Optimization And Prediction of Chip Thickness Profiles of Machined Heat Affected Zone Mild Steel Weld Using Genetic Algorithm

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Abstract- 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 genetic algorithm to optimizing and predicting chip thickness of machined affected zone of heat of mild steel weld. The design expert software was utilized to bring out a design matrix utilizing the class 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 speed of cutting, rate of feed, 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, contour plot and surface plot showed the interaction between the speed of cutting, rate of feed, and the chip thickness. The object produced have maximum strength and appropriate.

Indexed Terms- Chip thickness, Heat affected zone, Machined heat affected zone, Optimization, Prediction.

I. INTRODUCTION

1.1 Background to the Study

The finish of the surface of the machined parts is recognized to have acceptable impact on some features like wear resistance and strength of fatigue. 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. Research revealed that advanced numerical models can be utilized to demonstrate what is happening in this process. In this research study we will be developing mathematical models that can best explain and foretell the roughness of surface of a machined affected zone of heat of a tungsten inert gas welds.

II. LITERATURE REVIEW

Adnan et al, (2004) concentrated on the roughness of surface of abrasive water jet (AWJ) surfaces of cut. The study explained the impact of rate of feed and work piece thickness on the roughness. Considering impacts of the build of the object on roughness of surface, experimental data, were examined. The work also evaluated the deformation impact of AWJ on work pieces that have the same composition but different thickness. In the study pure aluminium, Al-6061 aluminium alloy, brass-353 (α+β brass), AISI 1030 and AISI 304 steel materials are cut with AWJ at different feed rates. Improvement in surface roughness of pure Aluminium remained in narrow limited range when compared with the ratio of decrease in feed rate. Experimental results explained "wear of cutting" and "wear deformation" mechanisms were impressive in the cutting of both the mild steel plus the fragile materials structure that have AWJ. The force of AWJ negatively impacts on the roughness of surface as well as the material thickness reduces. Brass and AISI1030 objects which contain maximum strength than Aluminium resulted in maximum roughness of surface for less thin work piece. Minimizing rate of feed from 20mm/min to 25mm/min minimized the properties of surface to 20mm of thickness work piece of AISI304, in comparison to other studied materials thickness.

Oraby and Hayhurst (2004) experimentally investigated tool life based on the measurement of wear and tool force ratio variation. Non-linear regression analysis methods were applied to build models life of tool determination and wear. The tool life determination was in aspects of the variations of force components acting at the tool tip ratio. It was emphasized that the methods of delineating failure and tool wear based on the utilization of databases plus interpolation with extrapolation methods as well as the utilization of clear mathematical correlations.

III. 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. method of data collection
4. method of data analysis

3.2 Research Design

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

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"

IV. RESULTS AND DISCUSSION

In this study, an attempt was made to build a second order mathematical relationship between some selected input variables, namely; cutting speed, feed rate, nose radius and depth of cut and two response variables, namely; surface roughness 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 (2n) 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 surface roughness response as presented in table 4.2

Table 4.3: Sequential sum of square for chip thickness

	Sum of		Mean	F	p-value	
Source	Squares	Df	Square	Value	Prob > F	
Mean vs Total	6.39	1	6.39			
Linear vs Mean	0.37	4	0.091	6.94	0.0007	
2FI vs Linear	0.21	6	0.036	5.84	0.0014	
Quadratic vs 2FI	0.11	4	0.027	66.47	< 0.0001	Suggested
Cubic vs Quadratic	5.646E-003	8	7.057E-004	9.34	0.0040	Aliased
Residual	5.291E-004	7	7.558E-005			
Total	7.09	30	0.24			

Table 4.5: Lack of fit test for chip thickness

	Sum of		Mean	F	p-value	
Source	Squares	Df	Square	Value	Prob > F	
Linear	0.33	20	0.016	8.83	0.0120	
2FI	0.12	14	8.259E-003	8.27	0.0145	
Quadratic	6.175E-003	10	6.175E-004	0.28	0.9570	Suggested

Cubic	5.291E-004	2	2.645E-004	0.26	0.7788	Aliased
Pure Error	0.000	5	0.000			

Table 4.7: Model summary statistics chip thickness

	Std.		Adjusted	Predicted		
Source	Dev.	R-Squared	R-Squared	R-Squared	PRESS	
Linear	0.11	0.5263	0.4505	0.2786	0.50	
2FI	0.078	0.8334	0.7458	0.7059	0.20	
Quadratic	0.020	0.9911	0.9828	0.9488	0.036	Suggested
Cubic	8.694E-003	0.9992	0.9968	0.8903	0.076	Aliased

Table 4.9: Generated for chip thickness

	Sum of		Mean	F	p-value	
Source	Squares	Df	Square	Value	Prob > F	
Model	0.69	14	0.049	119.38	< 0.0001	significant
A-cutting speed	1.320E-003	1	1.320E-003	3.21	0.0935	
B-Feed rate	1.602E-004	1	1.602E-004	0.39	0.5422	
C-Nose radius	0.057	1	0.057	139.50	< 0.0001	
D-depth of cut	0.31	1	0.31	744.42	< 0.0001	
AB	3.600E-003	1	3.600E-003	8.74	0.0098	
AC	0.043	1	0.043	103.58	< 0.0001	
AD	0.015	1	0.015	37.05	< 0.0001	
BC	0.13	1	0.13	312.20	< 0.0001	
BD	0.022	1	0.022	54.29	< 0.0001	
CD	8.410E-004	1	8.410E-004	2.04	0.1734	
A^2	7.430E-005	1	7.430E-005	0.18	0.6770	
B^2	7.430E-005	1	7.430E-005	0.18	0.6770	
C^2	9.156E-003	1	9.156E-003	22.24	0.0003	
D^2	0.10	1	0.10	251.15	< 0.0001	
Residual	6.175E-003	15	4.117E-004			
Lack of Fit	6.175E-003	10	6.175E-004			
Pure Error	0.000	5	0.000			
Cor Total	0.69	29				

Table 4.11: goodness of fit statistics for chip thickness

Std. Dev.	0.020	R-Squared	0.9911
Mean	0.46	Adj R-Squared	0.9828
C.V. %	4.40	Pred R-Squared	0.9488
PRESS	0.036	Adeq Precision	47.016

Table 4.13: Coefficient estimates statistics generated for chip thickness

	Coefficient		Standard	95% CI	95% CI	
Factor	Estimate	Df	Error	Low	High	VIF
Intercept	0.53	1	8.283E-003	0.51	0.55	
A-cutting speed	7.417E-003	1	4.142E-003	-1.411E-003	0.016	1.00
B-Feed rate	-2.583E-003	1	4.142E-003	-0.011	6.244E-003	1.00
C-Nose radius	0.049	1	4.142E-003	0.040	0.058	1.00
D-depth of cut	0.11	1	4.142E-003	0.10	0.12	1.00
AB	-0.015	1	5.072E-003	-0.026	-4.188E-003	1.00
AC	-0.052	1	5.072E-003	-0.062	-0.041	1.00
AD	0.031	1	5.072E-003	0.020	0.042	1.00
BC	-0.090	1	5.072E-003	-0.10	-0.079	1.00
BD	-0.037	1	5.072E-003	-0.048	-0.027	1.00
CD	-7.250E-003	1	5.072E-003	-0.018	3.562E-003	1.00
A^2	-1.646E-003	1	3.874E-003	-9.903E-003	6.612E-003	1.05
B^2	-1.646E-003	1	3.874E-003	-9.903E-003	6.612E-003	1.05
C^2	-0.018	1	3.874E-003	-0.027	-0.010	1.05
D^2	-0.061	1	3.874E-003	-0.070	-0.053	1.05

Table 4.17: Diagnostics case statistics report of observed versus predicted chip thickness

					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	0.100	0.11	-8.292E-003	0.583	-0.633	-0.620	-0.734	0.037	16
2	0.20	0.19	5.375E-003	0.583	0.410	0.399	0.472	0.016	7
3	0.38	0.39	-5.125E-003	0.583	-0.391	-0.380	-0.450	0.014	23
4	0.39	0.41	-0.023	0.583	-1.791	-1.952	* -2.31	0.299	29

5	0.50	0.50	-3.125E-003	0.583	-0.239	-0.231	-0.273	0.005	1
6	0.39	0.38	0.011	0.583	0.843	0.834	0.987	0.066	15
7	0.42	0.42	1.542E-003	0.583	0.118	0.114	0.135	0.001	17
8	0.27	0.24	0.022	0.583	1.658	1.772	* 2.10	0.256	30
9	0.33	0.36	-0.030	0.583	-2.275	-2.715	* -3.21	0.483	2
10	0.56	0.57	-6.625E-003	0.583	-0.506	-0.493	-0.583	0.024	14
11	0.47	0.49	-0.016	0.583	-1.231	-1.255	-1.484	0.141	22
12	0.64	0.64	-4.958E-003	0.583	-0.379	-0.368	-0.435	0.013	26
13	0.75	0.73	0.018	0.583	1.403	1.454	1.721	0.184	10
14	0.73	0.73	-2.958E-003	0.583	-0.226	-0.219	-0.259	0.005	9
15	0.48	0.50	-0.013	0.583	-1.028	-1.030	-1.218	0.099	21
16	0.45	0.44	3.208E-003	0.583	0.245	0.237	0.281	0.006	28
17	0.53	0.51	0.021	0.583	1.635	1.743	* 2.06	0.250	8
18	0.53	0.54	-8.250E-003	0.583	-0.630	-0.617	-0.730	0.037	5
19	0.53	0.53	1.417E-003	0.583	0.108	0.105	0.124	0.001	27
20	0.53	0.52	0.012	0.583	0.897	0.891	1.054	0.075	20
21	0.40	0.36	0.038	0.583	2.895	** 4.21	* 4.98	0.782	3
22	0.53	0.55	-0.025	0.583	-1.890	-2.092	* -2.47	0.333	24
23	0.050	0.056	-6.417E-003	0.583	-0.490	-0.477	-0.565	0.022	19
24	0.53	0.51	0.020	0.583	1.495	1.566	1.853	0.209	12
25	0.53	0.53	0.000	0.167	0.000	0.000	0.000	0.000	13
26	0.53	0.53	0.000	0.167	0.000	0.000	0.000	0.000	6
27	0.53	0.53	0.000	0.167	0.000	0.000	0.000	0.000	25
28	0.53	0.53	0.000	0.167	0.000	0.000	0.000	0.000	18
29	0.53	0.53	0.000	0.167	0.000	0.000	0.000	0.000	4
30	0.53	0.53	0.000	0.167	0.000	0.000	0.000	0.000	11

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

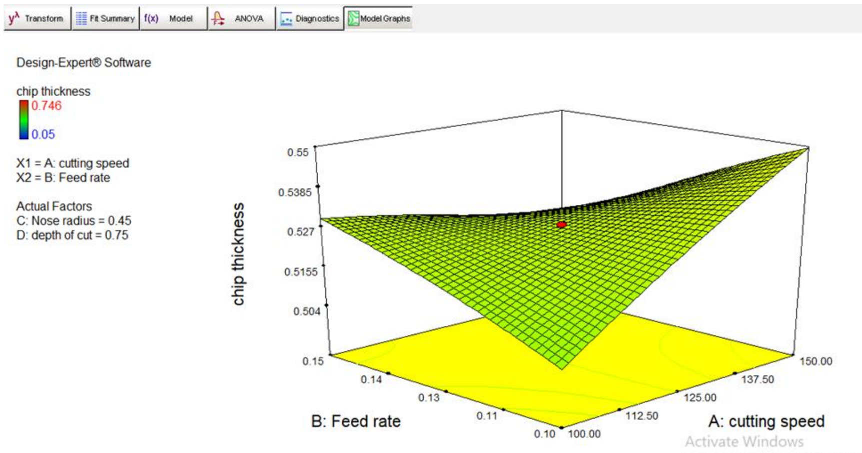

Table: G.A optimal solution for surface roughness and chip thickness

Cutting speed	Feed rate	Nose radius	Depth of cut	Surface roughness	Chip thickness
149.94	0.10	0.30	0.53	0.0719	0.230
150.00	0.11	0.30	0.50	0.0909	0.224
146.60	0.10	0.36	0.50	0.1103	0.237
100.43	0.10	0.30	0.56	0.1705	0.169
100.66	0.10	0.35	0.50	0.1818	0.187
150.00	0.14	0.60	0.50	0.2033	0.279
150.00	0.10	0.48	0.50	0.1724	0.328
144.61	0.14	0.60	0.50	0.2173	0.291
149.99	0.11	0.46	0.50	0.1937	0.319
149.98	0.10	0.51	0.50	0.1749	0.342
150.00	0.11	0.60	0.50	0.1800	0.344
150.00	0.13	0.30	0.50	0.2214	0.309
143.39	0.10	0.60	0.50	0.1737	0.399
100.00	0.10	0.30	0.85	0.2931	0.338
100.45	0.10	0.30	0.92	0.3037	0.356
150.00	0.15	0.60	0.78	0.2970	0.415
100.00	0.13	0.30	1.00	0.2853	0.434
150.00	0.15	0.60	0.82	0.3018	0.428
100.00	0.15	0.30	1.00	0.2519	0.490
100.02	0.15	0.60	1.00	0.2575	0.503

V. DISCUSSION

In this work, the genetic algorithm was used for optimizing and predicting surface roughness, and chip thickness. The input parameters are speed of cutting, rate of feed, nose radius, depth of cut, while the responses are roughness of surface, and chip thickness. 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 radius nose and cutting depth has a significant effect of the chip thickness with P-value of 0.00001 and 99% coefficient of determination.

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The study has successfully built a genetic algorithm model by using the design expert software to produce optimal sets of welding and machining experiments. optimal solutions were obtained for the chip thickness and surface roughness responses.

Result of the study have shown that the radius of nose and cutting depth has significant effect on the output responses.

5.2 Recommendation

Arising from the results of this study the following recommendation are made for further studies.

1. Further work on the utilization of other machine learning algorithm such as simulated adaptive neuro fuzzy inference system (ANFIS) and the fuzzy logic methods

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