Experimental Investigation of Stainless Steel 316L Micro Electro Chemical Process using RSM and ANFIS

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Abstract — **The micro components for electronics and medical industries are fabricated predominately using the micro electro chemical machining technique. Hence, we need to control the process parameters to achieve the better Material Removal Rate (MRR) and Over Cut (OC). In the current paper, we aim to drill a micro holes using tungsten electrode of 500µm on the work piece of stainless steel 316L by controlling the intervening process variables current, frequency and duty cycle. The Taguchi practice is applied to determine the optimum process parameters and the number of experiments required to model the objectives. The mathematical models for the objectives have been developed using Response Surface Methodology (RSM) and Artificial Neuro Fuzzy Inference Systems (ANFIS). The analysis has been made using the surface plots to study the effect of the process parameters on MRR and OC. An error analysis is done to predict the MRR and OC during machining the micro hole on stainless steel 316L and found that ANFIS model is well suited for the prediction of responses.**

Keywords — Material Removal Rate, Over Cut, Response Surface Methodology, Stainless Steel 316L, ANFIS

1. Introduction

As the developments in the process of miniaturization, new fields are evolving which have a need for micro fabricated components. To meet the demands of such applications like biotechnology, microsurgery and high temperature environments, special harder materials are required. Examples of such applications are miniaturization of medical tools, fuel injection nozzles for automobiles etc. The unconventional machining processes such as Laser Beam Machining (LBM), Electro Discharge Machining (EDM), Plasma Arc Machining (PAM), etc are causing thermal distortion on the machined surface. Micro Electro Chemical Machining (microECM) is thermal free process with reasonable alternative that provides the necessary accuracy as well as economic production capability.

Lee et al [1] have studied the process of ball burnishing AISI 316L stainless steel, in which they have used Taguchi techniques for the statistical design of experiments for achieving good surface finish on flat specimens. Gurgui et al [2] have addressed the innovative manufacturing process in the field of medical and conducted experiments in stainless steel 316L to achieve the micro cavities with error below 5%. Chan Hee et al [3] suggest that for machining internal features, the micro electro chemical machining is used. The process parameters like pulse on time, voltage, machining time are varied to make hole entrance size smaller than the inside. Reversed-tapered and barrel-shaped holes were fabricated and use of insulation on the electrode will prevent the over-dissolution is suggested.

Yong & Ruiqin [4] presented an electro machining process of tapered holes for fuel jet nozzles using ECM and straight cylindrical pilot hole is drilled by EDM. The pulse voltage, tool electrode feeding speed, pulse duration and duty ratio are examined for the diameter variance in ECM. Minh Dang Nguyen et al [5] have studied to predict the analytical model for identifying the critical conditions for the transitions of material removal mechanisms in hybrid machining process under low resistivity deionised water. The critical feed rate for transitions of material removal mechanisms are then predicted using double layer theory, Butler–Volmer equation and Faraday's law of electrolysis. For high feed rate with the thickness of material layer of the electrochemical reaction could dissolve is smaller than the roughness of the microEDM surface, machining mode is changed to µEDM milling. For the vice versa case, material removal mechanism is converted to pure microECM.

Kannan & Baskar [6] have also suggests that RSM to predict the MRR and surface roughness of aluminium and resolved that the hybridization of RSM and genetic algorithm is an efficient methodology for machining parameter optimization. Rajesh & Dev Anand [7] have presented a practical method of optimizing MRR and surface roughness with current, voltage, flow rate, pulse on time, pulse off time and spark gap which are the machining parameters for EDM. With the use of grey relation analysis and RSM, the objectives are combined and a linear regression model is obtained.

Guojun Zhang et al [8] have proposed the optimal process parameter settings with maximum MRR and minimum 3D surface quality for medium speed WEDM machining of SKD11 steel simultaneously. They have concluded that the hybrid method of RSM and NSGA-II is an effective way for multi-objective optimization. Kannan et.al [9] used the adaptive neuro-fuzzy inference system (ANFIS) to predict the Surface Roughness of the nano copper suspended electrochemically machined Inconel 718 and they concluded that the ANFIS model with gbellmf is accurate.

Periyakgounder Suresh et.al [10] explored the intervening variables in micro electric discharge machining using a genetic algorithm and Response Surface methodology for Stainless Steel 316L. The results revealed that optimal intervening parameters improved the chosen objectives significantly. Prabhu et al attempted [11] Taguchi-fuzzy logic-neural network analysis for the prediction of Surface Roughness using for mixed nanofluids (CNTs) in grinding process of AISI D3 Tool steel.

From these, it can be inferred that not much work has been carried out to investigate the responses Material Removal Rate (MRR) and Over Cut (OC) along with the process parameters like current, frequency and duty cycle on Stainless Steel 316L (SS316L).

2. Experimental Detail

The experiments were performed on an indigenously developed micro Electro Chemical Machine (microECM) as shown in figure 1 with a tungsten electrode of 500µm diameter for machining SS316L of 50mm diameter and 2 mm thickness. The electrolyte used for experiment was NaNo3 solution with a concentration of 0.3 moles. The chemical composition of SS316L is shown in the table 1.

TABLE 1

Composition of stainless steel 316L

Elements	C	Mn	Si	P	S	Cr	Mo	Ni	N
%age	0.03	2.0	0.75	0.045	0.03	18.0	3.00	14.0	0.10

Figure 1. Machining Setup

Taguchi's method is a powerful tool that provides an well-organized and systematic approach to optimize the performance, which is drastically used to avoid number of experiments that are required to model response functions. The process parameters chosen are current, frequency and duty cycle with three levels in order to study the MRR and OC. The machining process parameters and their levels for the L27 orthogonal array are given in the table 2.

TABLE 2

Machining parameters and their levels

Parameters	Level 1	Level 2	Level 3
Current [A]	2	3	4
Frequency [Hz]	100	200	300
Duty cycle [%]	30	60	90

The MRR for each experiment is calculated as per the equation 1. The OC is calculated based on the data from the microscopic image taken for each experiment. As a sample, a microscopic image is shown in the figure 2.

$$\text{MRR} = \frac{\text{Before machining weight of work piece} - \text{After machining weight of work piece}}{\text{Machining time}} \quad \ldots(1)$$

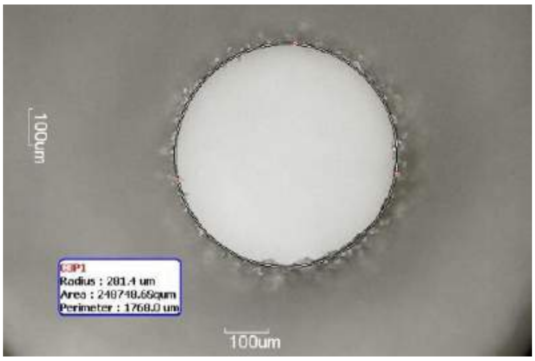

Figure 2. Sample microscopic image

3. Mathematical Modeling using Responses Surface Methodology

Response Surface Methodology (RSM) is used to examine the relationship between one or more output variables and a set of input variables, in the experiments conducted. A second order mathematical model can significantly improve the optimization process. The process parameters current, frequency and duty cycle are selected to obtain the mathematical model for MRR and OC. The general form of second-order polynomial model is

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} a_{ii} x_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j \quad _{i<j} \quad \text{....(2)}$$

Where x_i and x_j are the design variables and 'a' are the tuning parameters.

Design Expert software is employed to predict the mathematical models of MRR and OC for the experiments conducted and given in the equation 3 and 4 respectively.

MRR = +0.48416-0.49314*x(1)+0.00303977 * x(2)+0.019827 * x(3) - 0.000461046 *x(1)*x(2)+0.000530632*x(1)*x(3) - 0.00000202675*x(2)*x(3) + 0.085128 *x(1)*x(1)-0.00000501537*x(2)* x(2) - 0.000122586 * x(3) * x(3) …(3)

OC = + 23.31333 + 2.02444 * x(1) - 0.031533 * x(2) - 0.13374 * x(3) + 0.011133 * x(1) * x(2) + 0.029444 * x(1) * x(3) + 0.000123333 * x(2) * x(3) - 1.12000 * x(1) * x(1) - 0.000018000*x(2)*x(2)-0.000814815 * x(3) * x(3) …(4)

Where x(1) is current , x(2) is frequency , and x(3) is duty cycle.

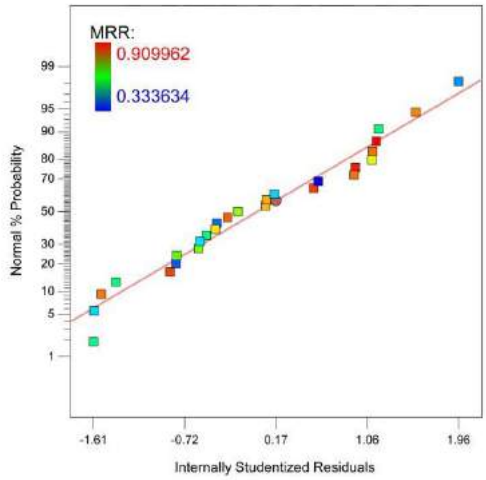

Figure 3 (a) The Normal % Probability of MRR

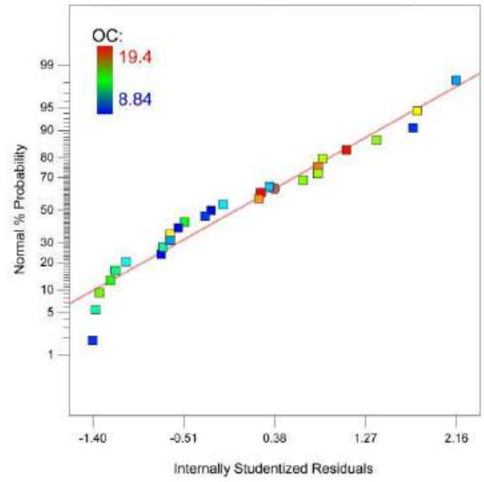

Figure 3 (b) The Normal % Probability of OC

Figure 3(a) and (b) show the normal plot of residuals for MRR and OC respectively. In order to check whether the model is fitted with the experimental values, the multiple regression coefficients R2 is calculated for MRR and OC.

The values are found to be 0.9439 and 0.8943 respectively. Since the values of R2 is at 95% confidence, this shows that the developed models are statistically considerable.

TABLE 3

ERROR PREDICTION USING RSM PREDICTED MODEL

#	Measured Values		Predicted values		Error %age	
	MRR	*OC*	*MRR*	*OC*	*MRR*	*OC*
	mg/min	*%age*	*mg/min*	*%age*		
1	0.5559	19.40	0.5102	19.17	8.21	1.20
2	0.8032	16.04	0.7998	15.09	0.42	5.92
3	0.8571	8.84	0.8688	9.55	1.36	8.02
4	0.5428	19.28	0.5655	18.07	4.18	6.28
5	0.8942	12.96	0.8490	14.36	5.06	10.84
6	0.8431	8.92	0.9118	9.19	8.15	3.05
7	0.4582	15.32	0.5204	16.61	13.57	8.44
8	0.8480	12.48	0.7978	13.28	5.92	6.39
9	0.8755	10.56	0.8546	8.48	2.39	19.74
10	0.3944	17.84	0.4126	17.59	4.60	1.41
11	0.7087	13.80	0.7181	14.40	1.32	4.31
12	0.8450	9.40	0.8029	9.74	4.98	3.58
13	0.3835	16.84	0.4217	17.60	9.96	4.54
14	0.6934	15.56	0.7211	14.78	4.00	5.00
15	0.7800	10.88	0.7999	10.49	2.55	3.56
16	0.4183	18.16	0.3305	17.26	20.99	4.95
17	0.5577	15.76	0.6238	14.81	11.87	6.04
18	0.7464	9.32	0.6965	10.89	6.68	16.84
19	0.4630	12.44	0.4851	13.77	4.77	10.68
20	0.8102	11.32	0.8066	11.46	0.45	1.24
21	0.8740	9.36	0.9073	7.68	3.81	17.90
22	0.4553	16.88	0.4481	14.90	1.57	11.74
23	0.8368	11.68	0.7635	12.96	8.76	10.96
24	0.9100	8.92	0.8582	9.55	5.69	7.11
25	0.3336	14.48	0.3109	15.67	6.83	8.21
26	0.5479	15.64	0.6201	14.10	13.18	9.85
27	0.6780	10.44	0.7087	11.06	4.54	5.98
Average					6.14	7.55

The table 3 indicates that the % of error obtained between the measured value and RSM predicated value of the MRR and OC. The average % of error is about 6.14 and 7.55 for RSM and OC respectively.

4. PROCESS MODELING USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is a recent predictive technique that uses both meanings of neural network and fuzzy logic for modeling of complex processes in which many inputs are contributed and the amount of experimental data are small. We employed ANFIS MATLAB tool box to train the experimental values. Even though various membership functions are available in MATLAB for training ANFIS, the Bell membership (gbellmf) function provides the lowest training error and hence it was selected for the training process in this work. Separate models have been developed for the modeling of MRR and OC.

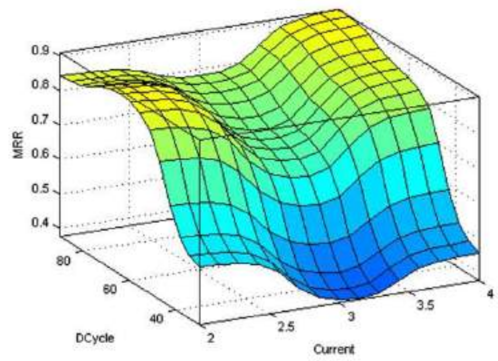

Figure 4 (a) MRR variation with respect to current & duty cycle

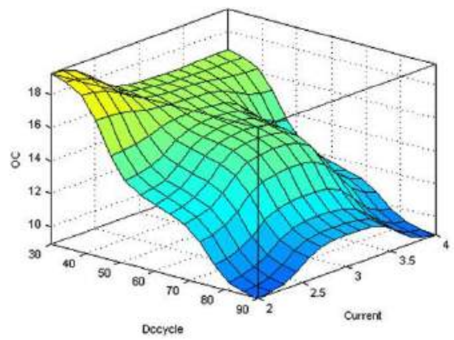

Figure 4 (b). OC variation with respect to current & duty cycle

The figure 4 (a) and (b) shows that the behaviour of MRR and OC with respect to the current and the duty cycle.

TABLE 4

ERROR PREDICTION USING ANFIS PREDICTED MODEL

#	Measured Values		Predicted values		Error %age	
	MRR	*OC*	*MRR*	*OC*	*MRR*	*OC*
	mg/min	*%age*	*mg/min*	*%age*		
1	0.5559	19.40	0.5681	19.15	2.19	1.29
2	0.8032	16.04	0.8291	15.56	3.22	2.99
3	0.8571	8.84	0.8874	9.22	3.53	4.30
4	0.5428	19.28	0.5318	19.03	2.03	1.30
5	0.8942	12.96	0.9281	13.28	3.79	2.47
6	0.8431	8.92	0.8333	9.23	1.17	3.48
7	0.4582	15.32	0.4451	16.21	2.86	5.81
8	0.8480	12.48	0.8567	13.54	1.03	8.49
9	0.8755	10.56	0.8564	9.51	2.19	9.94
10	0.3944	17.84	0.4113	17.20	4.28	3.59
11	0.7087	13.80	0.6987	13.31	1.41	3.55
12	0.8450	9.40	0.8225	10.10	2.66	7.45
13	0.3835	16.84	0.4112	17.12	7.23	1.66
14	0.6934	15.56	0.7111	14.89	2.56	4.31
15	0.7800	10.88	0.7681	11.19	1.52	2.85
16	0.4183	18.16	0.3992	17.54	4.57	3.41
17	0.5577	15.76	0.5874	14.68	5.33	6.85
18	0.7464	9.32	0.7012	9.55	6.06	2.47
19	0.4630	12.44	0.4553	13.20	1.67	6.11
20	0.8102	11.32	0.7987	11.38	1.42	0.53
21	0.8740	9.36	0.8874	8.74	1.54	6.62
22	0.4553	16.88	0.4682	15.56	2.83	7.82
23	0.8368	11.68	0.8065	12.28	3.62	5.14
24	0.9100	8.92	0.8741	8.52	3.94	4.48
25	0.3336	14.48	0.3227	13.88	3.28	4.14
26	0.5479	15.64	0.5781	14.63	5.51	6.46
27	0.6780	10.44	0.6871	10.10	1.35	3.26
Average					3.07	4.47

The table 4 indicates that the % of error obtained between the measured value and ANFIS predicated value of the of MRR and OC. The average % of error is about 3.07 and 4.47 for RSM and OC respectively.

5. ERROR ANALYSIS BETWEEN RSM AND ANFIS

In this research work, the RSM and ANFIS models are employed to predict MRR and OC while machining SS316L using microECM. From the table 3 and 4, the predicted values of the MRR and OC are close to the RSM results, but ANFIS model provides a better performance for most of the tested values. This is due to the fact that in ANFIS, both the learning and reasoning capabilities of a neural network and fuzzy logic are combined in order to predict the output performance in a single methodology.

To gain more understanding into the prediction results, the percentage of error values plotted for MRR and OC are shown in Fig 5 (a) & (b).

These figures point out that the RSM model has more error values than the ANFIS model. Thus, the ANFIS model can be considered as better prediction models over the RSM model while machining SS316L in microECM process.

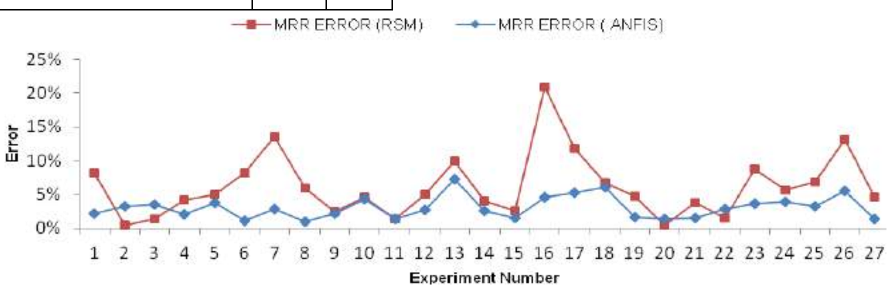

Figure 5(a). The percentage of error values plotted for MRR

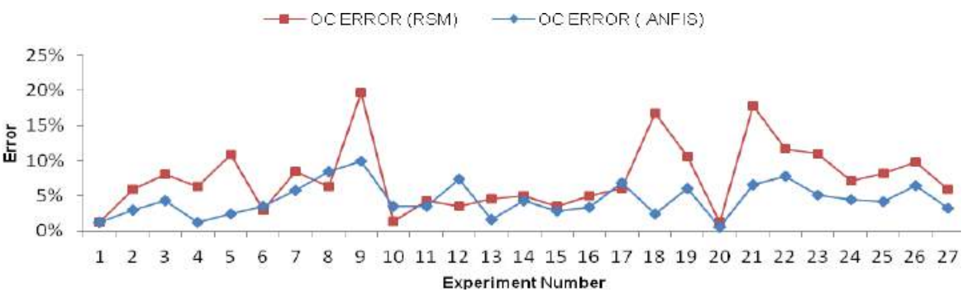

Figure 5(b). The percentage of error values plotted for OC

6. CONCLUSIONS

The prediction of MRR and OC with the process parameters such as current, frequency and duty cycle while machining micro hole on SS316L material using 500µm tungsten electrode was studied through Response Surface methodology (RSM) and Adaptive Neuro fuzzy Inference Systems (ANFIS). The following conclusions are drawn from the present research work.

The predicting ability of the RSM approach is found to be 93.86 % and 92.45 % for MRR and OC respectively. Subsequently, the association between the process parameters and responses are effectively established by the ANFIS approach with 96.93 % for MRR and 95.53% for OC.

Due to its optimistic prediction ability, the ANFIS approach is found to be agreeable to predict MRR and OC for machining of SS316L using microECM process.

Thus the ANFIS is considered to be a powerful tool to predict the model for industrial problems.

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