welded materials. The goodness of fit statistics for the thermal expansion confirms the suitability of the quadratic model used. The cook's distance plot showed that there is no outliner in the quadratic model selected. The two dimensional graphs, 3D surface plots and conmtour plots all further established the suitability of the model in analyzing the the thermal expansion duly. Thus, it has been successfully demonstrated that response surface methodology (RSM) may be used to maximize and forecast the thermal expansion of TIG mild steel welds utilizing the central composite design approach and genetic algorithm. The study's findings demonstrate that the RSM and GA are very useful tools for forecasting and optimizing the output reactions of TIG mild steel welds.

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