ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Advanced Machining Performance Study on Hardened Steel EN 31: A Differential Evaluation Approach

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ABSTRACT

Electrochemical machining (ECM) has inaugurated itself as one of the major other possible way to conventional methods for machining hard materials and complicated outlines not having the properties like residual stresses and tool wear. Studies on Material Removal Rate (MRR) and Surface Roughness (Ra) are of extremely important in ECM, since it is one of the factors to be determined in the process decisions. Machining parameters provided by the machine tool builder cannot meet the operator's requirements. Since for an arbitrary desired machining time for a particular job, they do not provide the optimal conditions. So the aim of present work is to investigate the MRR and Ra of EN19 alloy steel in the form of cylindrical (16mm Diameter and 32mm Height) dimensions copper electrode and solution of Sodium Chloride (NaCl) in water as electrolyte by using computational approach. To solve this task, multiple regression model and Differential Evaluation Model (DOE) model are developed as efficient approaches to determine the optimal machining parameters in ECM. Current (c), Voltage (V), Electrolyte Concentration (E) and Feed Rate (F) are considered as machining parameters and MRR and Ra are the output responses. This multi response has been modified as a single objective by a Grey Relational Analysis (GRA). Grey grade has been calculated for representing the multi-objective model. The predicted grade has been found and then the percentage deviation between the experimental grade and predicted grade has been calculated for multiple regression linear model & DOE model. Then optimizing to find best setting of process variables for higher MRR and lower Ra. Based on the testing results of the DOE the operating parameters are optimized. The designs are based on Response Surface Methodology (RSM), with the aid of MINITAB software. The optimum value has been determined which is suitable for both MRR and Ra.

KEY WORDS: ECM, GRA, RSM, ANOVA, DOE and Material.

1. INTRODUCTION

ECM is one of the nontraditional machining processes used to machine extremely hard materials that are difficult to machine cleanly using conventional methods. ECM has been used widely in the manufacturing of semiconductor devices and this process is also used in Automotive, Aircrafts, Petroleum, Aerospace, Textile, Medical and Electronic industries. Hocheng (2004), have proposed a method to predict the machine profile of the work piece. They have developed the machine profile as a function of time and the changing gap opening. Bhattacharyya (2006), have investigated the influence of tool vibration on machine performance such as MRR and accuracy in electrochemical micro-machining of copper. Some authors have worked on Electrochemical Discharge Machine (ECDM). They have concentrated on the improvement of machine performance. Munda (2006), have investigated the electrochemical micromachining through RSM approach. Keeping this consideration in view, we have attempted to develop multi-objective models to study the influence of machining parameters on machining performance criteria such, as MRR and Ra.

Past studies: ECM is one of the profitable machining processes used for accurate and high precision geometry of the work piece. ECM can become more reliable by doing the research on performances to be obtained by it. Some of the research areas in ECM are shown in Fig.1.

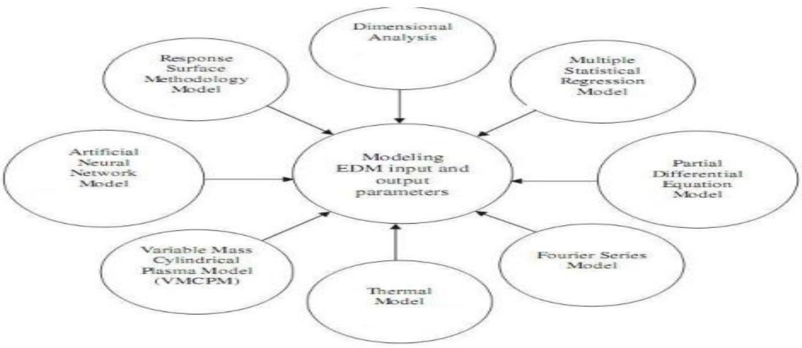

Fig.1.Shows theoretical model available in literature for simulating the input and output model

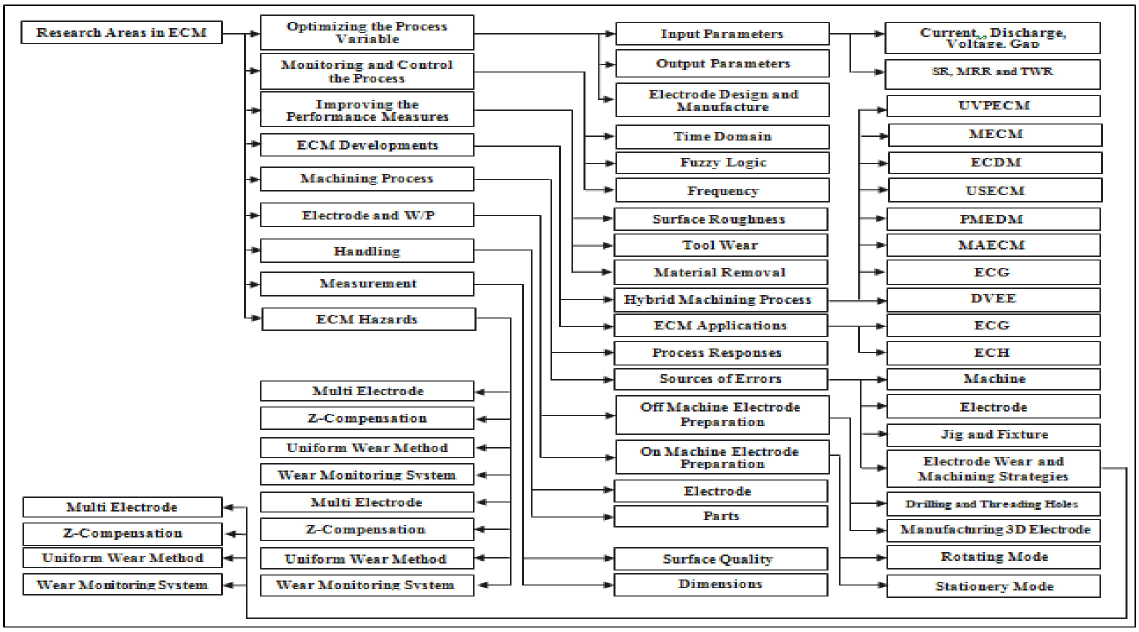

Fig.2.Classification of ECM research areas

2. EXPERIMENTAL DETAILS

A number of experiments were conducted in order to investigate the performance and study the effects of various machining parameters of ECM process on Hardened Steel EN 31 in the form of cylindrical blank of test pieces (16mm Diameter and 32mm Height) dimensions. These studies have been undertaken to investigate the effects of Current, Voltage, Electrolyte Concentration and Feed Rate on MRR and SR.

The experimental setup is shown in Fig. 3 and details are in Table 1. The setup consists of three major sub-systems along with tool and work piece material:

- **i.** Machining Cell
- **ii.** Control Panel
- **iii.** Electrolyte Circulation

Table.1.The experimental details

Conditions	Descriptions
Machine	MTEATECH ECM machine
Test Specimen	Hardened Steel EN 31 (C=0.916, Mn = 0.354, Si = 0.203, S = 0.050, P = 0.053, Cr = 0.990, Ni = 0.029, Mo = 0.005, Hardness = 205BHN)
Tool	Copper Electrode of Diameter 10mm
Tool Polarity	Positive
Dielectric Fluid	Kerosene
Flushing Type	Internal
Depth of Cut	1mm
Electrode Polarity	Positive
Dielectric Flushing	Flushing
Supply	AC
Weight Measuring Instrument	Digital Balance (FX-3000)
SR Measuring Instrument	Portable SR Tester SJ201

Fig.3.Experimental setup of ECM machining

Work Material: The work materials selected for the study was Hardened Steel EN 31 in the form of cylindrical blank of test pieces (16mm Diameter and 32mm Height) dimensions and are fabricated using suitable optimization method. Table–2 shows the chemical composition of Hardened Steel EN 31material.

Table.2.Physical and mechanical properties of Hardened Steel EN 31

Material	Density (gms/cm^3)	Thermal Conductivity (W/mK)	Hardness (BHN)	Electrical Resistivity (x°C-cm)	Specific Capacity (J/g°C)
Hardened SteelEN31	7.81	46.6	205	0.0000218	0.475

Table.3.Chemical composition of Hardened Steel EN 31

Work Material	Hardened Steel EN 31
Mn (%)	0.580
C (%)	1.070
Si (%)	0.320
S (%)	0.030
P (%)	0.040
Cr (%)	1.120
Ni (%)	0.029
Mo (%)	0.005
Fe	Balance
V	-

Tool Material: Copper is often used as the electrode material. Brass, graphite, and copper-tungsten are also often used because they are easily machined, they are conductive materials, and they will not corrode. The cylindrical tool electrode consists of tool holder, flexible pipes, copper tool and 10 mm diameter plastic spur gear. In this experiment copper is taken as electrode material as cathode. Tool is designed to cut the cavity on Hardened EN31 steel in the similar profile.

Experimental procedure:

Machining Processes: The job to be machined is fixed in the vice. The specimen is prepared as a cylindrical blank of 16mm diameter and 32mm height and is made up of hardened steel which is machined by ECM. The number of runs was decided to be 31 with different parameter combinations as shown in Table 4.

Table.4.Different variables used in the experiment and their levels

Items	Levels				
Parameters	-2	-1	0	1	2
Current (amps)	100	130	160	190	220
Voltage (volts)	5	7	9	11	13
Electrolyte	5	8	11	14	17
Feed Rate	0.1	0.2	0.3	0.4	0.5

Measurement Procedure: Roughness measurement has been done using a portable roughness tester SJ201. This instrument (Surtronic 3^+) is a portable, self-contained instrument for the measurement of surface texture. The parameter evaluations are microprocessor. MRR is calculated by measuring the time of machining using the formula. The values were tabulated in the Table 2 and Table 3.

$$MRR(mg/min) = \frac{\text{(Initial weight-Final weight)}}{\text{(Machining time)}}$$

The observations of the machining process are based on second order central composite rotatable design. A total of four machining parameters (Current, Voltage, Flow Rate and Gap) were chosen. The machining results after ECM process are evaluated based on two machining performances, MRR and SR. The observation of the ECM process is shown in Table 5.

Table.5.Process variables and their corresponding responses

Current (A)	Voltage (V)	Electrolyte Concentration	Feed Rate	MRR (g/min)	SR (μm)	Current (A)	Voltage (V)	Electrolyte Concentration	Feed Rate	MRR (g/min)	SR (μm)
130	11	14	0.2	0.017	3.20	130	11	8	0.4	0.028	3.10
130	11	8	0.2	0.034	3.20	160	9	11	0.5	0.017	3.40
190	7	8	0.2	0.029	1.90	190	11	8	0.4	0.034	4.10
160	5	11	0.3	0.056	1.50	130	7	14	0.2	0.029	3.30
190	7	8	0.4	0.032	2.90	190	11	14	0.4	0.056	3.70
160	9	11	0.3	0.034	3.50	130	7	8	0.4	0.032	2.60
160	9	11	0.3	0.042	3.50	160	9	11	0.3	0.034	3.50
130	7	8	0.2	0.030	2.90	160	9	11	0.3	0.042	3.50
190	11	14	0.2	0.035	3.00	160	9	17	0.3	0.030	3.30
160	9	11	0.3	0.035	3.50	130	11	14	0.4	0.035	2.50
220	9	11	0.3	0.031	3.20	160	13	11	0.3	0.035	2.70
130	7	14	0.4	0.032	2.60	190	7	14	0.4	0.031	2.90
160	9	11	0.1	0.019	3.30	160	9	11	0.3	0.032	3.40

160	9	5	0.3	0.028	3.38	100	9	11	0.3	0.019	3.00
190	11	8	0.2	0.035	3.10	190	7	14	0.2	0.028	2.60
160	9	11	0.3	0.025	3.50						

Multi Response Model Using Grey Relational Analysis

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

i). Normalizing the experimental results of MRR and SR to avoid the effect of adopting different units to reduce the variability.

Z = Y- MIN/ MAX –MIN (1)

Z = MAX- Y/ MAX- MIN (2)

ii). Performing the grey relational generating and calculating the grey coefficient for the normalized values yield.

$R = \Delta_{min} + €\Delta_{max}/\Delta_{oj} + €\Delta_{max}$ (3)

iii). Calculating the grey relational grade by averaging the grey relational coefficient yield.

$S = 1/k\sum r_{ij}$ (4)

Where sis the grey relational grade for the j^{th} experiment and k is the number of performance characteristics. Equation (1) is used to normalize the experimental value when the target of the original value is having the characteristic of 'higher the better'. Here MRR is normalized using the above equation. When the 'lower the better' is a characteristic of the original sequence, then the original sequence is normalized using Eq. (2), i.e., SR is normalized using this equation. Using Eq. (3), we calculate the grey relational coefficient for MRR and SR as shown in Table 6.

Table.6.Grey relational coefficients and the grey relational grade

Normalized value for MRR	Normalized value for SR	GRC value for MRR	GRC value for SR	Grade	Normalized value for MRR	Normalized value for SR	GRC value for MRR	GRC value for SR	Grade
0	0.3461	0.3333	0.4333	0.3833	0.2820	0.3846	0.4105	0.4482	0.4294
0.4358	0.3461	0.4698	0.4333	0.4516	0	0.2692	0.3333	0.4062	0.3698
0.3076	0.8461	0.4193	0.7646	0.5920	0.4358	0	0.4698	0.3333	0.4016
1	1	1	1	1	0.3076	0.3076	0.4193	0.4193	0.4193
0.3846	0.4615	0.4482	0.4814	0.4648	1	0.1538	1	0.3714	0.6857
0.4358	0.2307	0.4698	0.3939	0.4319	0.3846	0.5769	0.4482	0.5416	0.4949
0.6410	0.2307	0.5820	0.3939	0.4880	0.4358	0.2307	0.4698	0.3939	0.4319
0.3333	0.4615	0.4285	0.4814	0.4550	0.6410	0.2307	0.5420	0.3939	0.4680
0.4615	0.4230	0.4814	0.4642	0.4728	0.3333	0.3076	0.4285	0.4193	0.4239
0.4615	0.2307	0.4814	0.3939	0.4377	0.4615	0.6153	0.4814	0.5651	0.5233
0.3589	0.3461	0.4381	0.4333	0.4357	0.4615	0.5384	0.4814	0.5199	0.5007
0.3846	0.5769	0.4482	0.5416	0.4949	0.3589	0.4615	0.4381	0.4814	0.4598
0.0512	0.3076	0.3451	0.4193	0.3822	0.3846	0.2692	0.4482	0.4062	0.4272
0.2820	0.2769	0.4105	0.4087	0.4096	0.0512	0.4230	0.3451	0.4642	0.4047
0.4615	0.3846	0.4814	0.4482	0.4648	0.2820	0.5769	0.4105	0.5416	0.4761
0.2015	0.2307	0.3861	0.3939	0.3900					

Model development:

Multiple Regression Models:

Model I: Linear Model Excluding Interaction Terms: This model is a linear multiple regression model without considering interaction terms. A multiple regression model using independent variables C, V, E and F and dependent variable grade can be represented as:

Grade = b0 + b1 C + b2 V + b3 F + b4 G

Where b_0, b_1, b_2, b_3 and b_4 are the regression coefficients to be estimated. The regression model developed using MINITAB software based on these equations.

The regression equation is

G = 0.518 + 0.000594C - 0.0217V + 0.0026 E + 0.089F

The predicted values are calculated through the regression Eq. 4. The percentage deviations are computed for both data's and the results are listed below.

Differential evaluation model: The general Evolutionary Algorithm steps are Initialization, Mutation, Recombination and Selection. Suppose we want to optimize a function with D real parameters

Initialization: we must select the size of the population N (it must be at least 4). The parameter vectors have the form:

$x_{i,G} = [x_{1,i,G}, x_{2,i,G}, \ldots x_{D,i,G}]$ i = 1, 2, . . . ,N.

Where G is the generation number.

Define upper and lower bounds for each parameter: $x^L_j \leq x_{j,i,1} \leq x^U_j$

Randomly select the initial parameter values uniformly on the intervals $[x^L_j, x^U_j]$. Each of the N parameter vectors undergoes mutation, recombination and selection.

Mutation: It expands the search space for a given parameter vector xi,G randomly select three vectors $x_{r1,G}$, $x_{r2,G}$ and $x_{r3,G}$ such that the indices i, r1, r2 and r3 are distinct random numbers. Add the weighted difference of two of the vectors to the third.

$$v_{i,G+1} = x_{r1,G} + F_{(xr2,G - xr3,G)}$$

The mutation factor F is a constant from [0, 2], $v_{i,G+1}$ is called the donor vector

Recombination: It incorporates successful solutions from the previous generation. The trial vector $u_{i,G+1}$ is developed from the elements of the target vector, $x_{i,G}$, and the elements of the donor vector, $v_{i,G+1}$ Elements of the donor vector enter the trial vector with probability CR

$$u_{j,i,G+1} = \begin{cases} v_{j,i,G+1} \text{ if } rand_{j,i} \leq CR \text{ or } j = I_{rand} \\ x_{j,i,G} \text{ if } rand_{j,i} > CR \text{ and } j \neq I_{rand} \\ i = 1, 2, \ldots, N; j = 1, 2, \ldots, D \end{cases}$$

r and $_{j,i}$ ~ U[0, 1], I_r and is a random integer from [1, 2, ...,D]

I_r and ensures that $v_{i,G+1} \neq x_{i,G}$

Selection: The target vector $x_{i,G}$ is compared with the trial vector $v_{i,G+1}$ and the one with the lowest function value is admitted to the next generation

$$x_{i,G+1} = \begin{cases} u_{i,G+1} \text{ if } f(u_{i,G+1}) \leq f(x_{i,G})\ x_{i,G} \\ x_{i,G} \quad \text{otherwise} \quad i = 1,2,\ldots N \end{cases}$$

Mutation, recombination and selection continue until some stopping criterion is reached.

Optimization process: These are the nonlinear equations to find the fitness values in optimization process.

MRR = $-0.058007+0.000253C+0.011500V+0.008014E-0.250000F-0.000003C^2-0.001187V^2-0.000375E^2+ 0.400000F^2+ 0.000044CV+0.000017CE+0.000417CF+0.000167VE+0.006250VF-0.007917EF$

SR = 2.0411-0.0254C+1.3904V+0.3726E-10.5101F-0.0001C2-0.0865V2-0.0040E2-3.3512F2 +0.0031CV+ 0.0003CE+ 0.1000CF-0.0229VE+0.1875VF-0.4167EF.

Program sequence

```
Optimization Program for MRR
clear all
clc
close all
global lb ub Fx pop newpop rands
lb=[5,25,15,1,20];
ub=[25,75,25,2.0,30];
[sol, fval] = diffevolve(@objfnm, 10, lb, ub)
A=sol(1);
B=sol(2);
C=sol(3);
D=sol(4);
MRR=-0.058007+ 0.000253*C+0.011500*V+0.008014*E-0.250000*F-
0.000003*C.^2-0.001187*V.^2-
0.000375*E.^2+0.400000*F.^2+0.000044*C.*V+0.000017*C.*E+
0.000417*C.*F+0.000167*V.*E+0.006250*V.*F-0.007917*E.*F ;
SR=-2.0411-0.0254*C+1.3904*V+0.3726*E-10.5101*F-0.0001*C.^2-
0.0865*V.^2-0.0040*E.^2-
3.3512*F.^2+0.0031*C.*V+0.0003*C.*E+0.1000*C.*F -
0.0229*V.*E+0.1875*V.*F-0.4167*E.*F;   fprintf(' \n\n')
fprintf('   Current = %g',A),fprintf(' A \n\n')
fprintf('   Voltage = %g',B),fprintf(' V \n\n')
fprintf('   Electrolyte Concentration = %g',C),fprintf(' \n\n')
fprintf('   Feed Rate = %g',D),fprintf(' mm \n\n')
fprintf('   Material Removal Rate = %g',MRR),fprintf(' mg/min \n\n')
figure(1)
fprintf('   Surface Roughness= %g', Ra),fprintf(' µm \n\n')
figure(2)
plot(1./Fx,'k')
xlabel('Iterations')
ylabel('Fitness Value')
Differential Evolution optimization algorithm has converged at
MRR (mg/m) = 0.061335
SR (µm)   =2.77556
```

Table.7.Better output responses

Model	Current (A)	Voltage (V)	Electrolyte Concentration (%)	Feed Rate (mm)	SR (μm)	MRR (mg/m)	% of Deviation
LR	187.807	10.485	11.9992	0.5	2.77556	0.061335	13.74
DOE	187.807	10.485	11.9992	0.5	2.77556	0.061335	03.28

3. CONCLUSION

A practical method of optimizing cutting parameters for ECM based on multiple regression models and DOE Model are presented in this work. Current, Voltage, Electrolytic Concentration and Feed Rate have been considered as machining parameters. MRR and SR have been obtained as responses from the ECM process. MRR and SR are combined to have a single objective as grey relational grade by the application of GRA. Linear regression model and DOE MODEL have been developed to map the relationship between machining parameters and output responses. The average percentage deviation the linear regression model is 13.74 and DOE is 3.28. It is clearly noted that DOE model gives the better prediction based on the percentage deviation in machining data sets and the same has been used to find the optimal machining parameters of ECM. Finally the optimal conditions for MRR, Current = 187.807A, Voltage = 10.485V Electrolytic Concentration = 11.9992%, Feed Rate = 0.5mm and maximum MRR = 0.061335gm/min and minimum SR = 2.77556e-016 micro-m, for maximizing MRR and minimizing SR simultaneously among the 31 experimental data. The most influencing factor obtained by the response table is the current for the ECM process. The developed model has been validated experimentally and exhibit low values of error. It is also proposed to integrate the DOE and Intelligent Techniques for finding the optimal machining parameters as future scope of this work.

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