Modeling of magnetic assisted EDM of EN24 steel using artificial neural network

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ABSTRACT

EDM is a non-conventional method of electro-thermal machining process where electrical energy produces electrical sparks. To learn the performance of the process parameter on the response variable, the experiment was carried out on EN-24 steel with a copper electrode. For analysis, process parameters like current, pulse on time, voltage are considered. The Matlab ANN Toolbox is used for modeling purpose. ANN Model is developed with Traingdx, Learngdx, MSE, Logsig as training, learning, performance, and transfer functions, using a Feed-forward back-propagation as an algorithm with three nodes in the input layer and one node in the output layer for material removal rate (MRR), electrode wear rate (EWR), surface roughness (SR), using various nodes in hidden layers. Eight networks are tried 3-1-3, 3-3-3, 3-6-3, 3-7-3, 3- 1-3, 3-3-3-3-3, 3-6-6-3 and 3-7-7-3 structure. To predict the value of the response variable, a 3-7-3 network structure is found as best fit for the proposed model.

KEYWORDS

Artificial Neural Network,
Electro Discharge Machining,
Material Removal Rate,
Electrode Wear Rate,
Surface Roughness.

1. Introduction

An electric discharge machine (EDM) is an electrical-thermal machining process where electrical sparks are produced using electrical energy and are regulated by metal removal methods by spark erosion. To erode the surface of the component, the electrical spark is used to produce a solved part as a cutting tool to the necessary form. The metal removal method is done with the help of the application of pulsating electrical charges from high-frequency currents through electrode to workpiece. A tiny amount of the energy emitted by sparks is used to melt and evaporate work piece, while the residual energy is dispersed through the dielectric fluid through convection and radiation. Dielectric fluid is used to remove debris from the machinery zone during the time of pulse when it causes obstacles to eliminating debris. Debris accumulation in the gaps causes non-active pulses, such as short and open circuits and an electrically erratic discharge, thus disrupting the integrity of the EDM mechanism and affect the material removal rate (MRR), and surface roughness (SR), and the electrode wear rate (EWR). In this work, efforts have been made for the EDM process under the influence of permanent magnets installed around the workpiece.

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2. Literature Review

Govindan and Joshi [1] attempted experiments on dry electrical discharge drilling. They tested dry EDM by supplying sparking areas with cages (protectors). In addition to MRR and TWR analysis, this study reveals different characteristics of dry EDM processes with oversized calculations, analyzing the morphology of the machined surface. Gap voltage, release current, and electrode rotation speed has found significant parameters for MRR (with 95 percent confidence).

Joshi et al. [2] proposed a new hybrid solution to enhance the effectiveness of the operation by the use of a pulsating magnet field for dry EDM plasma and it has been observed that the magnetic field enables further thermal energy transfers to work pieces due to higher plasma conflicts and storage.

Beravala and Pandey [3] carried out comparative studies to calculate performance of EDM, aided together by magnetic fields and dielectric liquid-cum-gas. The MRR in the air aided EDM increased by 21% to 41% with tests, and the EWR grown by 7% to 14% due to the rise in ionized phase correspondence in the magnetic field merging. EWR in the magnetic field is reduced by 7-16 percent, due to the argon gas character that prevents the exothermic reaction of liquid metal into the crater.

Gangil and Pradhan [4] highlighted on the Importance of optimal gap conditions of Electric discharge Machining and its influence on variables in terms of MRR, EWR, and surface roughness. They also concluded that to achieve the optimal machining gap, the effect of magnetic fields was very helpful.

Chekuri et al [5] studied on die sinking EDM of Nimonic C-263 super alloy with an intelligent approach to predict the process parameters using ANN. The analysis of the response variables considered were the material erosion rate (MER), the electrode wear rate (EWR) and the surface roughness (SR), dimension overcut (DOC). From the analysis of machining characteristics the most important parameters for the mechanism affecting on all responses was the peak current. They compared regression analysis and ANN modeling and from that 6-6 architecture has been reported to be extremely accurate by 99.71% compared to 93.55% by regression method.

Chandramouli and Eswaraiah [6] developed ANN model for EDM processin machining of 17-4 pH steel. As a response variable, MRR and Ra with process parameters like current, pulse on time, off time and tool lift time. Artificial neural network models was developed using the Levenberg-Marquardt Back propagation method. The findings reported that, it was possible to forecast dynamic EDM processes with the proposed model.

Mhatre et.al [7] estimated parameters of the EDM with Artificial Neural Network (ANN). The findings reported that the ANN model could be used to easily forecast output parameters and thus helped to choose machining parameters for process design and process parameters optimization in EDM.

Kumar and Sharma [8] studied artificial neural networks. Explained that neural networks are interconnected neurons hierarchical structure that provides a very fascinating approach for solving difficult issues and other applications that can play an important part in today’s science. Thus, researchers from different fields build artificial neural networks to solve problem like as pattern detection, forecasting, optimization, associative memory and power. They presented fundamental science, its features and artificial neural network implementation.

Andromeda et.al [9] estimated EDM material removal rate by artificial neural networks for high gap currents (I). In EDM process, they presented estimates of material removal rate (MRR) by using artificial neural networks (ANN). The Die Sinking EDM device collects experimental data with copper electrode and steel material. They formed a behavior model using raw data input-output patterns of the EDM process test. The behavior model was used for MRR predictions and MRR was predicted against the current MRR values. The results provided a good agreement of MRR predicted between them.

3. Experimental Setup and Procedure

The experiments were carried out on the CNC EDM S50 (Make-Electronica) for EN-24 steel workpiece material and copper as an electrode with the dielectric fluid.

Table 1 shows the details of machining process parameters and their levels and Table 2 shows the response variables assessment. Fig 1 shows the experimental setup.

The results obtained from EDM process experimentation are shown in the table3.

4. Artificial Neural Network

Artificial neural networks (ANN) is flexible modeling and simulation technique that allow nonlinear systems to study a math mapping between the variables input and output. This is one of the most effective techniques currently

Table 1
Process parameters and their levels.

Sr. No.	Process Parameter	Levels		
		1	2	3
1	Current (I) [A]	20	25	30
2	Pulse on Time (POT)[μs]	100	200	-
3	Voltage (V) [V]	40	50	60

Table 2
Response variables evaluation.

Response Variables	Formula	Elements
MRR (mm^3/min)	$\frac{\pi * D^2 * L}{4 * 180}$	D and L denote the hole diameter and the depth of the material removed.
EWR (mm^3/min)	$\frac{\pi * d^2 * l}{4 * 180}$	D, l refers to the copper electrode diameter and tool wear length, respectively.
Ra (µm)	Measurement of surface roughness is taken by Taylor Hobson's surface roughness tester.	

Fig. 1. Experimental set-up.

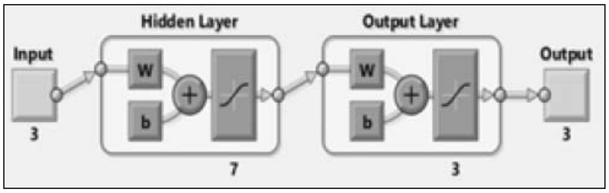

Fig. 2. Network structure.

Table 3
Taguchi L_{18} Array with measured response variables.

Trial No.	POT (µs)	I (Amp)	V (v)	MRR (mm^3/min)	EWR (mm^3/min)	Ra (µm)
1	100	20	40	0.782	0.209	3.858
2	100	20	50	0.791	0.215	3.62
3	100	20	60	0.792	0.218	3.892
4	100	25	40	0.813	0.232	4.028
5	100	25	50	0.793	0.228	4.031
6	100	25	60	0.842	0.228	4.128
7	100	30	40	0.848	0.242	4.286
8	100	30	50	0.855	0.244	4.282
9	100	30	60	0.845	0.252	4.108
10	200	20	40	0.872	0.249	5.223
11	200	20	50	0.870	0.257	4.343
12	200	20	60	0.865	0.256	4.342
13	200	25	40	0.722	0.283	4.792
14	200	25	50	0.928	0.281	4.843
15	200	25	60	0.928	0.279	5.208
16	200	30	40	0.943	0.282	3.992
17	200	30	50	0.947	0.292	5.112
18	200	30	60	1.028	0.289	5.442

being used in various fields of engineering, where complex relations with physical models are difficult to explain. ANN is related to the modeling field and simulation of the machining process. To create a relationship between input and output, neural networks that are fully connected with feed-forward three layers are used. It contains different data preparation steps, the development of network structures, training, testing, and validation data. Feed forward propagation algorithms are mostly used for ANN modeling [9]. During the modeling, three layers of the network were used such as layers of input, hidden and output as shown in fig 2.

5. Artificial neural network (ANN) analysis

The artificial neural network (ANN) model was created with the help of MATLAB ANN toolbox. By using the ANN simulation technique, the machining parametersthat most affected on the expected values of the MRR, EWR, and SR are current, pulse on time, voltage. An ANN model development for this study consists of the following steps:

- For this study, the input layer has three neurons, the output layer has three neurons, and the number of nodes in the hidden layer was calculated by "n/2," "1n," "2n," and "2n + 1," where n is the number of input nodes. The suggested number of nodes in the hidden layer is (3)/2 = 1.5=1, 1(3) = 3, 2(3) = 6, and 2(3) + 1 = 7.
- By applying the trial-and-error procedure with two hidden layers, the following eight network architectures were tested: 3–1–3, 3–3–3, 3–6–3, 3–7–3, 3–1–1–3, 3–3–3, 3–6–6–3, 3–7–7–3, 3–1–1–3, 3–3–3–3, 3–6–6–3 and 3–7–7–3.
- Out of 18 experiments, 12 samples were selected for training and 6 samples were selected for the testing with a 70:30% ratio for the training and testing.
- Normalization was carried out to get the real data obtained from experiments into one range
- For this study, feed forward back propagation were used as a network algorithm because it provides more accurate results.
- A BP algorithm must minimize the size of an error between current outputs and forecast as much as possible. For this study, the logsig transfer function was selected.

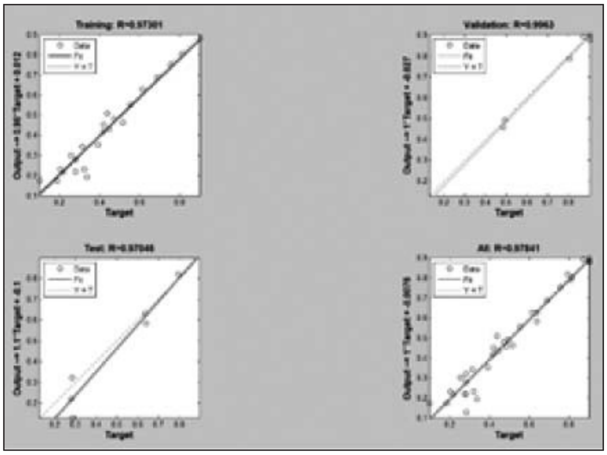

Fig. 3. Regression plot training, validation, testing, and overall correlation coefficient.

- Regarding the choice of performance functions, Mean Square Error (MSE) was used for this research. The level of learning and momentum factor must be chosen as small as possible for the true approach that $\eta = 0.01$ and $\alpha = 0.05$.
- Amongst various training and learning functions, Traingdx and Learngd were used as training and learning functions for this study. The modeling process was done to produce output which was the value specified from the estimated MRR, EWR, SR. Accuracy of output parameters can be increased by adjusting the value of hidden layers and neurons.

From Figure 3 it was observed that the average correlation coefficient between the expected ANN model findings and the trial value was 0.97841. This shows this technique gives good predictions under this attempted study.

To analyze the performance of neural networks after being trained, the plot results show a regression plot for training, validation, and testing data. Plots indicate that how many output estimates deviate from the actual target. In the ideal case, both output and the target remain the same, where deviations are located almost on the dotted line as shown in the plot.

The co-relation coefficient R represents the percentage of the data closest to the most suitable line. The overall co-relation coefficient value of neural network models was found as 0.97841, which indicates the suitability of the developed model.

Figure 4-6 shows a variation between predicted ANN and the experimental value of MRR, EWR,

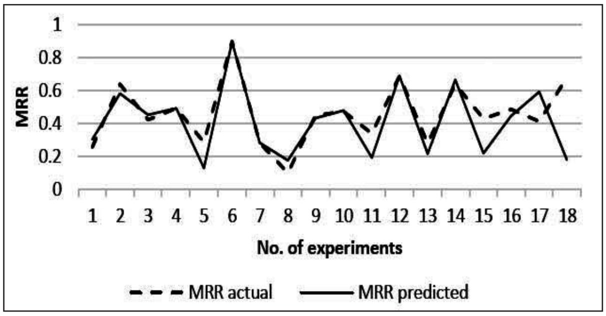

Fig. 4. Time series plot for measured MRR and predicted MRR.

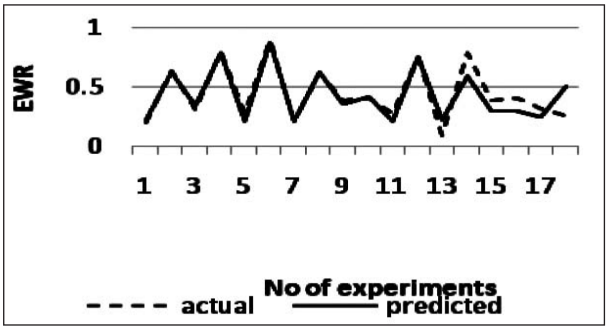

Fig. 5. Time series plot for measured EWR and predicted EWR.

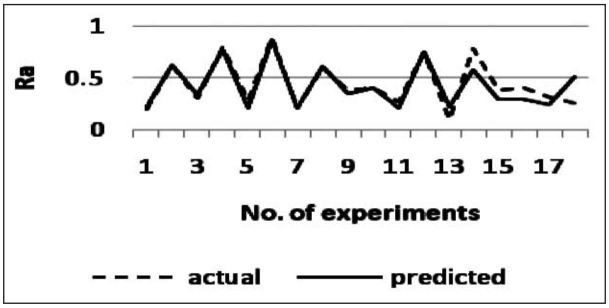

Fig. 6. Time series plot for measured Ra and predicted Ra.

Table 4

L_{18} Array with normalized input and ANN predicted percentage error w.r.t experimental value.

Trial No.	POT(μs)	I (Amp)	V (v)	MRR (absolute error in %)	EWR (absolute error in %)	Ra (absolute error in %)
1	0.1	0.1	0.1	0.171046	0.722134	0.128104
2	0.9	0.5	0.5	0.087012	0.03085	0.013546
3	0.1	0.9	0.9	0.071888	0.099636	0.088191
4	0.9	0.1	0.1	0.000843	0.056583	0.020407
5	0.1	0.5	0.5	0.552038	0.12882	0.221812
6	0.9	0.9	0.9	0.003064	0.025656	0.025375
7	0.1	0.1	0.9	0.00612	0.067363	0.01339
8	0.9	0.5	0.1	0.745446	0.007865	0.01985
9	0.1	0.9	0.5	0.033047	0.16374	0.093509
10	0.9	0.1	0.9	0.014271	0.002218	8.49E-05
11	0.1	0.5	0.1	0.428899	0.2828	0.214954
12	0.9	0.9	0.5	0.000911	0.016431	0.000561
13	0.1	0.1	0.5	0.23567	0.044849	1.296709
14	0.9	0.5	0.9	0.041917	0.00397	0.257658
15	0.1	0.9	0.1	0.488789	0.491149	0.236657
16	0.9	0.1	0.5	0.086113	0.526672	0.280479
17	0.1	0.5	0.9	0.433895	0.322687	0.234113
18	0.9	0.9	0.1	0.735651	0.045781	0.949438

and Ra for response variables during machining. Table 4 shows ANN Prediction percentage error w.r.t experimental value.

6. Conclusion

The ANN model has been developed in this research with the EDM process on EN24 steel using dielectric liquid.

- In this research, the ANN model has been developed using a feed-forward propagation algorithm for the material removal rate (MRR), the electrode wear rate (EWR), surface roughness (Ra) as a response variable.
- In this study, different network structures were tried to develop the ANN model and the 3-7-3 structure was found to be the best suitable for MRR, EWR, and Ra.
- Experimental value and ANN Prediction of MRR, EWR, and Ra values were compared and the result shows that the overall correlation coefficient was 0.97841 which indicates good predictive performance accuracy of the developed ANN Model.
- An overall effectiveness of an ANN trained model with the mean prediction accuracy for MRR =83.33%, EWR = 80.55%, Ra = 85.18%.

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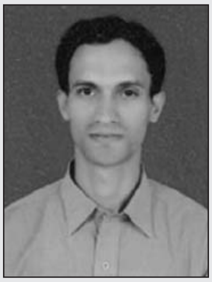

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