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# Parameter Optimization Model in Electrochemical Micromachining Process

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**ABSTRACT:** The electrochemical micromachining (EMM) belongs to the unconventional machining methods. EMM is suitable for hard and extra hard materials used for cutting and moulding tools manufacturing and also for special forms machine part manufacturing used in aeronautics, prothesis and hydropneumatic machinery. EMM is a very complex process as the result of a set of electric, mechanics and chemical parameters. So the analytical modeling of the process is difficult. Due to the large number of measurements required, the artificial neural network very greatly simplifies the relationship between the input and the output parameters. The neural network was trained with a set of data containing very different machining parameter choices. This paper presents the results obtained for the prediction of some output parameters. In this paper, artificial neural network (ANN) is used to establish the parameter optimization model. An ANN model which adapts Levenberg-Marquardt algorithm and Bayesian regularization has been set up to represent the relationship between machining rate, overcut and input parameters. The model is shown to be effective, and machining rate and overcut are improved using optimized machining parameters.

KEYWORDS: Machining rate, overcut, micro machining, Aritificial Neutral Network

### 1. INTRODUCTION

The need for developing new, multi-functional and multi-material micro-components has the optimum and at the same time selecting optimization parameters requires many costly considerably increased and improving manufacturing competency due to increased competition have posed new challenges in the manufacturing sectors (Qin et al. 2010). Micromachining is the process of removing material in the form of chips or debris having size in the scale of micron. Among the various competent processes, EMM is considered for its following advantages such as no residual stress, versatility to machine any kind of material, no problem of heat affected zone, no tool wear, short machining time, cost effective, high precision can be achieved and the quality of good surface finish makes this process more attractive for drilling holes on the components exposed to high temperature (Bhattacharyya et al. 2004).

At present EMM parameter selection in the industry are conservative and far from and time consuming experiments. Many researchers tried to optimize the machining performance by adapting different optimization techniques [3-7]. Artificial neural network (ANN) is an effective method to solve non-linear problem. There are many ANN applications in manufacturing processes. Predictions of surface finish for various work materials with the change of electrode polarity were compared based upon six different ANN models (Tsai and Wang, 2001). Gao et al.(2008) have used artificial neural network (ANN) and genetic algorithm (GA) together to establish the parameter optimization model for EDM. A method that can optimize the processing parameters was presented in the EDM sinking process with the application of ANN (Cao and Yang, 2004). Catalin Sorin Ungureanu (2006) modeled and simulated the ECM process using neural networks.

In the present work, ANN is used to establish parameter optimization model. An ANN model has been established to represent the relationship between machining rate, overcut and input variables (tool tip shape, machining voltage, pulse on-time and electrolyte concentration), which adapts Levenberg-Marquardt algorithm and Bayesian regularization.



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

#### **II. EXPERIMENTAL SETUP**

The developed EMM set-up basically consists of various elements and sub-systems. The mechanical machine unit consists of main machining body, tool electrode feeding attachment, work holding fixture and machining chamber. Main machine body is made up of mild steel and is chromium plated for corrosion resistance. The tool electrode feed mechanism, with resolution of 2  $\mu$ m, along Z axis are designed with stepper motor and 8051 microcontroller. The experiments were conducted with conical with rounded and truncated cone stainless steel electrode of  $\Phi$  464  $\mu$ m. Sodium nitrate of varying concentrations are used as electrolyte, it is preferred for low throwing power. 304 stainless steel of thickness 200  $\mu$ m was used as the workpiece. The tool electrode is made as a cathode and workpiece is made as anode.L<sub>36</sub> orthogonal array was chosen for experimentation for developing the ANN model. Experimental combination for L<sub>36</sub> orthogonal array is shown in Table 1.

### TABLE 1 EXPERIMENTAL COMBINATION FOR L<sub>36</sub> ORTHOGONAL ARRAY

Exp. No.	Tool Tip Shape	Voltage (V)	Pulse On- Time (ms)	Electrolyte Concentration (mole/l)	Diameter (µm)	Overcut (µm)	Machining time (sec)	Machining rate (µm/s)
1	Conical with rounded	8	7.5	20	472.5	11.25	57	3.51
2	Conical with rounded	9	10	25	516.6	33.3	32	6.25
3	Conical with rounded	10	15	30	627.9	88.95	17	11.76
4	Conical with rounded	8	7.5	20	472.5	11.25	57	3.51
5	Conical with rounded	9	10	25	516.6	33.3	32	6.25
6	Conical with rounded	10	15	30	627.9	88.95	17	11.76
7	Conical with rounded	8	7.5	25	506.7	28.35	52	3.85
8	Conical with rounded	9	10	30	570.1	60.05	25	8
9	Conical with rounded	10	15	20	556.3	53.15	23.5	8.51
10	Conical with rounded	8	7.5	30	527.1	38.55	44	4.55
11	Conical with rounded	9	10	20	516.6	33.05	41	4.88
12	Conical with rounded	10	15	25	594.3	72.15	20	10
13	Conical with rounded	8	10	30	546	48	28	7.14
14	Conical with rounded	9	15	20	541.8	45.9	29	6.9
15	Conical with rounded	10	7.5	25	502	26	29	6.9
16	Conical with rounded	8	10	30	546	48	28	7.14



(An ISO 3297: 2007 Certified Organization)

### Vol. 4, Special Issue 6, May 2015

17	Conical with rounded	9	15	20	541	45.9	29	6.9
18	Conical with rounded	10	7.5	25	502	26	29	6.9
19	Truncated cone	8	10	20	501.9	25.95	37	5.4
20	Truncated cone	9	15	25	632.1	91.05	22	9.1
21	Truncated cone	10	7.5	30	590.1	70.05	25	8
22	Truncated cone	8	10	25	546	48	32	6.25
23	Truncated cone	9	15	30	663.6	106.8	14	14.29
24	Truncated cone	10	7.5	20	556.5	53.25	32	6.25
25	Truncated cone	8	15	25	594.3	72.15	25	8
26	Truncated cone	9	7.5	30	537.6	43.8	26	7.7
27	Truncated cone	10	10	20	627.9	88.95	24	8.33
28	Truncated cone	8	15	25	594.3	72.15	25	8
29	Truncated cone	9	7.5	30	537.6	43.8	26	7.41
30	Truncated cone	10	10	20	627.9	88.95	24	8.33
31	Truncated cone	8	15	30	634.2	92.1	19	10.53
32	Truncated cone	9	7.5	20	606.1	28.05	38	5.26
33	Truncated cone	10	10	25	667.8	108.9	23	8.7
34	Truncated cone	8	15	20	516.6	100.5	29	6.9
35	Truncated cone	9	7.5	25	683	33.3	29	6.9
36	Truncated cone	10	10	30	716.1	116.25	15	13.33

#### **III. RESULTS AND DISCUSSION**

#### 3.1 Configuration of ANN

The network architecture or features such as number of neurons and layers are very important factors that determine the functionality and generalization capability of the network. For this modeling, standard multilayer feed forward back propagation hierarchical neural networks were designed with MATLAB R2008a Neural Network Toolbox.

Higher valued input variables may tend to suppress the influence of smaller ones. To overcome this problem, the neural networks were trained with normalized, leaving it to the network to learn weights associated with the connections emanating from these inputs. Hence, the input/output datasets were normalized within the range of -1 and +1. The normalized value  $(x_i)$  for each raw input/output dataset  $(y_i)$  was calculated as



(An ISO 3297: 2007 Certified Organization)

Vol. 4, Special Issue 6, May 2015

$$x_{i} = \frac{2(y_{i} - y_{\min})}{y_{\max} - y_{\min}} - 1$$

Where  $y_{max}$  and  $y_{min}$  are the maximum and minimum values of the raw data.

The networks consist of three or more number of layers: the input, hidden layers, and output layer. Architecture of feed-forward ANN schema developed with three inputs and four outputs is shown in Fig 3.



Fig. 3. Architecture of feed-forward ANN schema developed with three inputs and four outputs

In order to determine the optimal architecture, different architectures have to be studied. Each network here trained with Levenberg–Marquardt algorithm and Bayesian regularization was used. This training algorithm was chosen due to its high accuracy in similar function approximation. For all networks linear transfer function 'purelin' and tangent sigmoid transfer function 'tansig' were used in the output and hidden layer respectively.

For testing the prediction ability of the model prediction error in each output node has been calculated as follows.

The maximum, minimum and mean prediction errors for overcut and machining rate each network were calculated and shown in Table 2 and 3. The absolute maximum percentage error indicates the worst prediction error for each model. Performance of neural network with different architecture for overcut and machining rate is shown in table 4.

TABLE 2 PERFORMANCE OF NEURAL NETWORK WITH DIFFERENT ARCHITECTURE FOR OVERCUT

S. No.	Network Architecture	Maximum Prediction error (%)	Minimum Prediction error (%)	Mean Prediction error (%)	Correlation coefficient
1	4-15-2	1.431	-153.227	-58.867	0.873
2	4-20-2	46.988	-154.421	-18.005	0.403
3	4-25-2	56.027	-62.276	-4.882	0.763
4	4-30-2	60.027	-77.428	-2.111	0.605
5	4-32-2	46.781	-77.389	-27.6	0.931
6	4-35-2	1100.29	-105.431	119.502	0.801
7	4-2-2-2	49.251	-59.425	14.333	0.757
8	4-5-5-2	36.695	-163.022	-16.929	0.474
9	4-12-10-2	232.8676	-38.388	68.053	0.538
10	4-20-20-2	89.393	-159.204	-9.101	0.522
11	4-22-18-2	63.69	-733.059	-25.146	0.4



(An ISO 3297: 2007 Certified Organization)

### Vol. 4, Special Issue 6, May 2015

### TABLE 3 PERFORMANCE OF NEURAL NETWORK WITH DIFFERENT ARCHITECTURE FOR MACHINING

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S. No.	Network Architecture	Maximum Prediction error	Minimum Prediction	Mean Prediction	Correlation coefficient	
		(%)	error (%)	error (%)		
1	4-15-2	1.276	-43.1049	-4.719	0.637	
2	4-20-2	56.816	-94.560	-10.442	0.647	
3	4-25-2	37.520	-90.476	-21.635	0.505	
4	4-30-2	158.518	-34.69	31.041	0.408	
5	4-32-2	179.509	-32.771	34.710	0.905	
6	4-35-2	149.54	-42.529	29.243	0.882	
7	4-2-2-2	35.876	-32.179	0.956	0.769	
8	4-5-5-2	31.032	-37.936	-1.153	0.731	
9	4-12-10-2	139.57	-6.888	52.963	0.765	
10	4-20-20-2	31.000	-50.771	-1.916	0.776	
11	4-22-18-2	257.960	-65.548	26.6	0.757	

#### TABLE 4 PERFORMANCE OF NEURAL NETWORK

S. No.	Network	Correlation coefficient for	Correlation coefficient	
	Architecture	overcut	for machining rate	
1	4-15-2	0.873	0.637	
2	4-20-2	0.403	0.647	
3	4-25-2	0.763	0.505	
4	4-30-2	0.605	0.408	
5	4-32-2	0.931	0.905	
6	4-35-2	0.801	0.882	
7	4-2-2-2	0.757	0.769	
8	4-5-5-2	0.474	0.731	
9	4-12-10-2	0.538	0.765	
10	4-20-20-2	0.522	0.776	
11	4-22-18-2	0.4	0.757	

The model with 4-32-2 architecture is found the most suitable. It can be seen that the increase in the number of neurons in the hidden layer from 30 to 32 has improvement on the performance of the networks and then performance decreases. Thus, network having one hidden layer consists of 32 neurons (4-32-2), trained with Levenberg–Marquardt algorithm and Bayesian regularization, and was chosen as the optimum network and used for modeling the overcut and machining rate.

### **IV. CONCLUSIONS**

In this paper, one method to optimize EMM process parameters is introduced, which uses Levenberg-Marquardt algorithm. An ANN model was set up to represent the relationship between machining rate, overcut and input parameters. The model with 4-32-2 architecture is found the most appropriate. It can be seen that the increase in the number of neurons in the hidden layer from 30 to 32 has improvement on the performance of the networks and then performance decreases. Hence, network having one hidden layer consists of 32 neurons (4-32-2), trained with Levenberg–Marquardt algorithm and Bayesian regularization, and was chosen as the optimum network and used for



(An ISO 3297: 2007 Certified Organization)

#### Vol. 4, Special Issue 6, May 2015

modeling the overcut and machining rate. It shows that the net has better generalization performance, and convergence speed is faster.

#### REFERENCES

- [1] Yi. Qin, A. Brockett, Y. Ma, A.Razali, J.Zhao, C.Harrison, W.Pan X.Dai & D.Loziak, "Micro-manufacturing: research, technology outcomes and development issues", *Intl Journal of Adv Mfg Tech*, vol.47, 2010, pp 821–837.
- B.Bhattacharyya, J.Munda, & M.Malapati, "Advancement in electrochemical micromachining", (2004). J Mach Tools Manuf, Vol.44, 2004, pp1577-1589.
- [3] R.Thanigaivelan. and Arunachalam.RM., "Experimental study on the influence of tool electrode tip shape on electrochemical micromachining of 304 stainless steel", Journal of Materials and Manufacturing processes, 25, 1181-1185, (2010).
- [4] R.Thanigaivelan. and Arunachalam.RM., Optimization of process parameters on machining rate and overcut in electrochemical micromachining using grey relational analysis, Journal of scientific and industrial research 72, 36-42,2013.
- [5] R Thanigaivelan, RM Arunachalam, P Drukpa, 2012, Drilling of micro-holes on copper using electrochemical micromachining The International Journal of Advanced Manufacturing Technology,9-12,61, 1185-1190.
- [6] R Thanigaivelan, RM Arunachalam, B Karthikeyan, P Loganathan, (2013), Electrochemical micromachining of stainless steel with acidified sodium nitrate electrolyte, Procedia CIRP 6, 351-355.
- [7] R Thanigaivelan, RM Arunachalam 2010) Experimental study of overcut on electrochemical micromachining for 304 stainless steel, Trans NAMRI/SME 38, 253-260.
- [8] R Thanigaivelan, RM Arunachalam, J Jerald, T Niranjan ,2011, Applications of Taguchi technique with fuzzy logic to optimise an electrochemical micromachining process, International Journal of Experimental Design and Process Optimisation 2 (4) 283-298.
- K.M. Tsai, P.J.Wang, "Predictions on surface finish in electrical discharge machining based upon neural network models", *International Journal of Machine Tools and Manufacture*, Vol.41, 2001, pp.1385-1403.
- [10] F.G.Cao, Yang, D.Y. "The study of high efficiency and intelligent optimization system in EDM sinking process", Journal of Materials Processing Technology, Vol.149 (1-3): 2004, pp.83-87.
- [11] Qing GAO, Qin-he ZHANG, Shu-peng SU, Jian-hua ZHANG "Parameter optimization model in electrical discharge machining process", J Zhejiang Univ Sci A Vol. 9(1):2008,pp.104-108
- [12] Catalin Sorin UNGUREANU, "Modelling And Simulation of The Electrochemical Machining Using Neural Networks", http://www.fs.vsb.cz/transactions/2006-2/1557\_ungurenu\_catalin\_sorin.pdf, pp 197-202.