IJRIET

OPTIMIZATION OF MACHINING PARAMETERS FOR ECM USING GREY RELATIONAL ANALAYSIS

Azhagu Shankar.S.S[1], Meinathan.S[2], Mayilsamy.P[3], Balakrishnan.G[4]

[1]Assistant professor, Dept.of Mechanical Engg, Shree Venkateshwara Hi-Tech Engg.College, Gobi, Tamilnadu, India

[2]Assistant professor, Dept.of Mechanical Engg, Shree Venkateshwara Hi-Tech Engg.College, Gobi, Tamilnadu, India

[3]Assistant professor, Dept.of Mechanical Engg, Shree Venkateshwara Hi-Tech Engg.College, Gobi, Tamilnadu, India

[4]Assistant professor, Dept.of Mechanical Engg, Shree Venkateshwara Hi-Tech Engg.College, Gobi, Tamilnadu, India

E-mail-ID: [1]azhagushankarss@gmail.com, [2]s.meinathan@gmail.com, [3]mayilsvhec@ gmail.com, [4]balakrishnanmech1989@ gmail.com

Received 23 February 2016, Revised 03 March 2016, Accepted 04 March 2016
Available online 14 March 2016

Abstract

The use of Electrochemical Machining (ECM) as one of the best machining techniques for machining and electrically conducting tough and difficult to machine materials with appropriate machining parameters. In recent years, the utilization of titanium and its alloys, especially grade 2 materials in many different engineering fields has undergone a tremendous increase. The ECM process has a potential in the machining of grade 2. This work describes the development of the second order, non-linear mathematical model without interaction terms for establishing the relationship between machining parameters, such as electrolyte concentration, current, applied voltage and feed rate, with the dominant machining process criteria, namely the material removal rate (MRR) and surface roughness (SR). In this paper, an attempt has been made to machine the grade 2 material (LM6 Al/B2C) using the ECM process. The effects of various process/product parameters like applied voltage, feed rate, electrolyte concentration and percentage of reinforcement on the Material Removal Rate (MRR), surface roughness (SR) were observed. Multiple Regression models are developed based on Grey relational analysis using the relevant experimental data, which are obtained during an ECM operation on grade 2. Validity and creativeness of the developed mathematical models have also been tested through analysis of variance. Graphs, describing the direct effects of process variables on the responses, were plotted. The Optimal combination of these predominant machining process parameters is obtained from these mathematical models considering MRR and SR simultaneously for higher material removal rate and lower surface roughness value. The confirmation results reveal that, there is considerable improvement in Material Removal Rate, Grey relational grade are improved by 08.33 %, 41.17 % and 81.77 % respectively. It is observed that the machining performance can be effectively improved with respect to initial parametric setting. A statistical technique, fractional factorial experiments and analysis of variance (ANOVA), has been employed to investigate the influence of cutting parameters.

Keywords*:* ECM, GRA, Regression Model, ANOVA.

1. INTRODUCTION

In electrochemical machining, the metal is removed by the anodic dissolution in an electrolytic cell in which work piece is the anode and the tool is the cathode. The electrolyte is pumped through the gap between the work piece and the tool, while direct current is passed through the cell, to dissolve metal from the work piece. Ruszaj and Zybura-skrabalak developed a mathematical model for ECM utilizing a flat ended universal electrode.

The first introduction of ECM in 1929 by Gusseff, its industrial applications have been extended to electrochemical drilling, electrochemical deburring, electrochemical grinding and electrochemical polishing. The technique was applied in several ways as a machining technique in the 60's and 70's. Non-conventional machining processes, e.g. ECM, EDM, LBM and ultrasonic machining etc., have already been utilized for machining. EDM and LBM are thermal processes; therefore they cause the formation, however do not produce thermal or mechanical stresses on the work piece materials and they have versatility that they can machine any kind of material. They have also additional advantages, such as they leave no heat-effect layer and produce no tool wear. The machining performance in ECM is governed by the anodic behavior of the workpiece material in a given electrolyte. Hence ECM on the other hand appears to be very promising technique since in many areas of application it offers several advantages that include higher machining rate, better precision and controlled removal, and also a range of materials that can be machined. In ECM it is important to select machining parameters for achieving machining performance. Usually the desired machining parameters are determined based on experience or hand book values. However, this does not ensure that the selected machining parameters result in optimal or near optimal machining performance for that ECM and environment. Detailed analysis of cutting involves certain costs, particularly in case of small series. In case of individual machining it is particularly necessary to shorten as much as possible the procedures of determination of the optimal cutting parameters, otherwise the cost analysis might exceed the economic efficiency which could be reached if working with optimum conditions. In optimization of machining operations the quantitative methods have been developed with considerations of a single objective only, minimization of the cost or maximization of profit etc. In the process of single objective optimization several different techniques have been proposed, such as the differential calculus, regression analysis, linear programming, geometric, stochastic programming and computer simulation. While most hitherto researches are based on the single objective optimization, there have been some successful attempts also with the multi-objective optimization. Moreover, also the authors used ANN for the prediction of ECM process parameters. The output of the NN contains two outputs, such as MRR and SR, whereas the input layer is provided with three inputs, namely applied voltage, feed rate and electrolyte flow rate. Fuzzy logic had also been used by Ramarao et al. to model the ECM process with voltage, current, electrolyte flow rate and the gap between the electrodes as inputs and MRR and SR outputs.

2. EXPERIMENTAL WORK

2.1 Materials and Process

The base material used in the present work is LM6 which is an aluminum-silicon alloy containing 11 to 13% of silicon. The details of the LM6 chemical composition. In order to obtain different composition, B4C particles of 30microns size were added to the aluminum matrix in the proportion of 2.5%, 5% and 7.5% by weight.

In this study an attempt is made to establish the input-output relationship of electrochemical machining (ECM) of aluminium metal matrix composites. It is important to note that selection of the range of operating parameters is an important consideration. A pilot study has been conducted to determine the appropriate working range of the parameters.

Al	Cu	Mg	Si	Fe	Mn	Ni	Zn	Pb	Sn	Ti
87.7	0.08	0.1	11.2	0.46	0.14	0.01	0.01	0.01	0.01	0.16

Table: 1 Chemical Composition of Al- Si Alloy

2.2 Experimental Plan

Parameters	Levels				
	-2	-1	0	1	2
Electrolyte concentration (X_1) gm/lit	200	300	400	500	600
Current (X2) amps	220	240	260	280	300
Applied voltage (X3) volts	16	17	18	19	20
Feed rate (X4) mm/min	0.2	0.4	0.6	0.8	1

Table: 2 Experimental Parameters and their levels

The observation of the machining process is based on Second Order Central Composite Rotatable design [8,9]. A total of four machining parameters (Electrolyte concentration, current, applied voltage and feed rate) were chosen. The machining results after ECM process are evaluated based on two machining performances, metal removal rate (mg/min) and surface roughness (µm). The experimental parameters & their levels and observation

3. GREY RELATIONAL ANALYSIS

The grey system theory initiated by Deng in 1982 has been proven to be useful for dealing with poor, incomplete, and uncertain information [10]. The grey relation analysis based on the grey system theory can be used to solve the complicated interrelationships among the multiple performance characteristics effectively.

The following steps to be followed while applying grey relational analysis.

S. No.	Normalized values for MRR	Normalized values for SR	GRC values for MRR	GRC values for SR	Grade
1	0.6909	1	0.4198	0.3333	0.3765
2	0.6181	0.9473	0.4471	0.3454	0.3962
3	0.5545	0.9210	0.4741	0.3518	0.4129
4	0.5	0.9342	0.5	0.3485	0.4242
5	0.3636	0.9078	0.5789	0.3551	0.467
6	0.3090	0.9868	0.6180	0.3362	0.4771
7	0.0727	0.9736	0.8730	0.3393	0.6061
8	0.9727	0.8947	0.3395	0.3585	0.349
9	0.8090	0.7105	0.3819	0.4130	0.3974
10	0.9091	0.6578	0.3548	0.4318	0.3933

11	0.6636	0.6973	0.4297	0.4176	0.4236
12	0.6	0.6842	0.4545	0.4222	0.4383
13	0.5818	0.7894	0.4621	0.3877	0.4249
14	0.5363	0.8421	0.4824	0.3725	0.4274
15	0.2636	0.6578	0.6547	0.4318	0.5432
16	0.2727	0.6710	0.6470	0.4269	0.5369
17	0.9090	0.5789	0.3548	0.4634	0.4091
18	0.6090	0.5921	0.4508	0.4578	0.4543
19	0.5272	0.5263	0.4867	0.4871	0.4869
20	0.3636	0.3815	0.5789	0.5672	0.5730
21	1	0.3684	0.3333	0.5757	0.4545
22	0	0.3157	1	0.6129	0.8064
23	0.6363	0.3421	0.4400	0.5937	0.5168
24	0.5545	0.2894	0.4741	0.6333	0.5537
25	0.2454	0.2631	0.6707	0.6552	0.6629
26	0.2727	0.1184	0.6470	0.8085	0.7277
27	0.3	0.1184	0.625	0.8085	0.7167
28	0.390	0.1315	0.6179	0.7917	0.7048
29	0.3272	0.1052	0.6044	0.8261	0.7152
30	0.4181	0.0526	0.5446	0.9048	0.7247
31	0.3181	0	0.6111	1	0.8055

Table: 4 Grey relational coefficients and the GRG

S. No	Electrolyte Concentration (gm/lit)	Current (amps)	Applied voltage (volts)	Feed Rate (mm/min)	Grade
1	400	260	20	0.6	0.8064
2	400	260	18	0.2	0.5168
3	400	260	18	1	0.5537
4	400	260	18	0.6	0.6629
5	400	260	18	0.6	0.7277

SI. No	Electrolyte Concentration (gm/lit)	Current (amps)	Applied voltage (volts)	Feed Rate (mm/min)	Grade
1	300	240	17	0.4	0.3765
2	500	240	17	0.4	0.3962
3	300	280	17	0.4	0.4129
4	500	280	17	0.4	0.4242
5	300	240	19	0.4	0.467
6	500	240	19	0.4	0.4771
7	300	280	19	0.4	0.6061
8	500	280	19	0.4	0.349
9	300	240	17	0.8	0.3974
10	500	240	17	0.8	0.3933
11	300	280	17	0.8	0.4236
12	500	280	17	0.8	0.4383
13	300	240	19	0.8	0.4249
14	500	240	19	0.8	0.4274
15	300	280	19	0.8	0.5432

16	500	280	19	0.8	0.5369
17	200	260	18	0.6	0.4091
18	600	260	18	0.6	0.4543
19	400	220	18	0.6	0.4869
20	400	300	18	0.6	0.5730
21	400	260	16	0.6	0.4545

Table: 5 Training Data with experimental grade

4. MODEL DEVELOPMENT

In order to predict the behavior of grey relational grade, two approaches have been developed to map [11] the relationship between process parameters and output responses using multiple regression models. The process parameters, electrolyte concentration (X1), current (X2), applied voltage (X3), and feed rate(X4), are considered as independent variables and the grey grade as dependant variables

4.1 Multiple Regression Models

Multiple regression methods are used to analyze data from unplanned experiments, such as might arise from the observation of uncontrolled phenomena or historical data. Regression methods are also very useful in designed experiments where something has "gone wrong". The general purpose of multiple regressions is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The following two models have developed to analyze the process variable in ECM process.

- ✓ Model – I: Linear model excluding interaction terms.
- ✓ Model – II: Transformation of exponential model excluding interaction terms.

4.2 Model – I

This model is a linear multiple regression model without considering interaction terms. A multiple regression model using independent variables C, V, F and G and dependent variable grade can be represented as.

Grade = bo +b1 V + b2 V + b3F + b4 G + e

Grade = -0.720 -0.000050 X1 + 0.00114 X2 + 0.0530 X3 + 0.031 X4

SI.No	Experimental Grade	Predicted Grade	Percentage deviation
1	0.3765	0.452	16.68
2	0.3962	0.442	10.34
3	0.4129	0.4976	17.00
4	0.4242	0.4876	12.98
5	0.467	0.558	16.31
6	0.4771	0.548	12.94
7	0.6061	0.6036	0.43
8	0.349	0.5936	41.21
9	0.3974	0.4644	14.41
10	0.3933	0.4544	13.45
11	0.4236	0.51	16.92
12	0.4383	0.5	12.34
13	0.4249	0.5704	25.51
14	0.4274	0.5604	23.72
15	0.5432	0.616	11.82
16	0.5369	0.606	11.34
17	0.4091	0.539	24.1
18	0.4543	0.519	12.47
19	0.4869	0.4834	0.72
20	0.5730	0.5746	0.26
21	0.4545	0.423	7.47
Average percentage deviation			14.41

Table: 6 Percentage Deviations between EG and Predicted Grade values of multiple regression Model I of Train Data

SI. No	Experimental Grade	Predicted Grade	Percentage deviation
1	0.8064	0.635	21.26

2	0.5168	0.5166	0.058
3	0.5537	0.5414	2.221
4	0.6629	0.529	20.19
5	0.7277	0.529	27.31
6	0.7167	0.529	26.91
7	0.7048	0.529	24.94
8	0.7152	0.529	26.03
9	0.7247	0.529	27.00
10	0.8055	0.529	34.33
Average percentage deviation			20.95

Table: 7 Percentage Deviations between EG and Predicted Grade values of multiple regression Model I of Test Data

4.3 Annova for Model – I

The purpose of the ANOVA is to investigate the significance of training and test data sets. This is accomplished by separating the total variability of the percentage deviation between training and test data. The F-test is used to determine the significance between training and test data. The results of ANOVA (Table 4.3) indicate that there is no significant difference between training and test data. Hence this multiple regression model can be used as a Prediction model.

Source of variability	Sum of squares	Degrees of freedom	Mean square	F-ratio
Percentage Deviation	289.02	1	289.02	2.96
Error	2835.89	29	97.79	
Total	3124.91	30		

Table: 8 ANOVA for Model – I

4.4 Model II – Transformation of Exponenetial Model Excluding Interaction

This model is an exponential model with logarithmic transformed variables and the interaction terms are not considered. The functional relational ship between grade and Independent variables could be represented by.

$$\text{Grade} = \text{bo } X1_a\, X2_b\, X3_c\, X4_d$$

$$\ln \text{Grade} = -9.53 + 0.047 \ln X_1 + 0.630 \ln X_2 + 1.77 \ln X_3 + 0.076 \ln X_4$$

SI.No	Experimental Grade	Predicted Grade	Percentage deviation
1	-0.9766	-0.8639	13.03
2	-0.9256	-0.8399	10.19
3	-0.8843	-0.7669	15.31
4	-0.8573	-0.7428	15.41
5	-0.7614	-0.6671	14.14
6	-0.7400	-0.6430	15.07
7	-0.5006	-0.5699	12.18
8	-1.0527	-0.5459	92.81
9	-0.9226	-0.8113	13.72
10	-0.9332	-0.7872	18.53
11	-0.8588	-0.7142	20.24
12	-0.8249	-0.6902	19.51
13	-0.8559	-0.6144	39.30
14	-0.8498	-0.5904	43.93
15	-0.6101	-0.5173	17.94
16	-0.6218	-0.4932	26.04
17	-0.8938	-0.7006	27.57
18	-0.7890	-0.6489	21.56
19	-0.7197	-0.7732	6.93
20	-0.5567	-0.5779	3.67
21	-0.7883	-0.8765	10.06
Average percentage deviation			22.36

Table: 9 Percentage Deviation between EG and Predicted Grade Values of multiple regression Model II of Train Data

S.No	Experimental Grade	Predicted Grade	Percentage deviation
1	-0.2151	-0.4815	55.34
2	-0.6599	-0.7515	12.19
3	-0.5911	-0.6292	6.05
4	-0.4111	-0.6680	38.46
5	-0.3187	-0.6680	52.29
6	-0.3329	-0.6680	50.16
7	-0.3499	-0.6680	47.63
8	-0.3352	-0.6680	49.82
9	-0.3220	-0.6680	51.79
10	-0.2162	-0.6680	67.64
Average percentage deviation			40.13

Table: 10 Percentage Deviation between EG and Predicted Grade Values of multiple regressions Model II of Test Data

4.5 Annova for Model – II

The ANOVA is performed on the percentage deviations between training and test data sets. The results of ANOVA are shown in Table 12. From this, it is clear that there is no significant difference between train data and test data. Hence the model-II can also be used as a prediction model.

Source of variability	Sum of squares	Degrees of freedom	Mean square	F-ratio
Percentage Deviation	3538.186	1	3538.186	10.16
Error	10099.304	29	348.252	
Total	13637.49	30		

Table: 11 ANOVA for Model- II

The predicted values are calculated by using the developed regression equation and the percentage deviation is computed between the experimental grade and Predicted grade of both train data and test data of model I & II.

5. COMPARISON OF RESULTS

The percentage deviation between model I & II is compared. While examining the percentage deviation of both multiple regression models, it is found that model I has less percentage deviation. So that optimal parameters are selected based on the test data of model II. The figures 1 and 2 show the difference between experimental grade and predicted grade values for multiple regression models of test data.

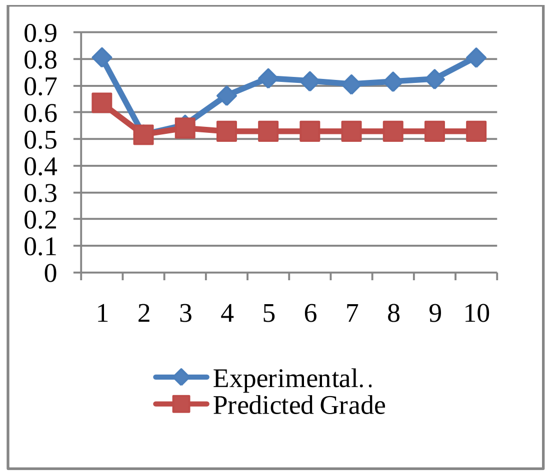

Figure: 1 Experimental Grade Vs Predicted grade values of Model I of Test Data

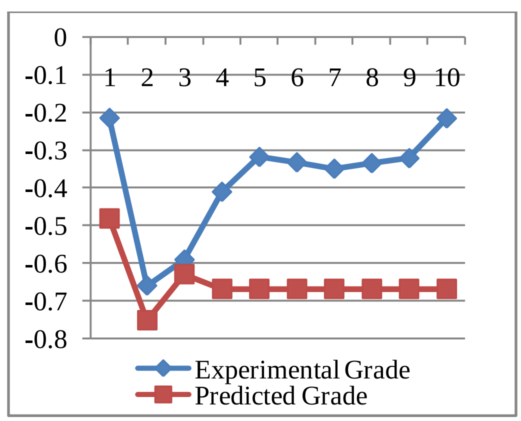

Figure: 2 Experimental Grade Vs Predicted grade values ofModel II of Test Data

	Training	Test
Model I	14.41	20.95
Model II	22.36	40.13

Table: 12 Percentage deviations between EG and predicted Grade Values of multiple regression Model I & II of Test data

5.1 Selection of Optimal Parameters

In this experiment four factors (electrolyte concentration, current, applied voltage and feed rate) are considered at different levels. Based on the testing results of the model I shown in Table 13 response table for predicted grey was formulated to find the influence of experimental factors. The higher grey relational implies the better response. Table 14 shows the mean effect response for the test data of model I. it is found that applied voltage is the most influencing factor for the test data. The optimal machining parameter levels for maximizing material removal rate and minimizing surface roughness can be given as electrolyte concentration at 400 gm/lit, current at 260 amps, applied voltage at 16V and feed rate 0.6mm/min.

Factor	Levels			Max.-Min.
	1	2	3	
Electrolyte concentration	0.5859	--	--	0.5859
Current	0.5859	--	--	0.5859
Applied Voltage	0.9876	0.2767	0.5743	0.7109
Feed rate	0.1262	0.6685	0.3844	0.5423

Table: 13 Results of the response performance indicating the optimal settings

6. CONCLUSION

In this paper a practical method has been carried out to optimize the electro chemical machining parameters for Titanium Alloy (Grade 2) based on multiple regression models. Grey relational analysis is also used to find the grade for optimal machining parameters from different levels by combining the multi-response characteristics like material removal rate and surface roughness. Linear regression model excluding interaction terms were developed by using the grey relational grade values of these models, model I has been selected to determine the optimal operating parameters of ECM. Higher the grade value will give the better response. This methodology is time saving, cost effective and precise in determining the machining parameters.

References

[1] N.K. Jain and V. K. Jain "Optimization of electrochemical Machining Process parameters Using Genetic Algorithms", DOI: 10.1080/10910340701350108.

[2] http://www.mtu.de/de/technologies/manufacturing_processes/electrochemical_removal/elektochem_abtragen_2.jpg

[3] http://www.electrochemicalmachining.com/wpcontent/themes/ecm/images/home-1.png.

[4] Ruszaj M, Zybura-Skrabalak M, 2001, J Mater Process Technol, 109: 333-338

[5] Hocheng H, Kao PS, Lin SC, 2005, Int J of Adv Manuf Technolo, 25: 1105-1112

[6] Ravikumar R, Ashokan P, Singh PN, 2008, J Manuf Eng, 3(2): 104-114.

[7] Davidson, M. J., Balasubramanian, K., and Tagore, G. R. N. 2008. Surface roughness prediction of flow-formed AA6061 alloy by design of experiments. Journal of Materials Processing Technology, 202: 41-46.

[8] Sorkhel, S. K. and Bhattacharya, B. 1992. Parametric combinations for controlled machined rate and surface quality in electrochemical machining. In proceedings of the 15th All India machine tool design and research conference, 421-426.

[9] Yang, W. H. and Tarng, Y. S. 1998. Design optimization of cutting parameters for turning operations based on the Taguchi method. Journal

of Materials Processing Technology, 84: 122-129

[10] Fortana, M. G. 1986. "Corrosion Engineering". McGraw-Hill, New York.P. C. Gope, "Machine Design, Fundamentals and Application", Published by PHI Learning Private Limited, pp 989-999 (1999)

A Brief Author Biography

S.S. Azhagu Shankar – M.E., Asst. Professor, Mechanical Engineering Department, Shree Venkateshwara Hi-Tech Engineering College, Erode.

S. Meinathan – M.E., Asst. Professor, Mechanical Engineering Department, Shree Venkateshwara Hi-Tech Engineering College, Erode.

P.Mayilsamy – M.E., Asst. Professor, Mechanical Engineering Department, Shree Venkateshwara Hi-Tech Engineering College, Erode.

G.BalaKrishan – M.E., Asst. Professor, Mechanical Engineering Department, Shree Venkateshwara Hi-Tech Engineering College, Erode.