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Prediction and optimization of micro EDM process parameter using multiple regression and artificial neural network

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ABSTRACT

The main objective of this paper is to find the optimum machining parameter for higher Material Removal Rate (MRR) in micro EDM on 316L stainless steel. The most important parameters like machining voltage, capacitance and sparkgap are considered in this experimentation. The experiments were conducted based on the full factorial design methodology. Multiple regression and Artificial Neural Network (ANN) techniques were applied to predict the MRR. The predicted results are quite closer with the experimental results. S/N ratio was calculated to find the optimum values. ANOVA is carried out and the influence of machining parameters was found. The results show that the voltage is highly significant and the capacitance is the next significant than sparkgap on MRR.

Introduction

In traditional machining process drilling of micro holes is very difficult in hard and recent developed materials. The application of micro holes is also essential in aviation, space, electronics and also in computer, medical and manufacturing of miniature components[1]. The micro EDM is one of the most important and suitable machining methods for drilling of micro holes. It is the non-contact type of machining process that the electrical energy discharges between anode and cathode the spark generates and erodes the material by vapour bubbles[2]. The circuit current, circuit voltage, capacitance, resistance, dielectric fluid are the parameters that affects the machining conditions. These parameters are important in material removal rate. Many studies have been conducted to find out the MRR by varying the machining conditions. An ultrasonic vibration introduced to the work-piece to maximize the MRR and minimize the tool wear. The ultrasonic vibration and peak power with capacitance are significant for improving MRR[3]. Optimized the powder mixed EDM parameters on Ti6A1-4U alloy. MRR, tool wear rate, overcut and taper are the responses chosen. The optimum results obtained through ANOVA and S/N ratio graph. They concluded that the peak current and pulse on time are most affected parameters[4]. A regression model developed and optimized the process parameters in PMEDM using Genetic algorithm. From the model they concluded that, reducing the machining time increases the production rate and reduces electrode wear[5]. A comparative investigation made by Kibria et al[6] on Ti-6Ai-4U alloy using pure de-ionized water and boron carbon (B_4C) mixed water. From the results, they concluded that, B_4C mixed water increase the MRR and reduces the tool wear rate also produced good surface with less recast layer. Kadirvel and Hariharan [7] reviewed the entire MEDM process, issues, output parameters, optimization techniques, and control systems. Natarajan and Arunachalam [8] optimized the machining parameter using Taguchi method and Gray relational analysis. They concluded that the pulse ontime was the most significant parameter during machining. Aravind et al [9] developed an artificial neural network model to predict MRR. Voltage, capacitance, feed and speed of the electrode were considered as input parameters. The experiments were conducted using design of experiments. They concluded that the developed model is suitable to predict the micro EDM process. Somashekar et al [10] developed a feed forward neural network with back propagation model to predict the MRR and overcut in micro wire electric discharge machining on aluminum plate. Voltage, capacitance and feed rate were chosen as input parameters. They concluded that the predicted ANN results well agreed with the experimental results. Yan et al (2001) [11] presented a feed forward neural network using a back propagation learning algorithm for the estimation of the work piece height in WEDM. They estimated the average error of workpiece height was 1.6mm. Lin and Lin (2005) [12] reported a new approach for the optimization of the EDM process with multiple performance characteristics based on grey relational analysis. The machining parameters, such as work piece polarity, pulse on time, duty factor, open discharge voltage, discharge current and dielectric fluid were optimized on the output characteristics of material removal rate, surface roughness, and electrode wear ratio. Kuriakose and Shunmugam (2005) [13] developed a multiple regression model to represent relationship between input and output variables. To optimize the wire-EDM process parameter a multi-objective optimization method based on a non-dominated sorting genetic algorithm (NSGA) is used. Saha et al (2008) [14] developed a second order multi-variable regression model and a feed-forward back-propagation neural network (BPNN) model to correlate the input process parameters. The input parameters of pulse on-time, pulse off time, peak current and capacitance with the performance measures like cutting speed and surface roughness in WEDM of tungsten carbide-cobalt (WC-Co) composite material. The neural network architecture provides the best

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prediction capability with 3.29% error overall and 6.02% error was revealed by regression model. The existing work shows that not much works carried out on 316L stainless steel to optimize the micro EDM process parameters. This paper helps to find out the optimum machining parameter on 316L stainless steel.

Experimental Setup

The single axis (Z) tabletop micro EDM setup was used for experiments. The set-up consists of various components such as machine structure, tool electrode feed system, closed loop sparkgap system, dielectric fluid supply and circulation system and Resistance Capacitance (RC) power supply. Figure 1 shows the developed single axis micro EDM setup. Pure Tungsten wire of diameter 380µm is used as a microelectrode for all trials. A 316L stainless steel is chosen as work material. The de-ionised water was used as dielectric medium.

In the present work three parameters were selected like voltage, capacitance and sparkgap. In each parameter three levels were chosen. The Table 1 shows the selected parameters and their levels.

Figure 1 Experimental setup of Micro Electric Discharge Machining (µEDM)

For three levels and three parameters full factorial [15] design was selected for experimentation. The plan of experiments is made of 27 tests and repeated once for better understanding. Totally 54 tests were conducted to study the objective. The MRR is the output of this study. Multiple regression and artificial neural networks (ANN) are used to predict the outputs. To validate the predicted models, the predicted output values are compared with the experimental values. Table 2 shows the experimental values and MRR.

Prediction Model for MRR

To improve the micro EDM, micro hole drilling process, it is necessary to develop the prediction model. Multiple regression analysis and ANN techniques are used to predict the MRR.

Multiple Regression Model for MRR

Multiple regression is commonly used traditional technique to predict various machining process Sidda Reddy et al (2008). The proposed multiple regression equation is as follows

$$Y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + ...nx_n \quad -(1)$$

Y – Standard variable

x_1, x_2 and x_3 are the predicted variables

Where

x_1 - Voltage

x_2 - Capacitance

x_3 - Sparkgap

a_0, a_1, a_2 and a_3 are the regression coefficients

The multiple regression equation 2 is used for MRR

= 0.454 + 0.00738 Voltage +0.000630 Capacitance - 0.0195 Sparkgap -(2)

To solve the regression equation a matrix is formulated to determine regression coefficients. The regression coefficients are used to estimate the MRR and it is shown in table (3). The predicted MRR values are compared with experimental values. The table (4) shows the predicted, experimental and errors values.

The ANN model for predicting the MRR

Nowadays ANN is widely used for optimization, prediction and image processing etc., A generalized feed forward network is used for developing ANN model. The feed forward neural network model consists of two stages such as training and testing of the experimental data. During the training of network, all the input parameters are considered and given equal important. The network has three inputs (voltage, capacitance and sparkgap) and one output (MRR). The present model consists of three neurons in the input layer and one neuron in the output layer. In the multi-layer feed forward network, the size of hidden layers is one of the most important considerations when solving the problems. In this model two hidden layers were adopted. The experimental data used for training is given in Table 4. The topology and training parameters are given in Table 5.

$$net_j = \sum_{j=0}^{N} x_i w_{ij} \quad (1)$$

where,

x_i = i^{th} input, N = number of inputs

w_{ij} = weight attached to the link connecting i^{th} input neuron and j^{th} hidden neuron.

The sigmoidal activation function is applied in this ANN model. Its output is given by,

$$f(net_j) = \frac{1}{1+e^{-\lambda(net_i+\theta)}} \quad (2)$$

The voltage, capacitance and sparkgap are three parameters given to input layer. In this model, the inputs and outputs are normalised to gain better results. To train the developed model, 15 data sets are used. To test the ANN model, 10 data sets are used. A 'C' program is written to train, test and predict the MRR values. The predicted results developed by the model are compared with experimental values and errors are shown in Table 6. From the results, it is clear that the developed model is well trained and possesses the capability to predict new outcomes from the past trends.

Optimization of Process Parameters

To optimize the µEDM process parameters, signal to noise (S/N) (Phillip Ross and Tapan Bagchi [16] ratio is calculated. The S/N ratio is the ratio between signal to noise, where the signal represents the desirable value and the noise represents the undesirable values. Therefore the S/N ratio is used to find the significant machining parameters through the analysis of variance (ANOVA). The higher observed value that represents higher MRR is known as Higher is Better (HB). The equation (1) is used to find out the S/N ratio for higher material removal rate (MRR).

$$\mathrm{HB} = -10\log(1/r(\sum_{i=1}^{n} 1/Y_i^2)$$

Analysis - Optimum Machining Parameters

The mean S/N ratio for MRR is displayed graphically in Figure 2. The MRR for each factors level indicates the relative effects of the various factors, A: voltage, B: capacitance and C: sparkgap on the machining performance and characteristics such as MRR is related to the µEDM operation during machining of 316L stainless steel. From the S/N response graph figure 2 for maximum MRR the optimal parametric combination is A3, B2, and C1.

Table 1. shows the parameters and their levels

Parameters	Voltage (V)	Capacitance (pF)	Sparkgap (μm)
Level 1	80	200	28
Level 2	100	300	32
Level 3	120	500	36

Table 2 shows the experimental and MRR values

Exp. No.	Input Parameters & Values			*MRR* $*e^{-3}$ (gm's/min)
	Voltage (V)	Capacitance (pF)	Sparkgap (μm)	
1	80	200	28	0.6365
2	100	200	28	0.7527
3	120	200	28	0.9022
4	80	300	28	0.7119
5	100	300	28	0.8527
6	120	300	28	0.9655
7	80	500	28	0.7998
8	100	500	28	0.9613
9	120	500	28	1.108
10	80	200	32	0.5544
11	100	200	32	0.6751
12	120	200	32	0.8146
13	80	300	32	0.6391
14	100	300	32	0.7586
15	120	300	32	0.9898
16	80	500	32	0.6983
17	100	500	32	0.8699
18	120	500	32	1.0191
19	80	200	36	0.4671
20	100	200	36	0.5998
21	120	200	36	0.7054
22	80	300	36	0.5453
23	100	300	36	0.6977
24	120	300	36	0.8484
25	80	500	36	0.6308
26	100	500	36	0.8013
27	120	500	36	0.9884

Table 3 Regression coefficients

Regression Coefficients	Values
a_0	0.454
a_1	0.00738
a_2	0.000630
a_3	- 0.0195

Table 4 Comparison of predicted with experimental values –Regression

Exp. No	Voltage	Capacitance	Spark Gap	MRR		
				Experimental	Predicted	Error
1	80	200	28	0.6365	0.6244	-0.0121
2	100	200	28	0.7527	0.772	0.0193
3	120	200	28	0.9022	0.9196	0.0174
4	80	300	28	0.7119	0.6874	-0.0245
5	100	300	28	0.8527	0.835	-0.0177
6	120	300	28	0.9655	0.9826	0.0171
7	80	500	28	0.7998	0.8134	0.0136
8	100	500	28	0.9613	0.961	-0.0003
9	120	500	28	1.108	1.1086	0.0006
10	80	200	32	0.5544	0.5464	-0.008
11	100	200	32	0.6751	0.694	0.0189
12	120	200	32	0.8146	0.8416	0.027
13	80	300	32	0.6391	0.6094	-0.0297
14	100	300	32	0.7586	0.757	-0.0016
15	120	300	32	0.9898	0.9046	-0.0852
16	80	500	32	0.6983	0.7354	0.0371
17	100	500	32	0.8699	0.883	0.0131
18	120	500	32	1.0191	1.0306	0.0115
19	80	200	36	0.4671	0.4684	0.0013
20	100	200	36	0.5998	0.616	0.0162
21	120	200	36	0.7054	0.7636	0.0582
22	80	300	36	0.5453	0.5314	-0.0139
23	100	300	36	0.6977	0.679	-0.0187
24	120	300	36	0.8484	0.8266	-0.0218
25	80	500	36	0.6308	0.6574	0.0266
26	100	500	36	0.8013	0.805	0.0037
27	120	500	36	0.9884	0.9526	-0.0358

Table 5 ANN topology and its training parameters

Parameters	Values
Number of input neurons	3
Number of hidden layers	2
Number of neurons in each hidden layer	5
Number of output neuron	1
Momentum factor	0.9
Learning rate	0.6
Number of iterations	200000

Table 6 Comparison of predicted (ANN) and experimental values

Exp. No	Actual MRR	Predicted MRR	Error
1	0.6365	0.612	0.0245
2	0.7527	0.7423	0.0104
3	0.9022	0.911	-0.0088
4	0.7119	0.6941	0.0178
5	0.8527	0.9241	-0.0714
6	0.9655	0.9865	-0.0211
7	0.7998	0.7658	0.0340
8	0.9613	0.9421	0.0192
9	1.108	1.092	0.0160
10	0.5544	0.5426	0.0118

Table 7 Experimental results and S/N ratios

Exp. No.	MRR (*e-3 mm^3/min)	S/N Ratio
1	0.6365	-3.92
2	0.7527	-2.47
3	0.9022	-0.89
4	0.7119	-2.95
5	0.8527	-1.38
6	0.9655	-0.30
7	0.7998	-1.94
8	0.9613	-0.34
9	1.108	0.89
10	0.5544	-5.12
11	0.6751	-3.41
12	0.8146	-1.78
13	0.6391	-3.89
14	0.7586	-2.40
15	0.9898	-0.09
16	0.6983	-3.12
17	0.8699	-1.21
18	1.0191	0.16
19	0.4671	-6.61
20	0.5998	-4.44
21	0.7054	-3.03
22	0.5453	-5.27
23	0.6977	-3.13
24	0.8484	-1.43
25	0.6308	-4.00
26	0.8013	-1.92
27	0.9884	-0.10

Table 8 Percentage contributions of the selected parameters for MRR

Source of variance	Degree of Freedom	Sum of squares	Variance	F- Ratio	F- Ratio Tabulated value	% Contribution
Voltage	2	50.92	25.46	292.25	3.37	56.25
Capacitance	2	22.49	11.25	129.09	3.37	24.84
Sparkgap	2	15.38	7.69	88.25	3.37	16.99
Error	20	1.74	0.09			1.92
Total	26	90.54				100

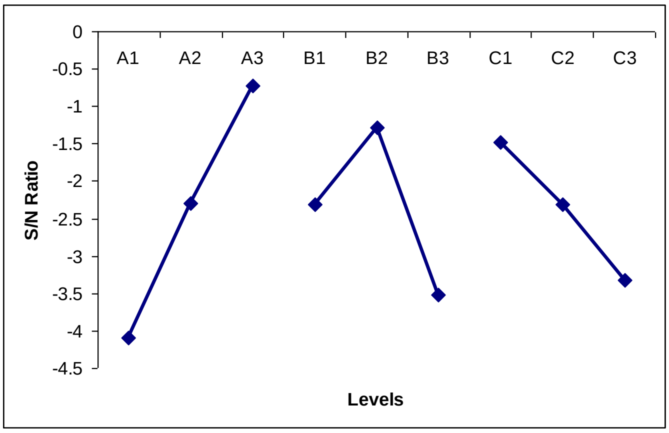

Figure 2 graphical representation of S/N ratio for MRR

Analysis of Variance (ANOVA)

The experiments were conducted based on the experimental plan given in Table 1. ANOVA was carried out to find the influence of machining parameters on MRR. The percentage contribution indicates the significant effect of parameters on MRR and it is given in the Table 3. F - Tests have been performed to find the significance of machining parameters. At 95% confidence level $F_{(0.05\%),\,2,26}$ = 3.37. The calculated value of the 'F' ratio of voltage, capacitance and sparkgap are more than the tabulated value. This shows that the voltage is highly significant and the capacitance is next significant to voltage for MRR. The percentage contribution of each parameter on MRR is shown in figure 3.

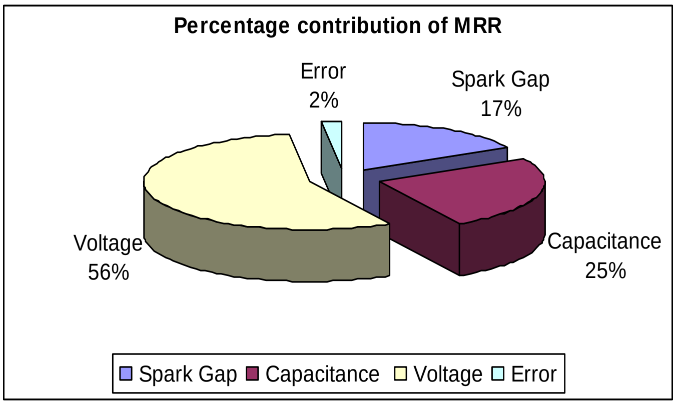

Figure 3 percentage contributions on MRR

Conclusions

A full factorial design was used to conduct the experiments. Three important machining parameters such as voltage, capacitance and sparkgap were considered for experimentation and MRR was calculated. Multiple regression and artificial neural network techniques are used to predict the MRR. To validate the developed model, the predicted values are compared with actual experimental results. ANOVA is carried out and the influence of machining parameters on MRR is found. The S/N ratio was calculated to find the optimum machining parameters. From the results, the following salient conclusions can be drawn.

1. The developed multiple regression model gives satisfactory results in many predictions.
2. The results attained from the ANN model gives better agreement with experimental values than the multiple regression.
3. From the S/N ratio, the optimum machining parameter for MRR is voltage of 120V, capacitance of 300 pF and sparkgap of 28 µm.

ANOVA results show that the voltage is the most dominating parameter that influences MRR, Capacitance is the second dominating parameter for MRR. The voltage contributes 56.25 %, capacitance contributes 24.84 % and sparkgap contributes 16.99 % towards the MRR.

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References

[1]. Mohan Sen and H.S. Shan, "A review of electrochemical macro- to micro-hole drilling processes", International Journal of Machine Tools & Manufacture, vol. 45, 2005, pages: 137–152.

[2]. SeongMin Son, HanSeok Lim, A.S. Kumar and M. Rahman, "Influences of pulsed power condition on the machining properties in micro EDM", Journal of Materials Processing Technology, vol 190, (2007), pages 73–76.

[3]. Murali M. Sundaram, Ganesh B. Pavalarajan, and Kamlakar P. Rajurkar, "A Study on Process Parameters of Ultrasonic Assisted Micro EDM Based on Taguchi Method", Journal of Materials Engineering and Performance, (2008), Vol.17, pp.210–215.

[4]. B.B.Pradhan, M.Masanta, B.R.Sarkar and B.Bhattacharyya, "Investigation of electro-discharge micro-machining if titanium super alloy", International journal of advancement in manufacturing technology (2009), vol: 41, pp. 1094-1106.

[5]. Farhad Kolahan and Mohamad Bironro, "Modeling and Optimization of process parameters in PMEDM by Genetic Algorithm", World academy of science, Engineering and Technology, 48,(2008), 480-484.

[6]. G.Kibria, B.B.Pradhan, B.R.Sarkar, B.Bhattacharyya, "Micro-hole Machining by EDM Employing Abrasive Mixed de-ionized Water", Sixth International Conference on "Precision, Meso, Micro and Nano Engineering", pp.C11-15, 2009.

[7]. A.Kadirvel and P.Hariharan, "A Review on Various Research Trends in Micro EDM", ",Sixth International Conference on "Precision, Meso, Micro and Nano Engineering", pp. C42-C46, 2009.

[8]. N.Natarajan and RM.Arunachalam, "Optimization of micro-EDM with multiple performance characteristics using Taguchi method and Grey relational analysis", Journal of Scientific and Industrial Research, vol.70, 2011, pg 500-505.

[9]. D.Aravind, A.Varun, R.Manu and Jose Mathew, "Modeling of Micro Electric Discharge Machining Process for MRR using Artificial Neural Networks", Sixth International Conference on "Precision, Meso, Micro and Nano Engineering", pp. C16-C19, 2009.

[10]. K.P.Somashekar, C.J.Robin, N.Ramachandran, Jose Mathew, "Neural Network Approach for the Estimation of Material Removal Rate and Overcut in M- WEDM", Sixth International Conference on "Precision, Meso, Micro and Nano Engineering", 11-12 December, 2009

[11]. Yan, M.T., Liao, Y.S., Chang, C.C. (2001), "On-line estimation of workpiece height by using neural networks and hierarchical adaptive control of WEDM", International Journal of Advanced Manufacturing Technology, 18, 884–891.

[12]. Lin, J.L., and Lin, C.L. "The use of grey-fuzzy logic for the optimization of the manufacturing process", Journal of Materials Processing Technology, Vol.160, pp. 9–14, 2005.
[13]. Kuriakose, S., Shunmugam, M.S. (2005), "Multi-objective optimization of wire-electro discharge machining process by non-dominated sorting genetic algorithm", Journal of Materials Processing Technology, 170,133-141.
[14]. Saha, P., Singha, A., Pal, S.K., Saha, P. (2008), "Soft computing models based prediction of cutting speed and surface roughness in wire electro-discharge machining of tungsten carbide cobalt composite", International Journal of Advanced Manufacturing Technology, 39.,74-84.
[15]. Douglas. C. Montgomery, "Design of Experiments", 5^{th} edition. John Wiley & Sons Canada, Ltd.; 2000.
[16]. Phillip.J.Ross, "Taguchi Techniques for Quality Engineering", McGraw-Hill, New York. 1996.
[17]. Bagchi Tapan P, "Taguchi Methods Explained: Practical Steps to Robust Design" Prentice Hall, 1993.