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OPTIMIZATION AND PREDICTION OF SURFACE ROUGHNESS OF MACHINED HEAT AFFECTED ZONE MILD STEEL WELD, USING RESPONSE SURFACE METHODOLOGY

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Abstract:

The service life of a weld fabricated engineering product is dependent on the surface finish of the product. Research has revealed that most of the failures observed in fabricated metal structures is linked to excessive heat input and large heat affect zone. This work is utilizing response surface method to optimizing and predicting the machined zone affected by heat of mild steel welds. The software was utilized to bring out a design matrix utilizing the group and level of the input parameters. The central composite design (CCD) was used. 30 sets of experiment were performed according to the design of experiment, the input parameters are cutting speed, feed rate, nose roughness and chip thickness. From the results obtained, the ANOVA showed that the second order polynomial was suggested as the best fit to predict the large response. The metals developed have high strength and adequately.

Keywords: Surface, Surface roughness, Heat, Heat affected zone, Optimization, Prediction

1. INTRODUCTION

1.1 Background to the Study

The operation of weld essentially contents the welded piece to heat cycles that cause the object to observe high temperatures, inducing non- linear mechanical behaviour in the weld region and the heat affected zone (HAZ).The HAZ is the area on the parent metal closest to the fusion zone that is affected by the heat applied to fuse the joint, this region experiences a grain growth resulting in microstructural alteration, and giving rise to undesirable residual stresses which affects the quality of the bead surface profile In the manufacturing industry, the surface must be within certain limits of roughness to improve corrosion resistance and to reduce life cycle cost The surface finish of machined parts is known to have considerable effect on some properties such as wear resistance and fatigue strength. Thus, the goodness of the surface is a significantly importance for evaluating the performance of machined mechanical parts. An appropriate machining condition is extremely important because these determines surface quality and service life of manufactured parts. This theory has been studied by (Hatamleh et al. 2009 and suggested that roughness of surface is a kind of irregularity influenced by the welding operation responsible of many cases of fatigue crack initiation due to generated stress concentrations. Therefore, in the case of improving quality of surface roughness joints, many researchers are devoted to define the welding parameters and tool geometry leading to welded joints with optimum surface roughness. However, in the field of manufacturing and fabrication, process optimization becomes necessary as this is a technique employed to strategically control the process parameters involved in the manufacturing process.

2. LITERATURE REVIEW

2.1 Optimization of Heat Affected Zone HAZ

Gunaraj and Murugan (1999) also analyzed the result of SAW factors on the heat input with the region of HAZ for reduced carbon steel plus two types of joints, bead-on-joint and bead-on-plate, using mathematical models developed by RSM. They found that for the same heat input, the area of the HAZ is greater for the bead-on-plate than that for bead-on-joint. They discovered that for that same heat input, the region of the impact of SAW factors on the region of HAZ in both cases follows the same trend. Ghosh et al (2011a) handled the subject linked to the doubts concerned with the heat affected zone (HAZ) within and around the weld manufactured by SAW operation. The more tricky subject is about HAZ less hardness that affects little doubts in the weld goodness. It maximizes the likelihood of tiredness failure at the most weak zones resulted by the warming and chilling period of the zone welded. They examined the zone affected by heat of submerged arc weld of the structural steel plates into the study of the structure of grain by way of digital image operating methods. It was concluded that the grains are predominantly of smaller variety and the counts for larger grain are almost negligible. Gunaraj and Murugan (2000) continued their previous study and successfully investigated the result of SAW factors on HAZ characteristics. They brought out the input of heat and wire-feed rate had a positive result, though speed of welding have effect that is negative on every HAZ feature. They included also that the width of HAZ is of a highest about 2.2 mm when the wire-feed rate and the speed welding are at their minimum limits.

Natarajan et al (2011) designed an experiment by considering the speed of spindle, rate of feed and cutting depth as parameters using C26000 metal in a CNC turning centre with a CNMG 120408 insert. The optimization was carried out using artificial neural network (ANN) to predict the roughness of surface. The authors concluded that the rate of feed is the most dominating parameter.
Suresh *et al* (2011) developed mathematical model to foretell the roughness of surface in machining of EN24 steel alloy. The optimization was carried out using Response Surface Method. The cutting factors like rate of feed were considered for the experiment. It was discovered that rate of feed had the most importance that speed of cutting and cutting depth. 3D plots were employed to discover the best arrangement for lowest roughness of surface.

3. METHODOLOGY

3.1 Introduction

In the previous chapter we made a perspective sketch of the various relevant research works surrounding the present research study. In this chapter we shall explain the research strategy employed to obtain and analyse data for the study. The methodological steps are outlined below.

1. Research design

2. sampling technique
3. technique of data collection
4. method of data analysis

3.2 Research Design

This is the overall strategies chosen to bring together the various research components in a agreeable and sensible manner so as to effectively handle the research challenge.

3.2.1 Design of experiment

Experimentation is a very important aspect of scientific study, which can be developed using computer soft wares like design expert and Minitab. For proper polynomial approximation an experimental design is used to collect the data. There are different types of experimental designs which includes central composite design, taguchi, D-optimal design, factorial design and latin hyper cube designs.

3.2.2 Identification of range of input parameters

The key parameters considered in this work are speed of cutting, rate of feed, cutting depth, and nose radius. The range of the process parameters obtained from literature is shown in the table below

Table 3.1: Process parameters and their levels

Parameters	Unit	Coded value	Coded value
		Low(-1)	High(+1)
Cutting speed	m/min	100	150
Feed rate	Mm/rev	0.1	0.15
Nose radius	Mm	0.3	0.6
Depth of cut	Mm	0.1	1.0

3.3 Method of Data Analysis

3.4 Models Employed

In this study, the Response surface methodology (RSM) was employed in the modeling, optimization and prediction.

A typical application of RSM proceeds in the following steps.

1. Identify the relevant input variables that will help to build up an appropriate response surface
2. Determine the optimal settings of the factors that will yield an optimum response
3. Optimize multiple responses"

4. RESULTS AND DISCUSSION

In this study, an attempt was made to build a second order mathematical relationship between some chosen input variables, like cutting speed, feed rate, nose radius and cutting depth, and two response variables, namely; roughness of surfac and chip thickness. The target of the optimization model was to:

i. Minimize surface roughness
ii. Minimize chip thickness

To generate the experimental data for the optimization process;

i. First, statistical design of experiment (DOE) using the central composite design method (CCD) was done. The design and optimization were executed with the aid of statistical tool. For this particular problem, Design Expert 7.01 was employed.
ii. Secondly, an experimental design matrix having six (6) center points (k), six (6) axial points (2n) and eight (8) factorial points (2^n) resulting to 30 experimental runs was generated.

Table 4.1:

Std	Run	Block	Cutting speed	Feed rate	Nose radius	Depth of cut	Surface roughness	Chip thickness
5	1	Block 1	100.00	0.10	0.60	0.50	0.256	0.5
9	2	Block 1	100.00	0.10	0.30	1.00	0.322	0.332
21	3	Block 1	125.00	0.13	0.15	0.75	0.09	0.395
29	4	Block 1	125.00	0.13	0.45	0.75	0.55	0.528
18	5	Block 1	175.00	0.13	0.45	0.75	0.402	0.528
26	6	Block 1	125.00	0.13	0.45	0.75	0.402	0.528
2	7	Block 1	150.00	0.10	0.30	0.50	0.08	0.2
17	8	Block 1	75.00	0.13	0.45	0.75	0.402	0.528
14	9	Block 1	150.00	0.10	0.60	1.00	0.59	0.728
13	10	Block 1	100.00	0.10	0.60	1.00	0.55	0.746
30	11	Block 1	125.00	0.13	0.45	0.75	0.402	0.528
24	12	Block 1	125.00	0.13	0.45	1.25	0.402	0.528
25	13	Block 1	125.00	0.13	0.45	0.75	0.402	0.528
10	14	Block 1	150.00	0.10	0.30	1.00	0.304	0.565
6	15	Block 1	150.00	0.10	0.60	0.50	0.11	0.394
1	16	Block 1	100.00	0.10	0.30	0.50	0.129	0.1
7	17	Block 1	100.00	0.15	0.60	0.50	0.285	0.425
28	18	Block 1	125.00	0.13	0.45	0.75	0.402	0.528
23	19	Block 1	125.00	0.13	0.45	0.25	0.098	0.05
20	20	Block 1	125.00	0.17	0.45	0.75	0.402	0.528
15	21	Block 1	100.00	0.15	0.60	1.00	0.22	0.485
11	22	Block 1	100.00	0.15	0.30	1.00	0.264	0.475
3	23	Block 1	100.00	0.15	0.30	0.50	0.455	0.382
22	24	Block 1	125.00	0.13	0.75	0.75	0.3	0.528
27	25	Block 1	125.00	0.13	0.45	0.75	0.402	0.528
12	26	Block 1	150.00	0.15	0.30	1.00	0.29	0.636
19	27	Block 1	125.00	0.08	0.45	0.75	0.402	0.528
16	28	Block 1	150.00	0.15	0.60	1.00	0.245	0.445
4	29	Block 1	150.00	0.15	0.30	0.50	0.362	0.39
8	30	Block 1	150.00	0.15	0.60	0.50	0.2	0.265

To validate the suitability of the quadratic model in analyzing the experimental data, the sequential model sum of squares was calculated for the roughness of surface response as presented in table 4.2

Table 4.2: Sequential sum of square for surface roughness

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Mean vs Total	3.15	1	3.15			
Linear vs Mean	0.12	4	0.030	1.73	0.1753	
2FI vs Linear	0.25	6	0.041	4.27	0.0069	
Quadratic vs 2FI	0.15	4	0.037	15.41	< 0.0001	Suggested
Cubic vs Quadratic	0.013	8	1.675E-003	0.53	0.8059	Aliased
Residual	0.022	7	3.180E-003			
Total	3.70	30	0.12			

To validate the suitability of the quadratic model in analyzing the experimental data, the sequential model sum of squares was calculated for the chip thickness response as presented in table 4.2

Table 4.4: Lack of fit test for surface roughness

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Linear	0.41	20	0.020	5.61	0.0324	
2FI	0.16	14	0.012	3.21	0.1023	
Quadratic	0.017	10	1.740E-003	0.48	0.8508	Suggested
Cubic	4.005E-003	2	2.003E-003	0.55	0.6090	Aliased
Pure Error	0.018	5	3.651E-003			

To test how good the quadratic model can analyse the variable linked to the experimental data, the lack of fit test was estimated for each of the responses. Model with significant lack of fit cannot be employed for prediction.

The model summary statistics computed for surface roughness response based on the model sources is presented in table 4.8

Table 4.6: Model summary statistics surface roughness

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	0.13	0.2166	0.0913	-0.1506	0.63	
2FI	0.098	0.6663	0.4906	0.3722	0.34	
Quadratic	0.049	0.9347	0.8737	0.7682	0.13	Suggested
Cubic	0.056	0.9592	0.8311	-0.1047	0.60	Aliased

Table 4.8: Surface roughness

Source	Sum of Squares	Df	Mean Square	F Value	p-value Prob > F	
Model	0.51	14	0.036	15.33	< 0.0001	significant
A-cutting speed	3.750E-003	1	3.750E-003	1.58	0.2283	

B-Feed rate	1.667E-005	1	1.667E-005	7.011E-003	0.9344	
C-Nose radius	0.019	1	0.019	7.87	0.0133	
D-depth of cut	0.096	1	0.096	40.29	< 0.0001	
AB	1.323E-004	1	1.323E-004	0.056	0.8167	
AC	6.400E-005	1	6.400E-005	0.027	0.8719	
AD	0.012	1	0.012	5.23	0.0371	
BC	0.075	1	0.075	31.35	< 0.0001	
BD	0.14	1	0.14	57.13	< 0.0001	
CD	0.023	1	0.023	9.47	0.0077	
A^2	2.552E-003	1	2.552E-003	1.07	0.3165	
B^2	2.552E-003	1	2.552E-003	1.07	0.3165	
C^2	0.10	1	0.10	43.50	< 0.0001	
D^2	0.062	1	0.062	26.19	0.0001	
Residual	0.036	15	2.377E-003			
Lack of Fit	0.017	10	1.740E-003	0.48	0.8508	not significant
Pure Error	0.018	5	3.651E-003			
Cor Total	0.55	29				

To validate the adequacy of the quadratic model the surface roughness goodness of fit statistics is presented in table 4.

Table 4.10:goodness of fit statistics for surface roughness

Std. Dev.	0.049	R-Squared	0.9347
Mean	0.32	Adj R-Squared	0.8737
C.V. %	15.05	Pred R-Squared	0.7682
PRESS	0.13	Adeq Precision	16.089

To obtain the optimal solution, we first consider the coefficient statistics and the corresponding standard errors. The computed standard error measures the disparity between the experimental terms and the corresponding predicted terms. Coefficient estimate statistics for roughness of suefaceresponse variable is presented in table 4.9

Table 4.12: Coefficient estimates statistics generated for surface roughness

	Coefficient		Standard	95% CI	95% CI	
Factor	Estimate	Df	Error	Low	High	VIF
Intercept	0.43	1	0.020	0.38	0.47	
A-cutting speed	-0.013	1	9.952E-003	-0.034	8.712E-003	1.00
B-Feed rate	-8.333E-004	1	9.952E-003	-0.022	0.020	1.00

C-Nose radius	0.028	1	9.952E-003	6.704E-003	0.049	1.00
D-depth of cut	0.063	1	9.952E-003	0.042	0.084	1.00
AB	2.875E-003	1	0.012	-0.023	0.029	1.00
AC	-2.000E-003	1	0.012	-0.028	0.024	1.00
AD	0.028	1	0.012	1.895E-003	0.054	1.00
BC	-0.068	1	0.012	-0.094	-0.042	1.00
BD	-0.092	1	0.012	-0.12	-0.066	1.00
CD	0.038	1	0.012	0.012	0.063	1.00
A^2	-9.646E-003	1	9.309E-003	-0.029	0.010	1.05
B^2	-9.646E-003	1	9.309E-003	-0.029	0.010	1.05
C^2	-0.061	1	9.309E-003	-0.081	-0.042	1.05
D^2	-0.048	1	9.309E-003	-0.067	-0.028	1.05

Variance inflation factor (VIF) value of 1.00 for the individual and combine terms, 1.02 for the quadratic terms as observed in table 4.14 and 4.15, indicate a significant model in which the variables are highly correlated with the responses.

The optimal equation which displays the individual impacts and joined interactions of the chosen input variables) against the mesured surface roughness is presented based on the coded variables in equation 4.1.

$$
\begin{aligned}
\text{face roughness} =\ & +0.43 \\
& -0.013 * A \\
& -8.333E\text{-}004 * B \\
& +0.028 * C \\
& +0.063 * D \\
& +2.875E\text{-}003 * A * B \\
& -2.000E\text{-}003 * A * C \\
& +0.028 * A * D \\
& -0.068 * B * C \\
& -0.092 * B * D \\
& +0.038 * C * D \\
& -9.646E\text{-}003 * A^2 \\
& -9.646E\text{-}003 * B^2 \\
& -0.061 * C^2 \\
& -0.048 * D^2
\end{aligned}
$$

Figure 4.19: Optimal equation in terms of coded factors for minimizing surface roughness

The optimal equation which shows the individual effects and combine interactions of the selected input variables against the mesured chip thickness is presented based on the coded variables in equation 4.2

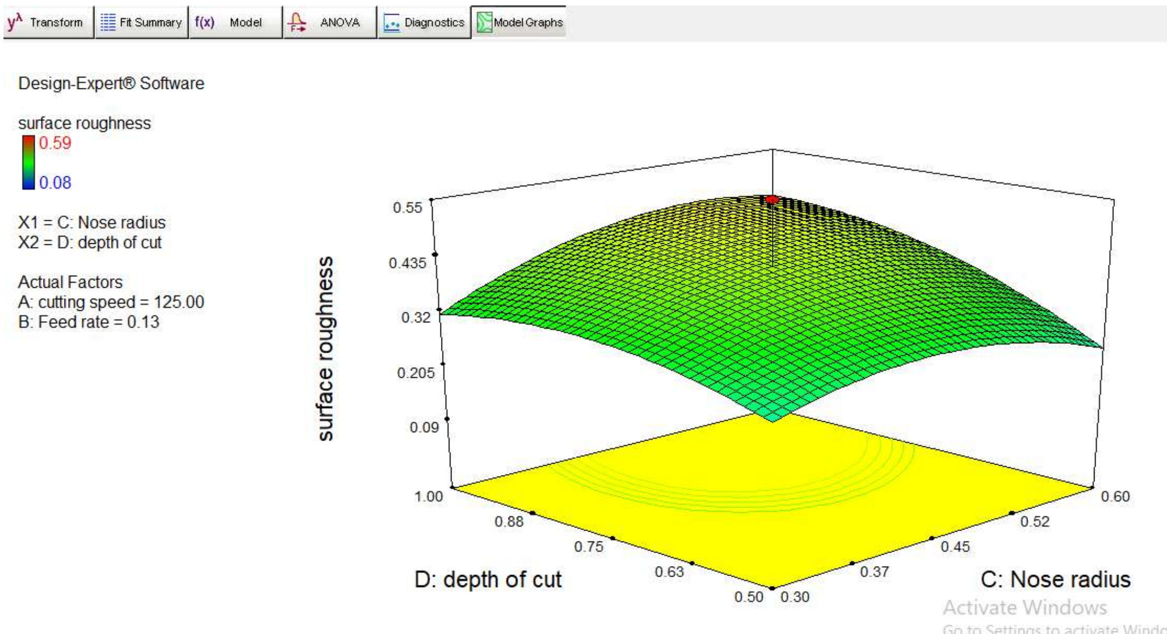
Figure 4.21: Optimal equation in terms of actual factors for minimizing surface roughness
The optimal equation that displays the individual impacts and joined interactions of the chosen input variables against the mesured chip thickness is presented based on the actual values in equation 4.4

Table 4.16: Diagnostics case statistics report of observed versus predicted surface roughness

					Internally	Externally	Influence on		
Standard	Actual	Predicted			Studentized	Studentized	Fitted Value	Cook's	Run
Order	Value	Value	Residual	Leverage	Residual	Residual	DFFITS	Distance	Order
1	2.00	1.95	0.053	0.670	0.505	0.486	0.692	0.052	8
2	1.60	1.67	-0.068	0.670	-0.650	-0.631	-0.898	0.086	14
3	1.30	1.40	-0.10	0.670	-1.000	-1.000	-1.424	0.203	2
4	1.39	1.42	-0.029	0.670	-0.283	-0.270	-0.384	0.016	13
5	2.00	2.01	-6.336E-003	0.670	-0.061	-0.058	-0.082	0.001	18
6	1.40	1.33	0.068	0.670	0.656	0.636	0.906	0.087	19
7	2.00	1.97	0.032	0.670	0.306	0.292	0.416	0.019	17
8	1.50	1.59	-0.088	0.670	-0.849	-0.836	-1.191	0.146	9
9	1.90	1.90	-1.860E-003	0.607	-0.016	-0.016	-0.019	0.000	7
10	1.40	1.35	0.053	0.607	0.462	0.444	0.552	0.033	6
11	1.30	1.35	-0.045	0.607	-0.397	-0.380	-0.473	0.024	1
12	1.20	1.10	0.096	0.607	0.843	0.830	1.033	0.110	10
13	2.20	2.13	0.071	0.607	0.627	0.606	0.754	0.061	12
14	2.30	2.32	-0.020	0.607	-0.181	-0.172	-0.213	0.005	5
15	2.40	2.10	0.30	0.166	1.824	2.119	0.947	0.066	16
16	2.00	2.10	-0.098	0.166	-0.593	-0.573	-0.256	0.007	11
17	2.10	2.10	1.885E-003	0.166	0.011	0.011	0.005	0.000	3
18	0.40	0.36	0.039	0.583	1.237	1.261	1.492	0.143	5
19	0.40	0.39	0.012	0.583	0.389	0.378	0.447	0.014	27
20	0.40	0.39	0.016	0.583	0.495	0.482	0.571	0.023	20
21	0.090	0.13	-0.035	0.583	-1.120	-1.130	-1.337	0.117	3
22	0.30	0.24	0.063	0.583	2.004	2.263	* 2.68	0.375	24
23	0.098	0.11	-0.012	0.583	-0.373	-0.362	-0.429	0.013	19
24	0.40	0.36	0.040	0.583	1.258	1.285	1.520	0.148	12
25	0.40	0.43	-0.025	0.167	-0.554	-0.541	-0.242	0.004	13
26	0.40	0.43	-0.025	0.167	-0.554	-0.541	-0.242	0.004	6

27	0.40	0.43	-0.025	0.167	-0.554	-0.541	-0.242	0.004	25
28	0.40	0.43	-0.025	0.167	-0.554	-0.541	-0.242	0.004	18
29	0.55	0.43	0.12	0.167	2.771	3.832	1.714	0.102	4
30	0.40	0.43	-0.025	0.167	-0.554	-0.541	-0.242	0.004	11

The diagnostics case statistics which shows the observed values of heat affected zone against their predicted values is presented in table 4.17. The diagnostic case statistics actually give insight into the model strength and the adequacy of the optimal second order polynomial equatios
indicators of a well fitted model.



The figure above shows effects current and voltage has on the percentage dilution

5. Discussion

In this study, the Response Surface methodology was used to optimize and predict surface roughness. The input parameters are cutting speed, feed rate, nose radius, depth of cut, while the response is surface roughness. The relationship between the nose radius, depth of cut parameters and the surface roughness shows a strong correlation having a P-value of 0.00001 and 93% coefficient of determination. The nose radius and depth of cut has a significant effect of the chip thickness with P-value of 0.00001 and 99% coefficient of determination.

The variance inflation factor (VIF) was 1.00 which indicates that the model is significant because a (VIF) greater than 10.00 is a cause for alarm. The ANOVA table shows that the model is significant and possess a very good fit with a P -value of < 0.0001. the goodness of fit statistics gave a Coefficient of determination R^2 indicating how well the model can predict the values of the selected variables. The models have a noise to signal ratio of 47 and 16, which is greater than 4 is desirable and indicates an adequate signal. .Finally, numerical optimization was performed to ascertain the desirability of the overall model. In the numerical optimization phase, we ask design expert to minimize surface roughness. From the results of table it was seen that a cutting speed (133.93) feed rate (0.10) nose radius (0.30)depth of cut 0.50 will produce a machined product with surface roughness 0.0796222. This solution was selected by design expert as the optimal solution having a desirability value of 0.911

Findings

From the study, the following are the findings

It was observed that the quadratic model was selected based on the lack of fit, goodness of fit, and anova tests.

1. Results obtained in this study showed that the interactive combination of nose radius , and depth of cut has a very significant influence on surface roughness.
2. The variance inflation factor has a value of 1 for the independent and combined level of the input factors
3. The model had a coefficient of determination value of 93% for surface roughness.

6. CONCLUSION

5.1 Conclusion

The study has successfully developed a response surface model by using the design expert software to produce optimal sets of welding and machining experiments. optimal solutions were obtained for the surface roughness response.

Result of the study have shown that the nose radius and depth of cut has significant effect on the output responses. The RSM model possess satisfactory statistical indices making it a highly effective tool to optimize and predict the target responses.

5.2 Recommendation

Arising from the results of this study, the following recommendation are made for further studies. Further work on the use of other machine learning algorithm such as simulated adaptive neuro fuzzy inference system (ANFIS) and the fuzzy logic methods

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