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Research Paper

ANN MODELLING FOR THE PREDICTION OF MATERIAL REMOVAL RATE AND MACHINED HOLE OVERCUT IN HOLE DRILLING ELECTRO DISCHARGE MICRO MACHINING

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Hole Drilling Electro Discharge Micro Machining (HD-EDMM), one of the Hybrid Machining Processes (HMPs) combining the features of Electro Discharge Micro Machining (EDMM)) and conventional drilling process is used for machining electrically conducting materials. In the present paper Artificial Neural Network (ANN) model has been proposed for the prediction of material removal rate (MRR), and machined hole overcut (MHO) in Hole Drilling Electro Discharge Micro Machining (HD-EDMM). For this purpose Matlab with the neural networks toolbox (nntool) has been used. The neural network based on process model has also been developed to establish relationship between input process conditions (gap voltage, capacitance, and revolution per minute of tool electrode) and process responses (MRR and MHO). The ANN model has been trained and tested using the data generated from an extensive series of experiments on HD-EDMM machine. The trained neural network system has been used to predict MRR and TWR for different input conditions. The ANN model has been found to predict accurately HD-EDMM process responses for chosen process conditions.

Keywords: Hole Drilling Electro Discharge Micro Machining (HD-EDMM), Artificial Neural Network (ANN), Back-Propagation (BP) algorithm

INTRODUCTION

In recent years, the need for the miniaturization of machining parts has been growing in a wide range of industrial production technologies. Miniaturized parts are becoming more and more valuable since they can provide more functions in limited space. Especially with the increasing need for the development of the micro-electro mechanical system, sub-micrometer or even nanometer parts are sought in various sectors. Electro Discharge Micro Machining (EDMM) has become one of

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the most important methods for manufacturing micrometer parts having ability to manufacture complicated shapes with high accuracy and to machine any electrically conductive materials regardless of hardness. It has been known that the material removal mechanism in EDMM is due to plasma formation, heat transfer, superheating of electrodes and ejection of material due to electrical discharge energy transfer of the order of less than 100 μJ. The power supply used in EDMM is either relaxation type pulse generator or transistor type pulse generator with MHz pulsating frequency. Various gap monitoring and control strategies have been developed to avoid any problem of arcing and short circuiting.

Based on the configuration of tool and workpiece as well as the type of feature EDMM has varied variations such as die sinking-EDMM, hole drilling-EDMM, die drilling-EDMM, pocket milling-EDMM, wire-EDMM, and grinding-EDMM.

Hole Drilling Electro Discharge Micro Machining (HD-EDMM) is a type of electro discharge micro machining in which a symmetrical solid tool is used to make a symmetrical hole of large depth to diameter ratio by providing rotation to the tool electrode. These micro holes are required for many industrial applications such as manufacturing of injection nozzles, starting hole for wire EDM, and micro fluidic systems.

LITERATURE REVIEW

The origin of EDM can be traced as far back as 1770, when English chemist Joseph Priestly discovered the erosive effect of electrical discharge. However it was only in1943 at the Moscow University where Lazarenko and Lazarenko exploited the destructive properties of electrical discharges for constructive use. They developed a controlled process of machining difficult to machine metals by vaporizing material from the surface of metal. Wong *et al.* (2003) have developed a single-spark generator to study the erosion characteristics from the micro crater size due to EDMM. Their experimental results suggested that volume and size of the micro craters are found to be more consistent at lower-energy discharges than at higher-energy discharges. An optical sensor has been developed by Lim *et al.* (2003) to measure and control the dimension of the thin electrode during the tool fabrication process. They observe that the rotating electrode shows the best performance in the high-aspect ratio tool-electrode fabrication and machining depth is inversely proportional to the feed rate. A 4-axis EDMM machine using DC servo motors was developed by Zhao *et al.* (2004). They used granite base to decrease the stray capacitance for lower discharge energy, also a 25 μm diameter micro-hole with aspect ratio over 10 was drilled on this machine. A 3-axis local actuator module for EDMM was developed by Yoshihito *et al.* (2004). This module had 200 Hz bandwidth and utilized the electromagnetic force for the holding and positioning of the electrode. A 60 μm diameter micro-hole with aspect ratio over 16 was machined by this module. Han *et al.* (2004) has developed a new transistor type isopulse generator and servo feed control to improve the machining characteristics of EDMM. It is observed that the transistor type isopulse generator is more useful in semi finishing than in finishing, whereas servo feed control is better in finishing as compared to semi finishing.

The factors which may affect minimum smallest possible rod diameter that can be obtained by EDMM was investigated by Fuzhu *et al.* (2006). It was observed that tungsten carbide and cemented tungsten carbide are better than tungsten because of both crystal grain size and size of defects among grains are smaller. The surface finish obtained with reverse polarity is better than straight polarity. SeongMin *et al.* (2007) investigated the influences of electrical pulse condition on the machining properties in EDMM. They found that the voltage and current are proportional to the material removal rate, while current is only proportional in the case of tool wear rate. Also shorter pulse on duration is profitable to make accurate machining with a higher removal rate and a lower tool wear rate. Jahan *et al.* (2009) studied the effect of different tool electrode materials (W, AgW, CuW) on workpiece material (WC) for Material Removal Rate (MRR) and Tool Wear Rate (TWR). It was observed that the AgW electrode produces smoother and defect-free nano surface among the three electrodes. Besides, a minimum amount of material migrates from the AgW electrode to the WC workpiece during the finishing EDMM. CuW electrode achieved highest MRR while W electrode has lowest tool wear among all electrodes. A new technique to measure the volume of material removed from the tool and the workpiece was proposed by Karthikeyan *et al.* (2010). It has been found that the rotation speed plays a significant role in achieving the desired MRR by enhancing flushing. The surface analysis shows that the debris formed by low value of speed and feed rate have resulted in bigger size debris at the edges.

Indurkhya and Rajurkar (1992) have developed a 9-9-2-size back-propagation neural network for orbital EDM modeling. Having compared the results of the neural network model with estimates obtained via multiple regression analysis, they concluded that the neural model is more accurate and also less sensitive to noise included in the experimental data. Assarzadeh and Ghoreishi (2008) have presented a new integrated neural network based approach for the prediction and optimal selection of process parameters in die sinking electro-discharge machining with a flat electrode. Basheer *et al.* (2008) have investigated the roughness of machined surfaces on Al/SiC metal metrix composites and developed an ANN-based model to predict surface roughness of machined surfaces using a feed-forward network and an algorithm involving Bayesian regularization combined with the Levenberg-Marquardt modification to train the neural network.

The present paper attempts to develop a feed forward BPNN model for the prediction of Material Removal Rate (MRR) and Machined Hole Overcut (MHO) due to HD-EDMM drilled holes. The developed model is used for the study of the effect of process parameters of HDEDMM process such as gap voltage, capacitance, and revolution per minute of tool electrode on performance parameters like material removal rate and machined hole overcut.

EXPERIMENTAL PLANNING

Hole Drilling Electro Discharge Micro Machining (HD-EDMM) was performed on multi process micro electro discharge machine (Model DT-100, Mikrotool Pte, Singapore), having fixed level of capacitance, and adjustable range of both voltage and spindle speed (revolution per minute). Tungsten carbide rod of 500micron diameter was used as tool electrode. The micro HD-EDMM operation was performed on rectangular section cuboid shape workpiece specimens made of Invar-36 having mean thickness of 0.5 mm, length 25 mm, and width 15 mm. The properties and composition of workpiece material is given in Tables 1 and 2 respectively. The removal of debris was achieved by lateral flushing with dielectric (EDM oil). The depth of cut was kept constant 510 micron for all experiments. In the present research, analysis of the effect of different parameter settings on material removal rate and Machined Hole Overcut (MHO) was carried out through Artificial Neural Network (ANN) modelling. After preliminary investigations, three process parameters were selected as gap voltage, capacitance of capacitor, and revolution per minute of the tool because they directly affect the performance parameters such as material removal rate and hole overcut. Selection of the range of process parameter settings was made after performing some pilot experiments within the stable domain of the machining. The levels of parameters selected are shown in Table 3.

Table 1: Properties of Invar-36

Property	Value (Units)
Density	8080 (kg/m^3)
Thermal Conductivity	10.5 (W/m/°K)
Specific Heat	515 (J/kg °K)
Melting Point	1427 (°C)
Electrical Resistivity	820 (microhm-mm)
Hardness	70 (HRB)
Tensile Strength	586 (MPa)

Table 2: Composition of Invar-36

Element	Percentage
Nickel	36
Manganese	0.50
Chromium	0.25
Silicon	0.25
Aluminum	0.10
Zirconium	0.10
Magnesium	0.10
Titanium	0.10
Sulfur	0.02
Phosphorus	0.02
Iron	Balance

The amount of material removed from the workpiece was measured with the help of citizen make micro weighing balance having least count of 0.0001 grams. Material Removal Rate (MRR) is defined as volume of material removed in unit time from workpiece. Hence, based on their density the MRR is calculated as;

Table 3: The Machining Parameters Considered and their Levels

Machining Parameters	Units	Level					
		1	2	3	4	5	6
Voltage	V	90	100	110	120	130	140
Capacitance	nF	10	100	400			
Spindle Speed	rpm	110	140	170			

$$MRR = \frac{\text{Mass of workpiece material removed}}{\text{Density of workpiece material} \times \text{Time to make hole}} \quad ...(1)$$

In order to find machined hole overcut, the diameter of hole at entrance sides was measured using optical measuring microscope (Model SDM-TR-MSU, Sipcon Instrument Industries, India) at 10x magnification Figure 1, and machined hole overcut was calculated as:

$$MHO = \frac{\text{Hole entrance diameter} - \text{Tool diameter}}{2} \quad ...(2)$$

Figure 1: Microscopic Views of Micro Drilled Holes with Hole Diameter at Entry

The values of MRR and MHO are calculated by using Equations (1-2) based on experimental results. The process parameters, the corresponding MRR and MHO values are again normalized using Equation (3).

$$X = 2 \times \frac{(R - R_{\min})}{(R_{\max} - R_{\min})} - 1 \quad ...(3)$$

where X is the normalized value of real variable, R is the real value of the variable, and $R_{\max}$ and $R_{\min}$ are the maximum and minimum values of the real variable. Normalization of the variables is in the range of –1 to +1 by using Equation (3). These normalized data set as given in Table 4 were used for training the network.

Table 4: Dataset for the Neural Network Model (the Values of Variables are Normalized)

1	–1.0000	–1.0000	–1.0000	–1.0000	–0.9375
2	–1.0000	–0.5385	0.0000	–0.2373	–0.4125
3	–1.0000	1.0000	1.0000	0.4035	–0.3625
4	–0.6000	–1.0000	–1.0000	–0.9652	–0.9625
5	–0.6000	–0.5385	0.0000	–0.2429	–0.0625
6	–0.6000	1.0000	1.0000	0.5555	–0.0125
7	–0.2000	–1.0000	0.0000	–0.9453	–0.6250
8	–0.2000	–0.5385	1.0000	–0.2145	–0.4000
9	–0.2000	1.0000	–1.0000	0.5027	–0.3250
10	0.2000	–1.0000	1.0000	–0.9340	–0.6250
11	0.2000	–0.5385	–1.0000	0.6367	–0.7875
12	0.2000	1.0000	0.0000	0.8101	0.9500
13	0.6000	–1.0000	0.0000	0.2690	–0.5250
14	0.6000	–0.5385	1.0000	–0.1837	0.0750
15	0.6000	1.0000	–1.0000	0.5936	–0.1750
16	1.0000	–1.0000	1.0000	0.1585	–0.8250

Table 4 (Cont.)

17	1.0000	–0.5385	–1.0000	0.6681	–0.6500
18	1.0000	1.0000	0.0000	0.8218	–0.2500
19	–1.0000	–1.0000	–1.0000	–0.9958	–0.8875
20	–1.0000	–0.5385	0.0000	–0.2393	–0.3625
21	–1.0000	1.0000	1.0000	0.3654	–0.3750
22	–0.6000	–1.0000	–1.0000	–0.9693	–0.9125
23	–0.6000	–0.5385	0.0000	–0.2453	–0.0125
24	–0.6000	1.0000	1.0000	0.5757	0.0125
25	–0.2000	–1.0000	0.0000	–0.9473	–0.5750
26	–0.2000	–0.5385	1.0000	–0.2320	–0.3500
27	–0.2000	1.0000	–1.0000	0.5073	–0.2750
28	0.2000	–1.0000	1.0000	–0.9760	–0.5750
29	0.2000	–0.5385	–1.0000	0.6367	–0.7375
30	0.2000	1.0000	0.0000	1.0000	1.0000
31	0.6000	–1.0000	0.0000	0.2690	–0.5250
32	0.6000	–0.5385	1.0000	–0.1817	0.1250
33	0.6000	1.0000	–1.0000	0.6188	–0.1250
34	1.0000	–1.0000	1.0000	0.1613	–0.7750
35	1.0000	–0.5385	–1.0000	0.6659	–0.6000
36	1.0000	1.0000	0.0000	0.8333	–0.2000
37	–1.0000	–1.0000	–1.0000	–0.9932	–0.9750
38	–1.0000	–0.5385	0.0000	–0.2369	–0.4500
39	–1.0000	1.0000	1.0000	0.4251	–0.4000
40	–0.6000	–1.0000	–1.0000	–0.9804	–1.0000
41	–0.6000	–0.5385	0.0000	–0.2358	–0.1000
42	–0.6000	1.0000	1.0000	0.6138	–0.0625
43	–0.2000	–1.0000	0.0000	–0.9427	–0.6625
44	–0.2000	–0.5385	1.0000	–0.1472	–0.4375
45	–0.2000	1.0000	–1.0000	0.5871	–0.3250
46	0.2000	–1.0000	1.0000	–0.8977	–0.6625
47	0.2000	–0.5385	–1.0000	0.6367	–0.8250
48	0.2000	1.0000	0.0000	0.7749	0.9125
49	0.6000	–1.0000	0.0000	0.2691	–0.5375
50	0.6000	–0.5385	1.0000	–0.1787	0.0375
51	0.6000	1.0000	–1.0000	0.6225	–0.2125
52	1.0000	–1.0000	1.0000	0.1648	–0.8625
53	1.0000	–0.5385	–1.0000	0.6754	–0.6625
54	1.0000	1.0000	0.0000	0.8103	–0.2875

Experiments were carried out using fractional factorial combinations of these factors and their different levels. During experiments the workpiece thickness was kept constant for all experimental run. Dielectric was also kept same for experimentation. As per Taguchi methodology an orthogonal array was selected based on the input parameters and their levels. Interaction effect was not taken into account. L_{18} orthogonal array was selected with two input parameters of three levels and one parameter of six levels. To achieve validity and accuracy, each test has been repeated three times. The responses considered were material removal rate and machined hole overcut of the micro drilled through holes. Based on the experimental inputoutput results an ANN model was developed through training and testing of the data set for input-output mapping. All the responses were set as targets while training of the network was ongoing, Table 4. The Levenberg–Marquadt (LM) algorithm was used as training algorithm, as it is the fastest and consumes the least memory (Fausett, 1994). The neural network toolbox of MATLAB software was used for modelling. After proper training of the network, the network was simulated with other input parameter combinations and the network responses compared with the experimental responses, Table 5. Thus validation of the developed model has been checked. The optimum parameter setting for the desired responses is then found by using the responses of the network model.

ANN MODELLING OF HD-EDMM PROCESS

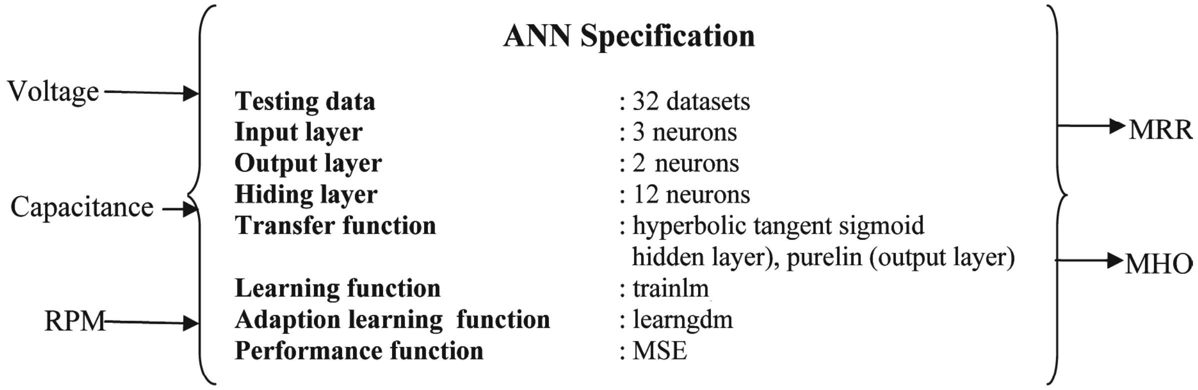
Modelling of machining, aimed at better understanding of process, has been a subject of interest for researchers in the past years. As a result, modelling of machining processes has been examined from different points of view by using different techniques. Large number of parameters, partially understood relations between parameters, complex, multi-dimensional, nonlinear and stochastic nature of machining offer modeling of machining processes a considerable task. In this respect Neural network proves itself as a suitable modelling tool by possessing many characteristics which make it suitable for addressing such responsibilities like universal function approximation capability, resistance to noisy or missing data, accommodation of multiple nonlinear variables for unknown interactions, and good generalization capability and adaptive nature. These capabilities of neural network are of primarily significance for modelling of HD-EDMM process. The superiority of using neural networks in modelling of machining processes has been reported in several studies (Tarng *et al.*, 1995; Dilma *et al.*, 1997; and Wang *et al.*, 2003). The block diagram of modelling of ANN for the present work is shown in Figure 2.

A neural network can be viewed as a function that maps input vectors to output vectors. The knowledge is presented by the interconnection weight, which is adjusted during the learning stage. In present study Matlab® with the neural networks toolbox (nntool) is used for formulation of artificial neural network and modeling of HD-EDMM. Matlab® is a well-known program used for modeling purposes. Its neural networks toolbox is user-friendly and the creation of neural networks is performed by using a small amount of commands

Table 5: Comparison of the Developed Model with Experimental Data and the Errors in Prediction

Exp. No.	Voltage	Capacitance	Spindle Speed	Experimental MRR ($x10^{-3}$ mm^3/min)	Experimental MHO (μm)	ANN Predicted MRR	ANN Predicted MHO	% Error in Prediction of MRR (Absolute)	% Error in Prediction of MHO (Absolute)
1	90	10	110	2.611	11.000	2.554	10.130	2.16	7.91
2	90	100	140	4.615	32.000	4.598	32.871	0.38	2.72
3	90	400	170	6.300	34.000	6.255	33.710	0.70	0.85
4	100	10	110	2.702	10.000	2.742	10.365	1.50	3.65
5	100	100	140	4.601	46.000	4.665	42.500	1.40	7.61
6	100	400	170	6.699	48.000	6.743	45.891	0.66	4.39
7	110	10	140	2.754	23.500	2.762	22.760	0.29	3.15
8	110	100	170	4.675	32.500	4.781	33.430	2.27	2.86
9	110	400	110	6.560	36.500	6.785	35.987	3.43	1.41
10	120	10	170	2.784	23.500	2.634	22.890	5.38	2.60
11	120	100	110	6.912	17.000	6.913	17.986	0.01	5.80
12	120	400	140	7.368	85.000	7.510	79.654	1.92	6.29
13	130	10	140	5.946	28.000	5.945	26.597	0.02	5.01
14	130	100	170	4.756	51.000	4.776	52.980	0.42	3.88
15	130	400	110	6.799	42.500	6.885	42.869	1.27	0.87
16	140	10	170	5.656	15.500	5.656	14.960	0.00	3.48
17	140	100	110	6.995	22.500	6.565	22.656	6.14	0.69
18	140	400	140	7.399	38.500	7.334	34.987	0.87	9.12
						Average (%) of error		1.60	4.02
Total average prediction error (%) = 2.81									

Figure 2: Neural Network Specifications

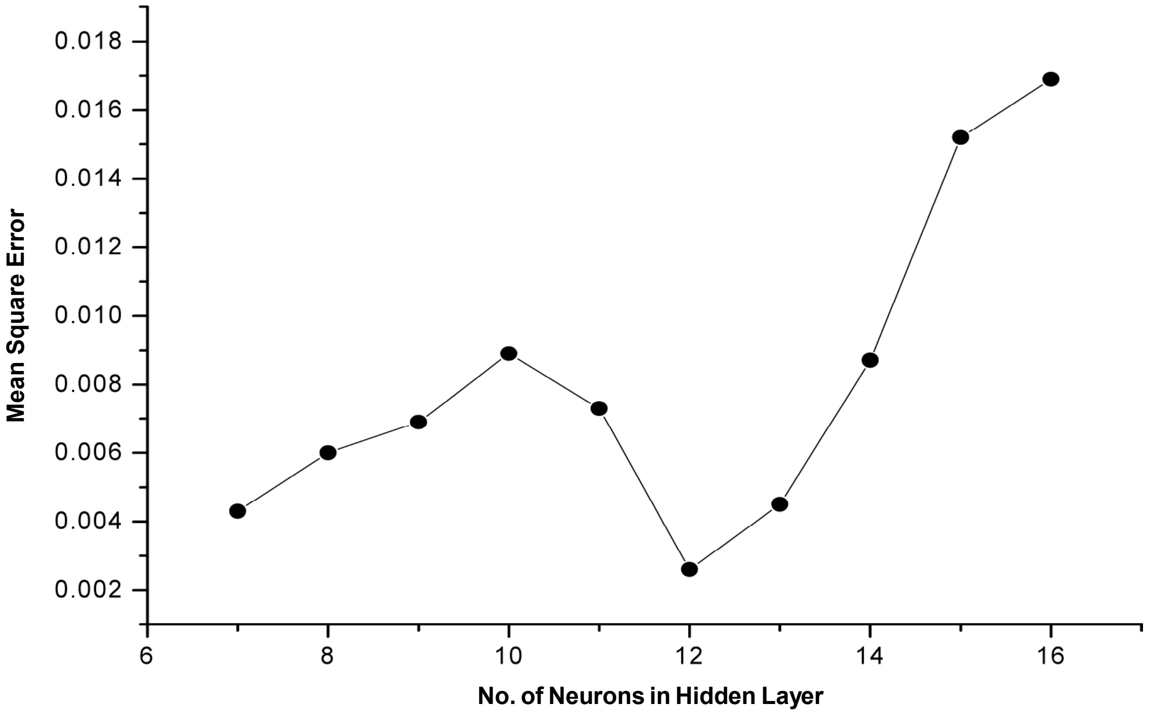


ANN Specification

Testing data : 32 datasets
Input layer : 3 neurons
Output layer : 2 neurons
Hiding layer : 12 neurons
Transfer function : hyperbolic tangent sigmoid hidden layer), purelin (output layer)
Learning function : trainlm
Adaption learning function : learngdm
Performance function : MSE

(Fausett, 1994). The program has a data base with functions, algorithms and commands for this purpose. In general, a neural network is characterized by its important features such as the architecture, the activation function and the learning algorithms. Several models were designed and tested with process parameter in order to determine the optimal architecture, the most suitable activation function and the best training algorithm suitable for the prediction of MRR and MHO in HDEDMM. Each model was tested more than once in order to assess whether it truly congregates at which point when the prediction error and mean square error were a minimum (Ffigure 3).

Figure 3: Effect of Number of Neurons in Hidden Layer on Mean Square Error



$$\text{Prediction error} = \left|\frac{(\text{Experimental result} - \text{Predicted result}) \times 100}{\text{Experimental result}}\right| \quad \text{...(4)}$$

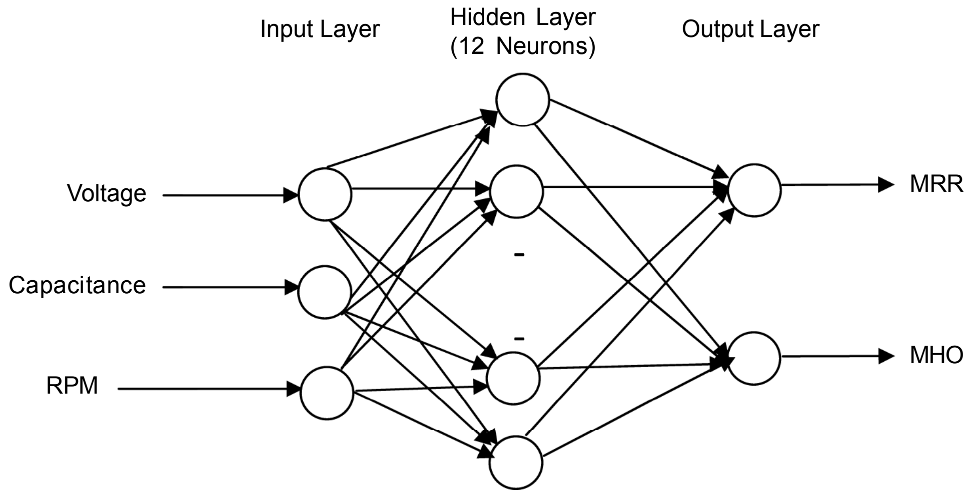
and

$$\text{Total average prediction error} = \frac{A_1 + A_2}{2}$$

where A_1 and A_2 are the average prediction error in MRR and MHO respectively.

After exhaustive number of trial and error procedure the model selected was a feed forward neural network with single hidden layer consisting of 12 neurons (Figure 3). Therefore a network of structure 3-12-2 is found to be the most suitable network for the present task. The activation function in the hidden layer was the hyperbolic tangent sigmoid transfer function (tansig) and in the output layer was the linear transfer function (pureline). The learning algorithm used was the back propagation algorithm. Back propagation is a systematic method for training multilayer artificial neural network (Wang *et al.*, 2003). It uses gradient-descent method to minimize the total mean square error of the output computed by the network. The developed model is shown schematically in Figure 4. The values of MRR and MHO are calculated by using Equations (1-2), and subsequently normalized by using Equation (3). Two third of the normalized experimental results shown in Table 4 are used to train the neural network, and rest is for testing. Selection of data for training and testing is in random fashion. Properly trained back-propagation network tends to give reasonable answers when presented with inputs that have never been fed before to it.

Figure 4: Selected Three Layer Neural Network



An experimental approach was adopted that involved testing the trained neural network against another set of experimental data, illustrated in Table 5. The errors in prediction are also presented in Table 5. It can be seen from Table 5 that the model predicted data followed the experimental data very closely except few calculations. It can be said that the error is within the tolerable limit. Moreover, the average error in the prediction was 1.60% for MRR, 4.02% for MHO, which were very small indeed. The

Table 6: Verification of the Developed Model with Experimental Data

Exp. No.	Voltage	Capacitance	Spindle Speed	Experimental MRR ($x10^{-3}$ mm^3/min)	Experimental MHO (µm)	ANN Predicted MRR	ANN Predicted MHO	% Error in Prediction of MRR (Absolute)	% Error in Prediction of MHO (Absolute)
1	95	10	115	2.5339	11.475	2.6335	10.943	3.93	4.64
2	105	10	145	2.5014	10.945	2.5184	11.254	0.68	2.82
3	115	400	165	6.3334	33.875	6.3671	30.365	0.53	10.36
4	125	100	145	6.1819	32.655	5.9879	31.675	3.14	3.00
5	135	400	115	7.2928	68.865	7.2190	67.975	1.01	1.29
6	95	100	145	4.8617	30.945	4.9925	34.186	2.69	10.47
7	105	100	165	4.8736	31.095	4.8947	31.865	0.43	2.48
8	115	10	145	3.0935	11.965	3.3245	11.437	7.47	4.41
9	125	400	115	6.4951	32.725	6.4398	29.473	0.85	9.94
10	135	100	165	6.1206	45.385	6.2602	44.975	2.28	0.90
						Average (%) of error		2.30	5.03
Total average prediction error (%) = 3.665									

total average prediction error of the network was calculated as 2.81%. The developed ANN model was validated with the new set of experimental data (unseen) for same output features. Table 6 contains the predicted output and percentage error in prediction of MRR and MHO. It is observed that the total average prediction error is 3.665 percent which is within tolerable limit. Generalization capabilities of the selected network can be easily verified by comparing the experimental results with modelling results (Figures 5-6).

PARAMETRIC STUDY

Developed ANN model (3-12-2) is used for the study of the effect of input parameters of HDEDMM process such as gap voltage, capacitance, and revolution per minute of tool electrode on performance parameter material removal rate and machined hole overcut considering one parameter at a time. In the present study effect of gap voltage and revolution per minute on performance parameter has been discussed as follows.

Figure 5: Comparison of the Material Removal Rate Between Validation and Experimental Result

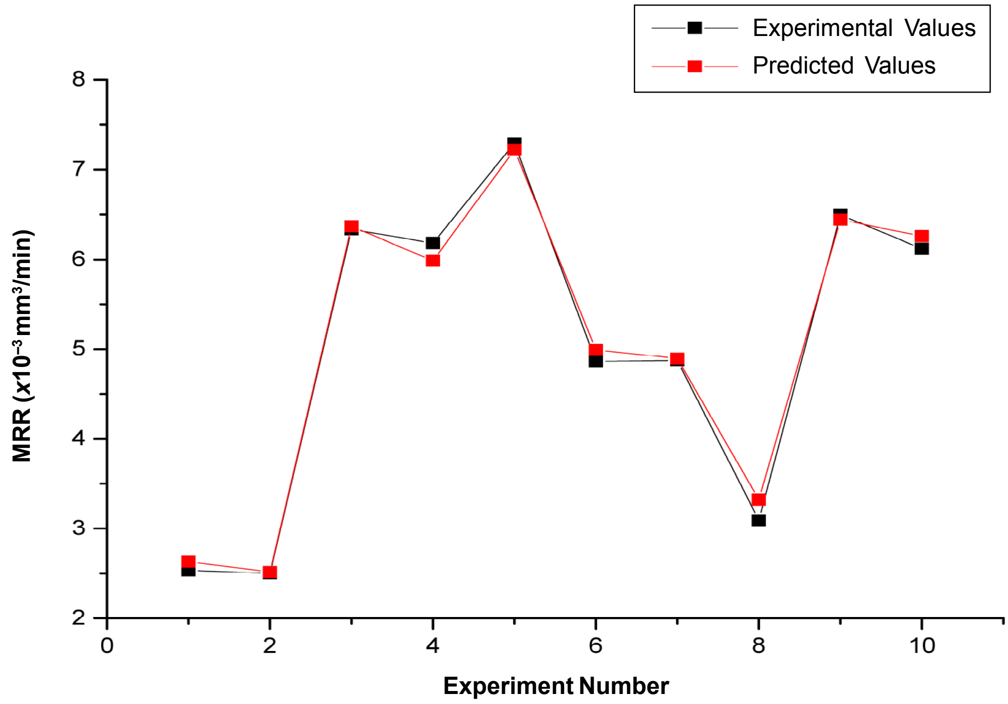
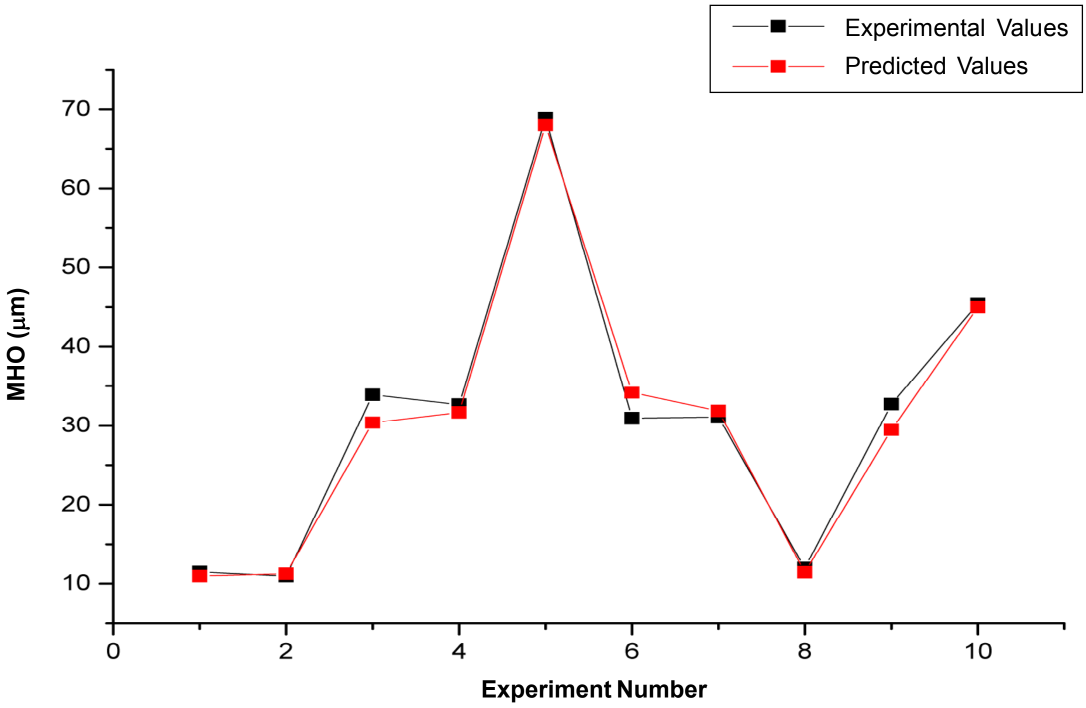


Figure 6: Comparison of the Machined Hole Overcut Between Validation and Experimental Result



Effect of Gap Voltage on MRR

The variation of MRR with the gap voltage has been shown in the Figure 7. It is observed that MRR increases with the increase in the gap voltage. The increase in gap voltage refers the raise of discharge energy in the machining zone. It is also observed that more material will get melted in unit time on the higher value of discharge energy. The discharge energy generated between the electrodes is defined as $E = \frac{1}{2}CV^2$, where '*C*' is the capacitance of capacitor, and '*V*' is the gap voltage. This energy depends on gap voltage and capacitance.

Effect of Gap Voltage on MHO

Figure 8 shows the variation of MHO with the gap voltage. The rise in gap voltage will

Figure 7: Variation of MRR with the Gap Voltage

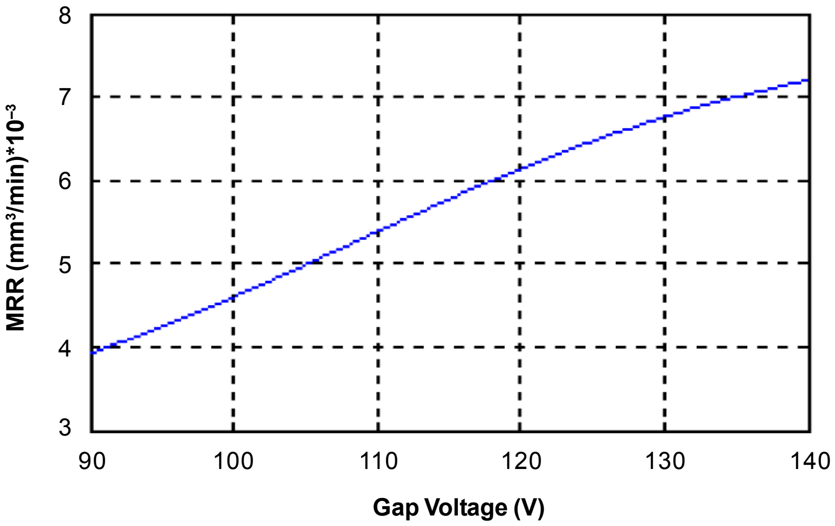
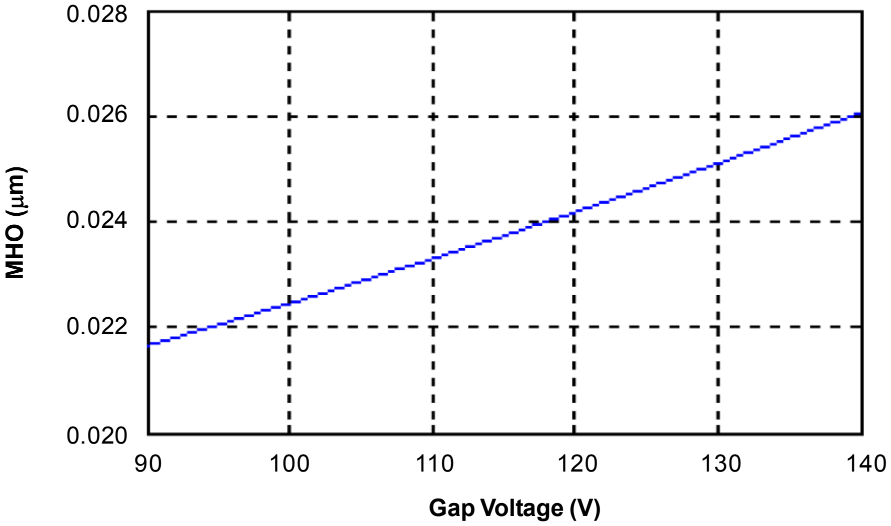


Figure 8: Variation of MHO with the Gap Voltage



increase the machined hole overcut due to high value of thermal energy transfer to the machining zone. This phenomenon leads to melting and vaporizing more material from workpiece surface. Therefore, the diameter of discharge crater is increased and large machined hole overcut occurs at high energy regime, in comparison of lower energy level.

Effect of Revolution per Minute on MRR

The effect of revolution per minute on MRR can be clearly seen in the Figure 9. The rise in revolution per minute will decrease the MRR. This phenomenon occurs due to decrease in number of sparks in the machining zone with the increase in revolution per minute therefore small amount of material gets melted and subsequently removed from the machining zone in unit time.

Effect of Revolution per Minute on MHO

Figure 10 shows the variation of MHO with the revolution per minute. It is observed from the figure that with the increase of revolution per

Figure 9: Variation of MRR with the Revolution per Minute

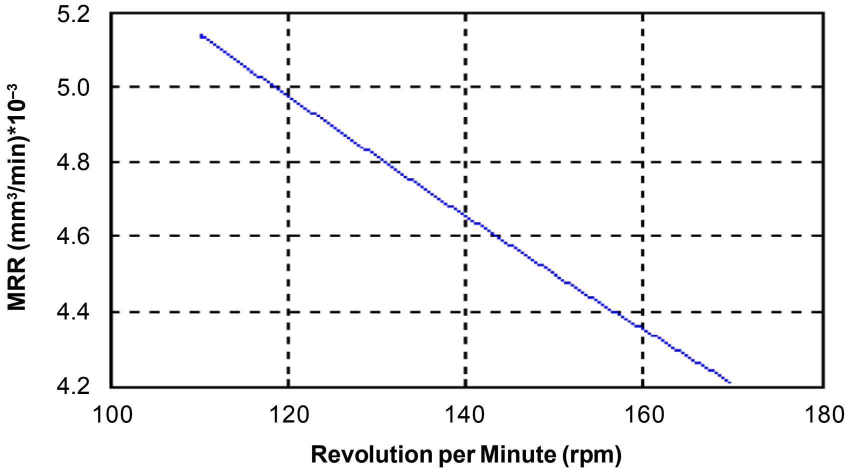
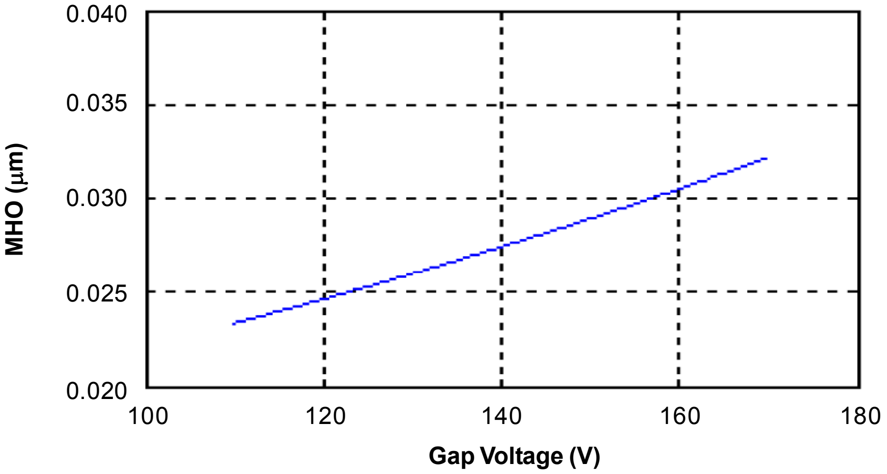


Figure 10: Variation of MHO with the Revolution per Minute



minute, the machined hole overcut increases but the rate of increment is small. This is because of the less amount of material melted at high revolution per minute due to small number of stable sparks in machining zone.

CONCLUSION

The present paper introduced a multi input output ANN based predictive model for prediction of performance parameter such as material removal rate and machined hole overcut in HD-EDMM process. The model served as a tool to calculate the performance parameter based on the variation of process parameters without any experimental work. The results of present study are summarized as follows:

- It has been found that among several neural configurations a feed-forward backpropagation ANN of type 3-12-2, having single hidden layer with twelve neurons can provide the best prediction.
- The average error in the prediction of developed model was very small indeed. It was 1.60% for MRR, and 4.02% for MHO, also the total average prediction error was 2.81%.
- When process moves from low energy regime to high energy one, the machined hole overcut increases due to increasing the sizes of discharge crater.
- It is observed that the amount of material removed decreases with increase in revolution per minute due to less number of stable sparks in machining zone.

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