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MATHEMATICAL MODELING OF PROCESS PARAMETERS IN ELECTRICAL DISCHARGE MACHINING ON 17-4 PH STEEL USING REGRESSION ANALYSIS

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ABSTRACT

Proper selection of machining conditions is one of the most important aspects in the die sinking Electrical Discharge Machining process. The objective of the present work is to develop empirical models and prediction of machining quality for Electrical Discharge Machining of martensitic Precipitation Hardening (PH) stainless steel with copper tungsten electrode. The important process input parameters such as peak current, pulse on time, pulse off time and tool lift time are selected to predict the machining qualities of Material Removal Rate (MRR) and Surface Roughness (SR). Taguchi experimental design (L27 orthogonal array) was used to formulate the experimental layout. The empirical models have been developed to predict the Material Removal Rate (MRR) and Surface Roughness (SR) using Regression Analysis (RA). Prediction capability of regression models are verified with experimental data. According to results, the regression model is better performed to predict the MRR and SR for a given range of process parameters of EDM.

Keywords: EDM, MRR, SR, regression analysis, ANN.

1. INTRODUCTION

Electric Discharge Machining (EDM) is a thermo-electric, non-traditional machining process used to machine precise and intricate shapes on difficult to cut materials and super tough metals such as super alloys, titanium, ceramics, precipitated hardened steels, cast-alloys, which are widely used in defense and aerospace industries and in many engineering applications. Electrical energy is used to generate electrical sparks and material removal mainly occurs due to localized melting and vaporization of material which is carried away by the dielectric fluid flow between the electrodes. The performance of this process is mainly influenced by many electrical parameters like, current, voltage, polarity, and pulse on time, pulse off time, electrode gap and also on non-electrical parameters like work and tool material, dielectric fluid pressure. All these electrical and non electrical parameters have a significant effect on the EDM output parameters like, Metal Removal Rate (MRR) and Surface Roughness (SR). The EDM is very complex and stochastic process and is very difficult to determine the optimal machining parameters. In the present study the machining qualities are MRR and SR which are conflicting in nature. MRR reflects the productivity and SR reflects the accuracy of the product. P. S. Bharti *et al.* [1] Experiments conducted on Inconel 718 as work piece and copper as tool electrode. Artificial neural network with back propagation algorithm had used to model EDM process. ANN has been trained with the experimental data set. Controlled elitist non-dominated sorting genetic algorithm has been employed in the trained network and a set of pareto-optimal solutions was obtained. The results concluded that the average percentage difference between experimental and ANN's predicted value was 4 and 4.67 for MRR and SR respectively. Sameh S. A Habib [2] developed ANN model for EDM process. concluded that the total average prediction error of experimental results for machining qualities with that values predicted from the developed neural network model prediction was calculated as 4.4616 %. Bhavesh A. Patel et al [3] for ANN Neural Network Toolbox in Mat lab 7.1 used for modeling. It was observed that ANN model has been found efficient to predict EDM process responses for selected process conditions. Vaishav A. Panchal *et al* [4] presented a research work on Effect of process parameters on MRR, SR and TWR was examined for Copper electrode in Die Sinking EDM process of SS 440C using ANN. It was observed that current increases, MRR increases and Surface Quality decreases. gap voltage increases, MRR decreases and Surface Quality increases. Shiba Narayan Sahu *et al* [5] studied the performance of the EDM process using ANN. The machining parameters discharge current, pulse duration; duty cycle and voltage were used as model input variables during the development of the models for Material Removal Rate (MRR). It was concluded that MRR of EDM process was successfully modeled and can be subsequently used. Krishna Mohana Rao and Hanumantha Rao [6] Work was aimed at optimizing the hardness of surface produced in die sinking electric discharge machining (EDM) by considering the simultaneous affect of various input parameters. Multiperceptron neural network models were developed using Neuro solutions package. Genetic algorithm concept was used to optimize the weighting factors of the network. It was observed that the developed models are within the limits of the agreeable error when experimental and network model results are compared. R. DAS *et al* [7] in this research the prediction of surface roughness in Electrical Discharge Machining of SKD 11 (AISI D2) Tool steel. The reported results indicate that the proposed model can satisfactorily predict the surface roughness in EDM and ANN a valuable tool for the process planning of

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EDM Machining. Ashikur Rahman Khan *et al* [8] proposed an ANN model with multi-layer perception neural architecture for the prediction of MRR on first commenced Ti-5Al-2.5Sn alloy in electrical discharge machining process. An error of 1.20-6.37% was found between desired and ANN predicted MRR which found to be in good agreement with the experimental results. M.M. Rahman [9] presented the artificial intelligence model to predict the optimal machining parameters for Ti-6Al-4V through EDM using copper as electrode. Radial basis function was used to develop the artificial neural networks modeling of MRR, TWR and SR. Design of experiments method by using response surface method(RSM) techniques are implemented. The results revealed that the lower the ampere, the higher the tool wear and vice versa. At high peak current and longer pulse on time, the MRR increases. Dragan Rodic *et al* [10] Experiments are carried out on manganese alloyed cold-work tool steel. The results indicated that the genetic programming technique gives slightly smaller deviation of the measured values of model than fuzzy logic and neural network.

The objective of the present work is to develop empirical models and prediction of machining quality for electrical discharge machining of Precipitation Hardening Stainless steel machined with copper tungsten electrode. The empirical models have been developed for electrical discharge machining using Regression Analysis and the Artificial Neural Network to predict the Material Removal Rate and Surface Roughness.

2. EXPERIMENTAL DETAILS

The experiments were conducted on V3525 precision die sink electric discharge machine as shown in Figure-1 which consist a work table, a servo control system and a dielectric supply system. The machine has 8 current settings from 3A to 24A; pulse on time, pulse off time and electrode lift each have 9 settings with different ranges.

2.1 Work piece and tool electrode

The work piece used for the experiments is Precipitation Hardening Stainless steel used in aerospace, chemical, petro chemical, food processing and die manufacturing. The work piece is in the form of a rectangular plate with dimensions of 60mm X 50mm X 5 mm. Experiments were conducted using Copper Tungsten (80W:20Cu grade) which had good electrical conductivity, high wear resistance. Due to this reason tool wear minimum while machining with Copper Tungsten.

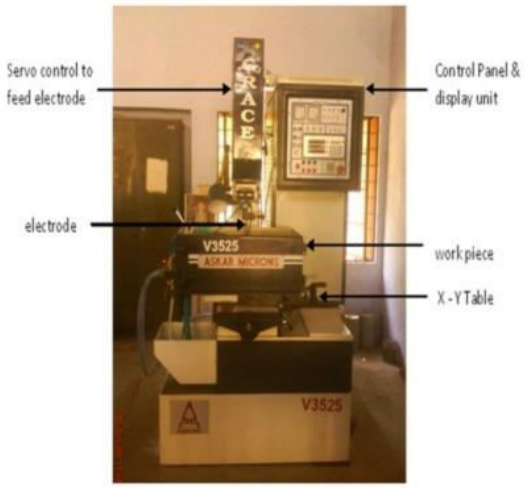

Figure-1. The Experimental equipment.

2.2 Experimental procedure

Before experimentation, the work piece top and bottom faces were ground to a good surface finish using a surface grinding machine. The bottom of the tool was polished using a very fine-grade emery sheet before each experiment. In order to measure the MRR it is necessary to obtain the initial weights of the work pieces and tools. It has been performed using the digital electronic weighing balance AY221 1mg accuracy. At the end of each experiment, the work piece and tool were removed, washed, dried, and weighed using digital weighing balance. The experiments are conducted for the machining time of the 10 minutes was determined using a timer. Machining was done with straight polarity and EDM oil Grade 30 used as the dielectric fluid. Gap voltage is 30 V and flushing pressure maintained constant. The input levels and number of experiments are decided based on the design of experiments. Process parameters and their levels are presented in Table-1. In this study, an L27 orthogonal array was used for experimentation. The material removed rate was calculated using the following formula:

$$MRR = 1000*(W_a - W_b) / T \quad mg/min \qquad (1)$$

W_b = Weight of the work-piece before machining (mg)
W_a = Weight of the work-piece after machining (mg)
T = Machining time (min)

Table-1. Process parameters and their levels.

S. No.	Process parameters	Symbol	Level 1	Level 2	Level 3
1	Discharge current (A)	A	9	12	15
2	Pulse on time (µs)	B	50	100	200
3	Pulse off time (µs)	C	20	50	100
4	Lift time (µs)	D	10	20	50

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3. RESULTS AND DISCUSSIONS

3.1 Development of Regression model for MRR and SR

Regression Analysis is a statistical tool for the investigation of relationships between variables. It is one of the commonly used techniques in predicting the output characteristics. Multiple Regression Analysis (MRA) is applied to determine the relationship between the predictor variables and criterion variables. It can be expressed as a second order model including an interaction terms written as equation (2).

$$y = \beta 0 + \beta 1\, X1 + \beta 1\, X1 + \beta 2\, X2 + \beta 3\, X3 + \beta 4\, X4 + \beta 5\, X5 + \beta 6\, X6 + \beta 7\, X7 + \beta 8\, X8 + \beta 9\, X9 + \beta 10\, X10 + \beta 11\, X11 + \beta 12\, X12 + \beta 13\, X13 + \beta 14\, X14 \quad (2)$$

Where y is a response variable either MRR or SR. $X1$, $X2$, $X3$, $X4$ are independent variables (current, pulse on time, pulse off time and lift time). $X5$, $X6$, $X7$ and are square terms of predictor variables. $X9$, X10, $X11$, X12, $X13$ and $X14$ are interaction terms of predictors. β1, β2, β3, β4, β6, β7 … β13 and β14 are regression coefficients.

The general regression model can be written in matrix notation using Equation (3) as given below:

$$y = X\beta + \epsilon \quad (3)$$

The solution for the regression coefficients are given by Equation (3)

$$\beta = (X^T X)^{-1} X^T y \quad (4)$$

Statistical software MINITAB 17 was used to develop a regression model for predicting MRR and SR. The matrix is formulated based on the proposed regression Equation (2). It is solved to compute regression coefficients and these coefficients are used to estimate the MRR and SR. The experimental data are used to perform regression analysis and the numerical values of coefficients are determined. The second order regression models including interactions for MRR and SR are given by equation (5) and equation (6). These are used for prediction of machining qualities as function of input process parameters (A, B, C and D).

$$MRR = 295 - 35.5\,A - 1.299B + 0.43C - 0.92D + 2.26\,A^2 + 0.0064\,B^2 - 0.00055\,C^2 + 0.0171\,D^2 - 0.0776\,AB - 0.0064AC - 0.094\,AD - 0.00143BC + 0.00555\,BD - 0.000053\,CD \quad (5)$$

$$SR = 11.7 - 1.126\,A + 0.0405B - 0.0404C + 0.0385D + 0.0520A^2 - 0.000146\,B^2 - 0.000128\,C^2 - 0.000450\,D^2 - 0.001960AB + 0.00529\,AC + 0.00281\,AD - 0.000039\,BC - 0.000241BD + 0.000003CD \quad (6)$$

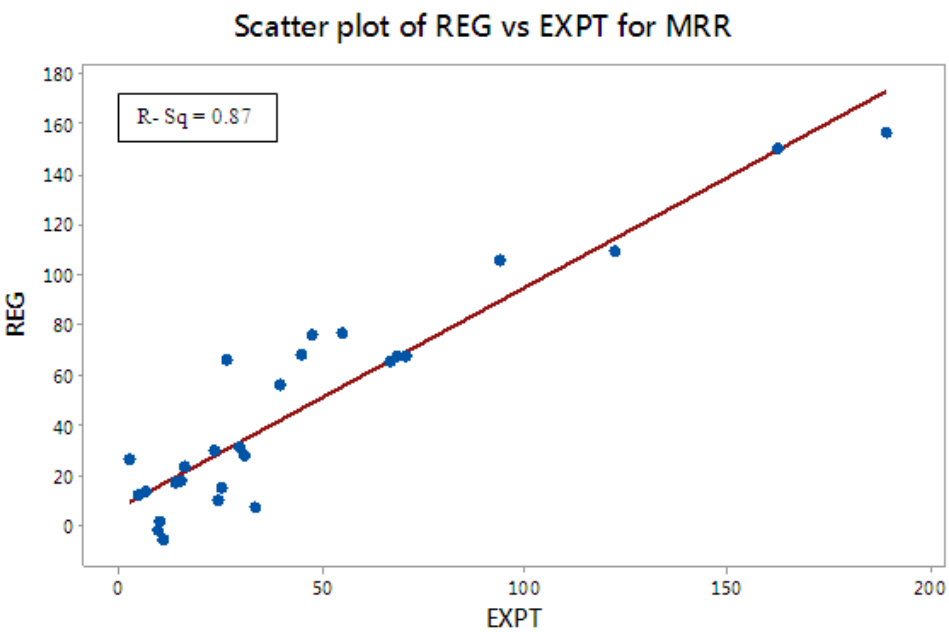

Figure-2. Comparison of predicted and experimental MRR.

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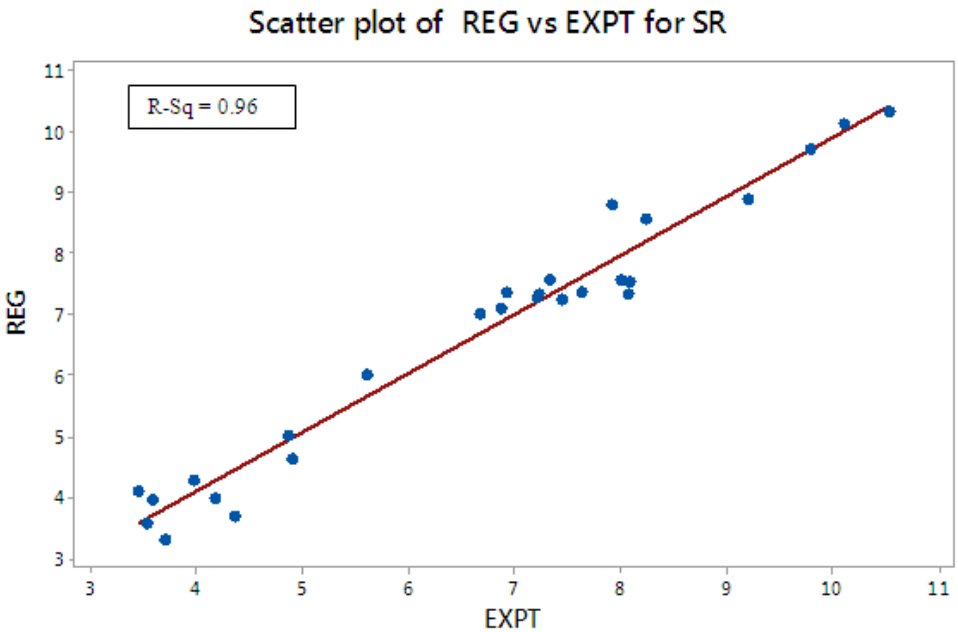

Figure-3. Comparison of predicted and experimental SR.

The predicted values of MRR and SR using Regression equation are given in Table-2. The Prediction models are verified against the experimental data and comparison is illustrated in Figure-2 and Figure-3. The results obtained from the model are very close to that of experiments conducted (Table-2). Error can be calculated using equation (7). It can be found that the predicted values and experimental values have less deviation for both MRR and SR. The average deviation estimated for MRR as 5.36% and for SR as 4.89%. It is clear that the experimental data agree very well with predictions. Therefore the regression models are used to estimate the both MRR and SR for machining of Precipitation Hardening Stainless using EDM for a given range of input parameters.

$$Error = \frac{1}{n}\sum\left[\frac{MRR_{expt}-MRR_{pred}}{MRR_{expt}}\right]\% \quad (7)$$

Table-2. Comparison of Predicted values with Experimental results for both MRR and SR.

S. No.	**MRR** (mg/min)			**SR** (µm)		
	Expt	**Regression**	**Error %**	**Expt**	**Regression**	**Error %**
1	68.73	67.30	2.08	6.88	7.083	2.95
2	66.96	65.34	2.41	7.63	7.35	3.54
3	70.70	67.34	4.71	7.20	7.28	1.06
4	20.37	18.98	6.50	8.07	7.31	9.41
5	25.3	27.80	8.17	5.60	6.00	7.14
6	10.5	10.14	3.35	3.97	4.27	7.55
7	9.24	9.034	2.27	3.51	3.31	5.69
8	98.07	103.55	5.58	8.01	7.55	5.74
9	29.8	31.30	4.89	6.67	6.99	4.79
10	30.3	27.84	8.11	6.92	7.34	6.06
11	120.6	108.95	9.65	3.55	3.68	3.66
12	16.4	17.5	6.7	3.52	3.51	1.10
	Average error		5.36	Average error		4.89

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4. CONCLUSIONS

In the present paper, the empirical models have been developed for EDM process for machining of matensitic Precipitation Hardening Stainless steel (PH steel) machined with copper tungsten electrode using Multiple Regression Analysis using MINI TAB 17. From the experimental investigation, the following conclusions are derived

- It has been observed that, there is good agreement between the regression model and the experimental results.
- The average error observed in regression model for MRR and SR as 4.14 and 2.42 respectively.
- The R^2 value for both MRR and SR are 87% and 96% respectively.
- Predication capability of SR model very close to experimental but in case of MRR prediction error more due to non linear variation and interaction effects of parameters.
- According to results the Regression model produced the better prediction for MRR and SR. It is clear that, the developed Regression models can be used to estimate the results of EDM for given range of process parameters.

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