Multi-Objective Optimization of Electrochemical machining of EN31 steel by Grey Relational Analysis

D. Chakradhar, A. Venu Gopal

***Abstract*—Electrochemical machining is one of the widely used non-traditional machining processes to machine complicated shapes for electrically conducting but difficult-to-machine materials such as superalloys, Ti-alloys, alloy steel, tool steel, stainless steel, etc. Use of optimal ECM process parameters can significantly reduce the ECM operating, tooling, and maintenance cost and will produce components of higher accuracy. This paper investigates the effect and parametric optimization of process parameters for Electrochemical machining of EN-31 steel using grey relation analysis. The process parameters considered are electrolyte concentration, feed rate and applied voltage and are optimized with considerations of multiple performance characteristics including material removal rate, overcut, cylindricity error and surface roughness. Analysis of variance is performed to get contribution of each parameter on the performance characteristics and it was observed that feed rate is the significant process parameter that affects the ECM robustness. The experimental results for the optimal setting show that there is considerable improvement in the process. The application of this technique converts the multi response variable to a single response Grey relational grade and, therefore, simplifies the optimization procedure.**

***Index Terms*—Electrochemical machining; Grey relation analysis; Material removal rate; overcut; Cylindricity error.**

I. INTRODUCTION

Electrochemical machining (ECM) is one of the important non-traditional machining processes in the present manufacturing industry to machine difficult to cut, high strength and heat resistant materials into complex shapes. Electrical current passes through an electrolyte solution between a cathode (tool) and an anode (workpiece). The workpiece is eroded in accordance with Faraday's law of electrolysis. Its industrial applications have been extended to electrochemical drilling, electrochemical deburring, electrochemical grinding and electrochemical polishing [1].

The electrolyte flows between the electrodes and carries away the dissolved metal. In this process, a low voltage (5-25V) is applied across two electrodes with a small gap size (0.2 mm – 0.5 mm) and with a high current density around 2000 A/cm^2. Electrolytes are either acids or more generally basic salts dissolved in water. Typically NaCl or $NaNO_3$ is supplied to flow through the gap with a velocity of 20-30 m/s. ECM generates no burrs, no stress, and has a long tool life, high material removal rate and good surface quality. The only restriction imposed, is that it must be sufficiently good conductor of electricity. Further, the tool material may have any strength irrespective of the strength of the workpiece which may be very high. The low temperature during the operation does not cause any thermal damage to the work piece. ECM process originally designed for manufacturing complex shaped components in defense and aerospace industries has been extended to many other industries such as automotive, forging dies, electric and surgical components [2].

The optimization of process parameters is essential for the achievement of high responsiveness of production, which is the preliminary basis for survival in today's dynamic market conditions. Due to the complexity of the electrochemical machining process it is very difficult to determine the optimal machining parameters for improving the output quality. Optimal quality of the workpiece in ECM can be generated through combinational control of various process parameters [3]. The various process parameters in electrochemical machining are electrolyte concentration, voltage, feed rate, inter-electrode gap and electrolyte feed rate. The selection of proper process parameters for electrochemical machining process is crucial to have the efficient and high quality output. Due to the complexity of electrochemical machining process it is very difficult to determine optimal machining parameters for improving the output quality. To select the process parameters properly, several researchers developed mathematical models based on statistical regression techniques or neural computing to establish the relationship between the machining performance and the machining parameters. Particle swarm optimization algorithm has been used to optimize electrochemical machining parameters like tool feed rate, electrolyte flow velocity and the applied voltage in order to improve dimensional accuracy, material removal rate and machining cost [4]. Multi-objective optimization of current, voltage, feed rate and gap was done for improving material removal rate and surface roughness using multiple regression models and artificial neural networks [5]. Mathematical models were developed for correlating the influences of various machining parameters on

number of experiments have to be performed and analyzed in order to build the mathematical models. Thus the required model building is very costly in terms of time and materials.

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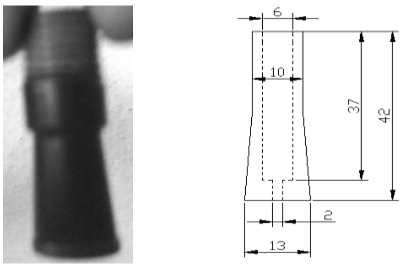
In this paper an attempt has been made to optimize the process parameters like electrolyte concentration, feed rate and applied voltage considering the multiple characteristics including material removal rate, overcut, cylindricity error and surface roughness by using Grey relation analysis. The grey relational theory provides an efficient management upon the uncertainty, multi-input and discrete data. On the other hand, the grey relational analysis reveals the necessary information of the interactions among parameters. It provides a solution of a system in which the model is unsure or the information is incomplete. It also provides an efficient solution to the uncertainty, multi-input and discrete data problem. The relation between machining parameters and performance can be found out with the Grey relational analysis [7]. Confirmation tests were conducted to check the validation of optimal process parameters.

II. Experimental Procedure

A. Experimental setup

Experiments were conducted on the Metatech (ECMAC) made Electrochemical machining equipment which is shown in Fig. 1. The ECM setup consists of machining chamber, control panel, electrolyte circulation system. The workpiece is fixed inside the machining chamber and the cathode (tool) is attached to the main screw which is driven by a stepper motor. For avoiding short-circuits, a current sensing circuit is interfaced between the tool and the stepper motor controller circuit. If the current exceeds an acceptable limit, a signal is sent to the stepper motor controller circuit which immediately reverses the downward motion of the tool. The process parameters like current, voltage and feed rate are varied by the control panel. The electrolyte is pneumatically pumped through a reservoir.

Figure 1: Electrochemical Machining setup



(a) (b)

Figure 2: (a) Copper electrode with epoxy coating (b) Dimensions of the tool

B. Selection of work piece and tool materials

Cylindrical block of 100 mm diameter and 25 mm height made of EN-31 steel which is a high carbon alloy steel with high degree of hardness with compressive strength and abrasion resistance is chosen as workpiece. It is popularly used in automotive type applications like axle, bearings, spindle and molding dies etc.

The electrolytic copper whose dimensions are shown in Fig. 2 was used as electrode. To avoid machining due to stray current, the tool was coated with a layer of 200 μm with epoxy powder resin, except for the base of the tool which will be the machining area. Electrolyte was axially fed to the machining zone through a hole provided centrally in the tool. NaCl solution was chosen as electrolyte, as it has no passivation effect [8].

C. Selection of the machining parameters and their levels

In this study, the experimental plan has three controllable variables, namely, electrolyte concentration, feed rate and applied voltage. On the basis of preliminary experiments conducted by using one variable at a time approach, the feasible range for the machining parameters was defined by varying the electrolyte concentration 10 – 30 %, feed rate 0.1 – 0.32 mm/min and voltage 10-30 V. In the machining parameter design, three levels of the cutting parameters were selected, shown in Table 1.

TABLE 1. Electrochemical machining process parameters

	Process parameter	***Level 1***	***Level 2***	***Level 3***
A	Electrolyte conc. (%)	10	15	20
B	Feed rate (mm/min)	0.10	0.21	0.32
C	Voltage (V)	10	15	20

TABLE2. Experimental layout using L9 orthogonal array

Exp No.	**A Electrolyte conc. (%)**	**B Feed rate (mm/min)**	**C Voltage (V)**
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

D. Design of experiments

The application of design-of-experiments (DoE) requires careful planning, prudent layout of the experiment, and expert analysis of results. Taguchi has standardized methods for each of these DoE application steps.

The experiment includes three process parameters electrolyte concentration, feed rate and voltage. In the present study, there are six degrees of freedom owing to the three-level polishing parameters, while the interaction between the parameters is neglected. Once the degrees of freedom are known, the next step is to select an appropriate orthogonal array. The degrees of freedom for the orthogonal array should be greater than or at least equal to those of the process parameters. In this study, an L9 orthogonal array is used because it has eight degrees of freedom in the polishing parameters. Each process parameter is assigned to a column and nine polishing parameters. There are hence nine experiments needed to study the entire process parameter space by using the L9 orthogonal array. The experimental layout for the process parameters is shown in Table 2.

TABLE3.EXPERIMENTAL RESULTS

Exp. No.	MRR (g/min)	Overcut (mm)	Cylindrity error(mm)	Surface roughness (μm)
1	0.141	1.345	0.546	0.37
2	0.315	0.821	0.388	0.43
3	0.600	0.566	0.233	0.36
4	0.257	0.491	0.473	0.24
5	0.407	1.096	0.168	0.32
6	0.393	0.641	0.202	0.31
7	0.317	0.941	0.402	0.22
8	0.272	1.088	0.249	0.31
9	0.496	0.420	0.322	0.27

III. GREY RELATIONAL ANALYSIS

A. Multi response optimization using orthogonal array with Grey relational analysis

Taguchi method is designed to optimize single response characteristic. The higher-the-better performance for one factor may affect the performance because another factor may demand lower-the-better characteristics. Hence, multi-response optimization characteristics are complex. In this section, the use of orthogonal array with the Grey relational analysis optimization methodology for multi-response optimization is discussed.

The optimization of the process was performed in the following steps:

1) Normalizing the experimental results of material removal rate, overcut and surface roughness.
2) Performing the Grey relational generating and to calculate the Grey relational coefficient.
3) Calculating the Grey relational grade by averaging the Grey relational coefficient.
4) Performing statistical analysis of variance (ANOVA) for the input parameters with the Grey relational grade and to find which parameter significantly affects the process.
5) Selecting the optimal levels of process parameters.
6) Conducting confirmation experiment and verify the optimal process parameters setting.

In Grey relational analysis [9], the complex multiple response optimizations can be simplified into the optimization of a single response Grey relational grade.

B. Grey relation generation

In the grey relational analysis, when the range of the sequence is large or the standard value is enormous, the function of factors is neglected. However, if the factors goals and directions are different, the grey relational analysis might also produce incorrect results. Therefore, one has to preprocess the data which are related to a group of sequences, which is called "grey theory relational generation" [10].

TABLE4.PREPROCESSED DATA RESULTS

No.	MRR	Overcut	Cylindricity error	Surface roughness
1	0	0	0	0.285
2	0.379	0.566	0.417	0
3	1	0.824	0.828	0.380
4	0.252	0.923	0.193	0.904
5	0.579	0.269	1	0.523
6	0.549	0.761	0.910	0.571
7	0.383	0.436	0.380	1
8	0.285	0.277	0.785	0.476
9	0.773	1	0.592	0.762

TABLE 5.GREY RETIONAL COEFFICIENT OF EACH PERFORMANCE CHARACTERISTIC

No.	MRR	Overcut	Cylindricity error	Surface roughness
Ideal	1	1	1	1
1	0.5	0.5	0.5	0.583
2	0.616	0.697	0.631	0.5
3	1	0.850	0.853	0.616
4	0.572	0.928	0.553	0.918
5	0.703	0.577	1	0.662
6	0.689	0.807	0.917	0.701
7	0.618	0.639	0.617	1
8	0.583	0.580	0.823	0.626
9	0.814	1	0.710	0.806

For higher-the-better quality characteristics data preprocessing is calculated by:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \quad (1)$$

For lower-the-better quality characteristics data preprocessing is calculated by:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \quad (2)$$

where $x_i(k)$ is the value after grey relation generation, $\min y_i(k)$ is the smallest value of $y_i(k)$ and $\max y_i(k)$ is the largest value of $y_i(k)$ for the k^th response.

C. Grey relational grade

In the grey relational analysis, the grey relational grade is used to show the relationship among the series. Let (X, Γ) be a grey relational space, X stand for the collection of the collection of grey relational factors, x_i be the compared series, and x_0 be the reference series:

$$x_i = (x_i(1), x_i(2), \ldots, x_i(n)),\ x_i \in X,\ i = 1, 2, \ldots, m \quad (3)$$
$$x_0 = (x_0(1), x_0(2), \ldots, x_0(n)),\ x_0 \in X \quad (4)$$

The grey relation coefficient is

$$\gamma\,(x_0(k), x_i(k)) = \frac{\Delta_{\min} + \zeta\,\Delta_{max}}{\Delta_{0i}(k) + \zeta\,\Delta_{max}} \quad (5)$$

where

$$\Delta_{0i}(k) = |x_0(k) - x_i(k)| \quad (6)$$

$$\Delta_{max} = \max_{i} \max_{k} \Delta_{0i}(k) \quad (7)$$
$$\Delta_{max} = {}_{i} \min_{k} \Delta_{0i}(k) \quad (8)$$
$$\zeta \in [\,0, 1\,] \quad (9)$$

The grey relational grade is obtained by:

$$\gamma\,(x_0, x_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma\,(x_0(k), x_i(k)) \quad (10)$$

TABLE6. INFLUENCE OF PROCESS PARAMETERS OF GREY RELATIONAL GRADE

No.	Grey relational grade	Order
1	0.520	9
2	0.611	8
3	0.829	2
4	0.742	4
5	0.735	5
6	0.778	3
7	0.718	6
8	0.653	7
9	0.832	1

Table 3 shows the experimental results obtained and Table 4 shows the pre-processed data results. The grey relation coefficients of each performance characteristic are calculated using (5) and are shown in Table 5. Table 6 shows the grey relational grade and order using the experimental layout. The higher value of the grey relational grade represents the stronger relational degree the reference sequence x_0(k) and the given sequence x_i(k).

D. Factor effects

Since the experimental design is orthogonal, it is then possible to separate the effects of each process parameter at different levels. For example, the mean of grey relational grade for the electrolyte concentration at level 1, 2 and 3 can be calculated by taking the average of the grey relational grade for the experiments 1–3, 4–6 and 7–9, respectively

The mean of the grey relational grade for each level of other machining parameters can be computed in the similar manner. The mean of the relational grade for each level of the combining parameters is summarized in the multi-response performance is shown in Table 7. Fig. 3 shows the influence of processes parameters on quality characteristics.

TABLE7.RESPONSE TABLE FOR GREY RELATIONAL GRADE

Process parameter	Grey relational grade			
	Level 1	*Level 2*	*Level 3*	*Max -Min*
Electrolye Conc.	0.653	**0.751**	0.734	0.098
Feed rate	0.66	0.666	**0.813**	0.153
Voltage	0.65	0.728	**0.760**	0.110
Mean value of grey relational grade = 0.532				

IV. ANALYSIS OF VARIANCE

Analysis of variance (ANOVA) was introduced by Sir Ronald Fisher [11]. The purpose of the analysis of variance (ANOVA) is to investigate which design parameters significantly affect the quality characteristic. The traditional statistic technique can only obtain one parameter in a single sequence; one has to do the analysis repeatedly to obtain other factors for the experiment [12].

TABLE 8.RESULTS OF ANALYSIS OF VARIANCE

	DOF	Sum of Squares	Mean of Squares	F	Contribution(%)
A	2	0.0165	0.0083	0.73	19.54
B	2	0.0449	0.0224	3.42	53.19
C	2	0.0193	0.0097	0.89	22.86
Error	2	0.0037	0.0018		4.41
Total	8	0.0844			100

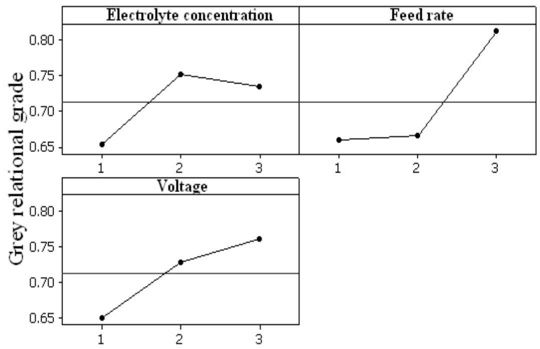


Figure 3: Influence of process parameters on multiple performance

ANOVA of the response quality characteristics was shown in Table 8 and it is observed that feed rate is the significant factor for maximizing the material removal rate and minimizing the overcut and cylindricity error. An increase in feed rate increases the material removal rate and reduces the overcut and cylindricity error. This happens due to the reduction in the inter-electrode gap that increases the current density in the gap with the consequent anodic dissolution.

Once the optimal level of the cutting parameters is identified, the following step is to verify the improvement of the performance characteristics using this optimal combination. Table 9 shows the comparison of the experiment results using the initial combination of the machining parameters with the optimal one.

TABLE 9. RESULTS OF CONFIRMATION TESTS

	Process parameter	MRR	Overcut	Cylindricity error	Surface roughness
Initial design	A2B2C2	0.418	0.876	0.182	0.36
Optimal design	A2B3C3	0.712	0.482	0.121	0.21

As observed in Table 9, material removal rate increases form 0.418 g/min to 0.712 g/min; overcut is reduced from 0.876 to 0.482 mm; cylindricity error was reduced from 0.182 to 0.121 mm and surface roughness value was reduced from 0.36 µm to 0.21 µm . Based on the above results, it is clearly observed quality characteristics can be greatly improved through this study.

V. CONCLUSIONS

The paper presented the optimization of the electrochemical machining of EN-31 steel by the grey relational analysis. The optimal process parameters that have been identified to yield the best combination of process variables are electrolyte concentration at 15 %, feed at 0.32 mm/min and voltage at 20 V. As a result, the target performance characteristics, i.e. material removal rate can be maximized and the overcut, cylindricity error and surface roughness can be minimized through this method. The effectiveness of this approach is verified by experiment and analysis of variance.

REFERENCES

[1] H. Hocheng, Y.H. Sun, S.C. Lin, P.S. Kao, "A material removal analysis of electrochemical machining using flat-end cathode," *J. Mater. Process. Technol.*, vol. 140, pp. 264-268, September 2003.

[2] K.P. Rajurkar and D. Zhu, **"**Improvement of Electrochemical Machining Accuracy by Using Orbital Electrode Movement," *Ann. CIRP*, vol. 48, pp. 139-142, 1999.

[3] Sorkhel S K, Bhattacharyya B, "Parametic control for optimal quality of the workpiece surface in ECM," *J. Mater. Process. Technol*., vol. 40, pp. 271-286, January 1994.

[4] Rao P V, Pawar P J, Shankar R, "Multi-objective optimization of electorchemical machining process parameters using a particle swarm optimization algorithm," *Proc IMechE, Part B*: *J. Engineering Manufacture*, vol. 222, pp. 949-958, 2008.

[5] P. Asokan & R, Ravi Kumar, R. Jeyapaul, M. Santhi, Development of multi-objective optimization models for electrochemical machining process, Int. *J. Adv. Manuf. Technol*., vol. 39, pp. 55-63, 2008.

[6] B. Bhattacharyya , S.K. Sorkhel, "Investigation for controlled ellectrochemical machining through response surface methodology-based approach," *J. Mater. Process. Technol.,* vol. 86, pp. 200-207, February1998.

[7] P. Narender Singh , K. Raghukandan , B.C. Pai, "Optimization by Grey relational analysis of EDM parameters on machining Al–10%SiCP composites," *J. Mater. Process. Technol.*, vol. 155–156,pp. 1658–1661, November 2004.

[8] Sorkhel SK, Bhattacharya B, "Parametic combinations for controlled machined rate and surface quality in electrochemical machnining," *Proc.15th AIMTDR conference,* pp. 421-426, 1992.

[9] J.L. Deng, "Introduction to Grey system," *J. Grey Syst*.,vol. 1, pp. 1–24, 1989.

[10] J. Deng, "A Course on Grey System Theory," *HUST Press, Wnhan, China, 1990*.

[11] Nicolo Belavendram, Quality by design, Prentice Hall, 1995.

[12] G. Taguchi, Introduction to Quality Engineering, Asian Productivity Organization, Tokyo, 1990.

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