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Artificial neural network models for the prediction of MRR in Electro-chemical machining

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Abstract

Electro-chemical machining (ECM) uses a set of intricate process to create a negative image of tool on workpiece by high rate anodic dissolution. A Full factorial (DOE) 2^4 is applied to determining the most important factors which influence MRR of AA6061 (T6). In the present work, experimental data collected are tested with analysis of variance (ANOVA) and Artificial Neural Network (ANN) model has been proposed for the prediction of response. For this purpose, the MATLAB has been used for training and testing of neural network model. The predicted results using ANN specify good agreement between the predicted values and experimental values. Multilayer perceptron model has been constructed with back-propagation algorithm using four process parameters viz. voltage, feed rate, electrolyte concentration and electrode (Cu, Brass) are considered in this study. Finally, ANN model has been found efficient to predict ECM process response for selected process conditions.

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Keywords: Electrochemical machining (ECM); Full factorial (DOE); Analysis of variance; Artificial Neural Network.

Nomenclature

ECM	Electro-chemical machining
DOE	Design of Experiments
V	Voltage in Volts
EC	Electrolyte Concentration (NaCl)
MRR	Material removal rate (mg/min.)
R^2	Coefficient of determination
Pred. R^2	Predicted R^2
Adj. R^2	Adjusted R^2
ANN	Artificial Neural Network

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LM	Levenberg- Marquadt
MAPE	Mean absolute percentage error

1. Introduction

Electrochemical machining (ECM) is one of the best process to machine hard materials of complex geometry. Hard materials shows better surface accuracy and integrity when machined by ECM, which makes it most popular and have increased use in industries like automotive, aircraft industries to machine turbine blades [1-4], casting industries to make dies [2] etc. So it is always needed to improve the process capabilities of ECM. Researchers are trying to increase the performance level of ECM by modifying the tool shape [3] rotating the tool [4], It is the basic requirement of any industry to produce the final product with the least time and at desired level of surface finish. From the economic point of view, maximum MRR is the objective of any process. Alternatively, surface roughness plays an important role for the tribological operation of any component. Proper selection of machining parameters for the best process performance is quiet a challenging job. Numerous researchers carried out various investigations for improving the process parameter optimization in ECM. Tiwari et al. [5] to develop a mathematical model for responses i.e., MRR and SR through regression analysis for ECM on EN-19 and ANOVA test is implement to check the suitability of the developed mathematical models. Giribabu et al. [6] multiple linear regression models are build up for MRR, SR and ROC. Optimum machinating parameters to maximize Material Removal Rate (MRR), minimize Surface Roughness (SR) and minimize Radial Over Cut (ROC) are found out using genetic algorithms. Patil et al. [7] have presented the study of the work has been undertaken to finding the material removal rate by electrochemical dissolution of an anodic ally polarized work piece with a circular-shaped copper electrode. Babar et al. [8] investigates the effect and parametric optimization of process parameters for Electrochemical machining of Titanium based alloy. The process parameters take into account are electrolyte concentration, applied voltage and feed rate are optimized in concern of material removal rate. Analysis of variance is performed to get contribution of each parameter on the performance characteristics and it was detected that feed rate is the significant process parameter that affects the ECM robustness. Senthilkumar et al. [9] have studied the effect of various process parameters such as electrolyte concentration, voltage, tool feed rate and electrolyte flow rate on MRR and surface roughness (Ra) and developed a mathematical model in terms of machining process parameters for Material Removal Rate (MRR) and surface roughness (Ra) prediction in Electrochemical machining of LM25 Al/10%SiCp composite. Goswami et al. [10] have optimized machining process parameters viz. voltage, tool feed and current with consideration of multiple performance characteristics including MRR and surface roughness for ECM of aluminium and mild steel material using Taguchi technique. Bahre et al. [11] have attempted to model and optimize the pulse electro chemical machining (PECM) process using Response Surface Methodology (RSM). The machining parameters considered in the study are voltage, pulse on time, frequency, feed rate, pressure, multiple responses are MRR and surface roughness (Ra). They have also tried to optimize MRR and Ra prediction model using RSM. Acharya et al. [12] have developed a MRR and surface roughness prediction model in electrochemical machining (ECM) of super alloys using RSM. Rao et al. [13] have found out the optimization machining process parameters for ECM of Al/5%SiC material using Taguchi design considering feed rate, voltage and electrolyte concentration as the process parameters. From Taguchi analysis, they have obtained an optimal combination of process parameters for maximum metal removal rate. Burger et al. [14] have investigated the effects of machining parameters on MRR and surface roughness in ECM/PECM of nickel-base single-crystal alloy (LEK94). Ali et al. [15] has developed a mathematical model and software for simulation, using ultra short (nanoseconds) pulses for generating complex 3-D microstructures of high accuracy. Samanta et al. [16] have used artificial bee colony algorithm for parametric optimization on MRR, over-cut (OC) and heat affected zone (HAZ) in some unconventional machining process including Electrochemical machining, electrochemical discharge machining and electrochemical micro-machining. Chakradhar et al. [17] have examined the optimization of an ECM process performed on EN31 steel considering electrolyte concentration, applied voltage, and feed rate as process parameters. They have optimized the multi response viz., overcut, cylindricity error, surface roughness and MRR using Grey relation analysis.The present study deals with the development of model and its application to optimize ECM process parameters using the full factorial (DOE) which is based on the robust design. Experimentation was executed as per full factorial design of experiments with 16 experimental runs. Each experiment has been performed under the effects of voltage, feed rate, electrolyte concentration and conductive electrode on MRR by artificial neural network (ANN) during electrochemical machining of AA6061. Based on this analysis, process parameters are optimized. ANOVA is implemented to determine the relative magnitude of the each factor on the objective function. Prediction and comparison of response was done using artificial neural network.

2. Experimental procedure

2.1. Experimental setup

The experiments were performed on METATECH (EC MAC-I) electrochemical machining equipment. The ECM setup consists of machining chamber, control panel, electrolyte circulation system. The work-piece is fixed inside machining chamber and cathode (tool) is attached to the main screw which is driven by a stepper motor. For avoiding short-circuits, a current sensing circuit is interfaced between the tool and the stepper motor controller circuit. If the current exceeds an acceptable limit, a signal is sent to the stepper motor controller circuit which immediately reverses the downward motion of the tool. The electrolyte is pumped from a tank, lined by corrosion resistant coating with the help of corrosion resistant pump & is fed to the job. Spent electrolyte will return to the tank. The hydroxide sludge arising will settle at the bottom of the tank & can be easily drained out. Electrolyte supply shall be governed by flow control valve. Extra electrolyte flow is by- passed to the tank. Reservoir provides separate settling and draw off compartments. All fittings are of corrosion resistant material. Flow chart of procedure for the data acquisition is illustrated in the Fig. 1. In this technique, even hardest possible material can be given a complex profile in a single machining operation.

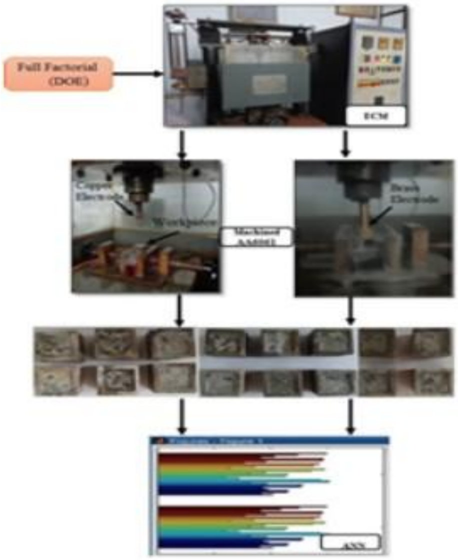


Fig. 1. Flow chart of machined EDM for ANN model

2.2. Selection of materials.

The performance tests were performed on AA6061 T6. The Rockwell hardness of the material is 49.23HRB. The workpiece material used has a dimension of 27 x 27 x 27 mm size. This material is suitable for a wide variety of automotive-type applications, Aircraft and aerospace component, Bicycle frames, Drive shafts, Brake components, Valve, Couplings, etc. Tool is made of copper and brass with square cross section base. The base of the tool is the machining area. Electrolyte is axially feeding to the machining zone through a hole provided centrally in the tool. NaCl solution selected as electrolyte, as it has no passivation influence on the surface of the work piece. The chemical composition of Aluminium alloy is specified in Table 1.

Table 1. Chemical Composition of A6061 T6 Aluminium alloy

Element	**Mg**	**Si**	**Fe**	**Cu**	**Ti**	**Cr**	**Zn**	**Mn**	**Al**
%	0.81	0.98	0.14	0.041	0.041	0.069	0.022	0.54	Balance

2.3. Design of experiment

The present study considers four design factor, namely, voltage, feed rate, electrolyte concentration and conductive electrode. The design factors were chosen based on review of literature and experts [18]. The design of experiment is generated using MINITAB 17.0 statistical package. Each time the experiment was performed, an optimized set of input parameters were chosen. In this study, the collection of experimental data adopts the full factorial design of experiments with two levels denoted in coded (-1, 1) and actual values as shown in Table. 2.

Table 2. Experimental parameters and their levels

Design Factor	Notation	Levels (Coded Value)	
		-1	1
Voltage(v)	β_1	6	10
Feed rate(mm/min)	β_2	0.16	0.23
NaCl Concentration(gm./l)	β_3	200	300
Conductive Electrode	β_4	Copper	Brass

3. Results and Discussions

3.1 Analysis of variance (ANOVA)

ANOVA is a statistical technique that can propose some important conclusions on the basis of analysis of the experimental data. The method is valuable for revealing the level of significance of influence of factor(s) or interaction of factors on a specific response. In the present study, ANOVA is performed using Minitab 17. The fit of the model was evaluated by means of ANOVA, revealing the effects of the model that were statistically significant for a confidence level of 95% (p-value <0.05), and those that were not statistically significant [19] full-factorial designs was based on the statistical analysis, the prediction precision and the efficiency. The experimental values obtained for the response variables were fitted to Eq. (1) by multiple regression analysis. The fit of the model was evaluated by means of ANOVA revealing the effects of the model that were statistically significant for a confidence level of 95% (p-value <0.05), and those that were not statistically significant. The best obtained model was further modified by eliminating insignificant terms. The results of the fit of the models to the experimental data by multiple regression analysis together with the values of coefficients and the model summary statistics for full-factorial designs are shown in Tables 3, respectively. It can be observed that the final models obtained were statistically important for a confidence level of 95% (p-value <0.05) and exhibit insignificant lack-of-fit. The model with the lower value for the sum of squares and mean square will fit the data better. FFD based model was characterized by (a) the lowest value of the total sum of squares (0.123893), (b) the lowest value of the regression (0.008260) and residual (0.000001) mean squares, as well as (c) the highest F-value (8224.68) with p-value lower than 0.009, confirming high accuracy of fitting and the statistical significance of the model. Moreover, ANOVA for the lack of fit test for the model was insignificant indicating that the model adequately fitted the experimental data. The values of R^2, which were 100.0% for FFD, respectively, confirmed that the correlation between predicted and actual values of responses is the best for FF model and more than 99.7% of the variance in the response can be explained by the empirical model obtained on the basis of FF design of experiments. The p-value and t-statistic were utilized in order to examine the importance of the model effects. The p-values estimated for factors β_1, β_2, β_3, β_4, $\beta_1 \beta_2$, $\beta_1 \beta_3$, $\beta_1 \beta_4$, $\beta_2 \beta_3$, $\beta_2 \beta_4$, $\beta_3 \beta_4$, $\beta_1 \beta_2 \beta_3$, $\beta_1 \beta_2 \beta_4$, $\beta_1 \beta_3 \beta_4$, $\beta_2 \beta_3 \beta_4$, $\beta_1 \beta_2 \beta_3 \beta_4$ were less than 0.05, indicating that these effects were significant in the prediction process. Negative and positive values of the coefficients represent, respectively, opposed and coordinated effect of each model term on the response of the system. The coded coefficient values for the model were further decoded in order to obtain the polynomial models for the response variables as a function of the actual independent variables {Eq. (1)}.

Table 3. ANOVA results of MRR

Source	**DF**	**Adj. SS**	**Adj. MS**	**F-value**	**P-value**
Model	15	0.123893	0.008260	8224.68	0.009
Linear	4	0.0432	0.010811	10765.11	0.007
2-way Interaction	6	0.06615	0.01102	10978.73	0.007
3- Way Interaction	4	0.003223	0.000806	802.46	0.026
4-Way Interaction	1	0.005283	0.005283	5260.85	0.009

Residual Error	1	0.000001	0.000001
Total	16	0.123894	

If F0 > F_(α,1,4(n-1)) then the effect of the factor is significant and if F0 < F_(α,1,4(n-1)) then the effect is not significant or zero.

Model Summary

S	R-sq.	R-sq. (adj)	R-sq. (pred)
0.0010021	100.00%	99.99%	92.27%

Besides, the obtained regression coefficients R^2 and R^2adj [20] are respectively of 99.99% and 92.27% for MRR, ensuring an excellent fitting for the relationship between the process parameters and the investigated machining criteria.Based on Eq.1 and using the results presented in Table 3**,** the mathematical relationship for correlating the MRR (g/min) and the considered process parameters was obtained as follows:

$$MRR=0.09001+ 0.06538\ \beta_1+ 3.7541\ \beta_2+ 0.008448\ \beta_3+ 0.3830\ \beta_4- 0.7694\ \beta_1*\beta_2- 0.000900\ \beta_1*\beta_3- 0.11058\ \beta_1*\beta_4- 0.051087\ \beta_2*\beta_3- 4.352\ \beta_2*\beta_4- 0.006875\ \beta_3*\beta_4+ 0.005569\ \beta_1*\beta_2*\beta_3+ 0.8545\ \beta_1*\beta_2*\beta_4+ 0.000868\ \beta_1*\beta_3*\beta_4+ 0.038938\ \beta_2*\beta_3*\beta_4 - 0.004770\ \beta_1*\beta_2*\beta_3*\beta_4 \quad \text{…………Eq.1}$$

3.2 Development of ANN model for prediction of MRR

ANNs are one of the most well-known predictive models that are able to estimate output(s) of the machining processes in the range of investigated input parameters. ANNs have been successfully used for modelling of electrochemical process by several researchers [20-24]. In present study, ANN is made up of some neurons connected together via links. Among various neural network models, the feed forward neural network based on back-propagation is the best general-purpose model. The network has four inputs of voltage, feed rate, electrolyte concentration and conductive electrode and one output of MRR. The training of the ANN for 16 input-output patterns has been carried out by using the Neural Network Toolbox available in MATLAB software package. Several models were designed and tested to determine the optimal architecture, the most suitable activation function and the best training algorithm. The main selection criteria used were mean absolute percentage error (MAPE) in prediction and the regression coefficient (R) values of the trained models. Numerous networks were designed with trial and error procedure and tested with validation dataset. The Levenberg-Marquadt (LM) algorithm was used for training the algorithm. LM algorithms are fast and consume less memory [25]. The common type of ANN consists of 3 layers viz., Input layer, Hidden layer and Output layer. A layer of input units is connected to a layer of hidden units which is connected to layer of output units. To train each network, the activation function of hidden and output neurons was selected as a hyperbolic tangent, and the error goal (mean square error, MSE) value was set at 0.0001, which means the training epochs are continued until the MSE fell below this value. To calculate connection weights, a set of desired network output values is needed. The best network was found to be a feed forward neural network with single hidden layer consisting of 4 neurons as shown in Fig. 2(a). Therefore, a network of structure 4-4-1 is found to be most suitable for the present research as it had the lowest mean absolute prediction error of 0.0067 as depicted in Fig.2(b). The regression coefficient (R) for validation data set was found to be 0.9693 which is close to 1, thus, indicating a strong correlation between the experimental output and network output. The network has been tested for the randomly selected six experimental values and it was found that the MAPE for the six values is very low (less than 0.04) as shown in Table 4. Validation is an important aspect used to confirm that the training of the network is sufficient. Less training makes the ANNs inefficient and may leads to inaccurate predictions. Table. 5 shows that the model and training are capable of accurately predicting then experimental results.

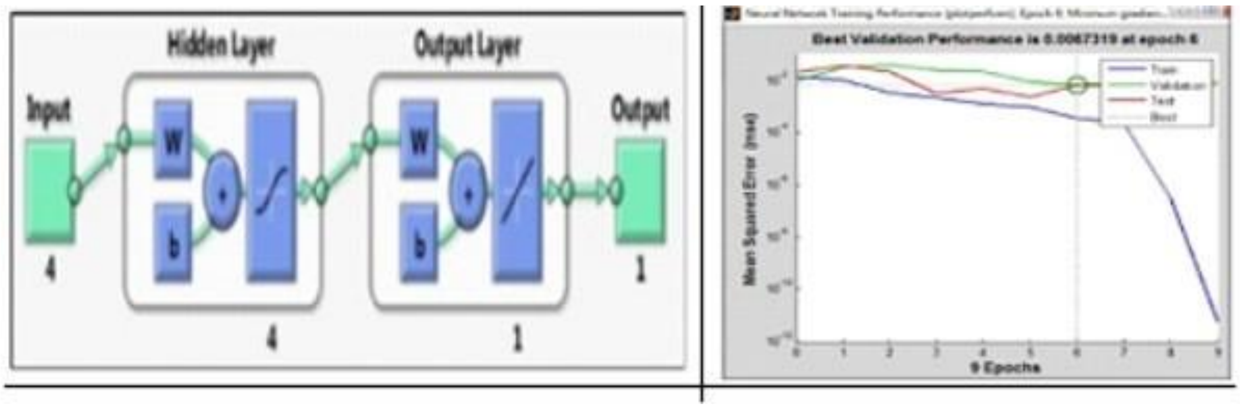
Table 4. Data for training and testing of the ANN.

Trial. No	Voltage(v)	Feed rate(mm/min)	NaCl Concentration(gm./l)	Conductive Electrode	MRR(gm./min)	Prediction ANN
1	6	0.16	200	Cu	0.23	0.230
2	10	0.16	200	Cu	0.18	0.229
3	6	0.23	200	Cu	0.12	0.170
4	10	0.23	200	Cu	0.14	0.137
5	6	0.16	300	Cu	0.25	0.250
6	10	0.16	300	Cu	0.24	0.180

7	6	0.23	300	Cu	0.09	0.078
8	10	0.23	300	Cu	0.17	0.170
9	6	0.16	200	brass	0.07	0.075
10	10	0.16	200	brass	0.21	0.201
11	6	0.23	200	brass	0.16	0.162
12	10	0.23	200	brass	0.34	0.335
13	6	0.16	300	brass	0.09	0.106
14	10	0.16	300	brass	0.31	0.304
15	6	0.23	300	brass	0.20	0.200
16	10	0.23	300	brass	0.35	0.347

Table 5. Comparison of measured and predicted ANN

Trial. No.	1	5	8	9	11	15
Voltage(v)	6	6	10	6	6	6
Feed rate(mm/min)	0.16	0.16	0.23	0.16	0.23	0.23
NaCl Concentration(gm/	200	300	300	200	200	300
Electrode	Cu	Cu	Cu	Brass	Brass	Brass
MRR(gm./min)	0.2325	0.2570	0.1712	0.0737	0.1625	0.2050
ANN predicted	0.2301	0.2502	0.1701	0.0710	0.1622	0.2005
% Error	0.0100	0.0260	0.0065	0.0372	0.0018	0.0219



(a) Architecture (b) Training and test performance graph

Fig. 2.Artificial Neural network ; (a) Architecture (b) Training and test performance graph.

4. Conclusion

This paper has presented an exploration on optimization and the effect of machining parameter on MRR in ECM operations. The level of importance on the machining parameters on MRR is determined by using ANOVA. The purpose of conducting the ANOVA is used to find out the relative magnitude of the effect of each factor on the objective function. Based on the ANOVA method the highly effective parameters on MRR were found as process parameters. The control factors considered for the studies are voltage, feed rate, electrolyte concentration and conductive electrode. Process parameters were selected based on full factorial design. It has been found that the feed-forward back propagation ANN of type (4-4-1) is giving best results for the prediction of MRR. The mean absolute percentage error (MAPE) in the prediction of developed predictive model is 0.0067. ANN used to predict the response variable viz., MRR. Back propagation feed forward neural network (BPNN) and Levenberg–Marquardt algorithm (LMA) used to train and build the network. It is observed that neural network contained with 70% of the data in training set gives good prediction results. Thus, predicted response variables of 70% training set associates well with the measured response variables.

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