Modeling of EDM Process Parameters in Machining of 17-4 PH Steel using Artificial Neural Network

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Abstract

**Objectives**: The present work on the development of artificial neural network modeling and prediction of the machining quality for Electrical Discharge Machining of martensitic Precipitation Hardening (PH) Stainless steel and copper tungsten as tool electrode. **Methods/Statistical analysis**: The important process parameters in this study are peak current, pulse on time, pulse off time and tool lift time with machining qualities as material removal rate and surface roughness. To conduct the experiments L27 orthogonal array was used. **Findings**: Prediction of Material Removal Rate and Surface Roughness with regression analysis when compared with the experimental results shows variation due to nonlinear complex phenomena which influence the accuracy and precision of the product. In such circumstances, a Artificial neural network model is developed using MATLAB programming on the Levenberg-Marquardt back propagation technique with appropriate architecture of the logistic sigmoid activation function to predict the responses. The experimental data were segregated in three parts to train the network, to testing for convergence and finally to validate the model. The developed model has been verified experimentally for training and testing in considering the number of iterations and mean square error convergence criteria. **Improvements/Applications** The developed model results are to approximate the responses quite accurately. Results revealed that the proposed model can be successfully employed in the prediction of the complex EDM process.

**Keywords**: Artificial Neural Network, EDM, Material Removal Rate, Surface Roughness

1. Introduction

Electric Discharge Machining (EDM) is a non-traditional, thermo-electric machining process used to machine precise and intricate shapes on difficult to cut materials and super tough metals such as super alloys, titanium, ceramics, precipitated hardened steels, cast-alloys, which are widely used in defense and aerospace industries and in many engineering applications. Electrical energy is used to generate electrical sparks and material removal mainly occurs due to localized melting and vaporization of material which is carried away by the dielectric fluid flow between the electrodes. The performance of this EDM process is mainly influenced by many parameters like, peak current, polarity, voltage pulse on time, duty factor, pulse off time, electrode gap and also on other parameters like work and tool material, dielectric fluid pressure. All these parameters have a significant effect on the EDM output parameters like, Metal Removal Rate (MRR) and Surface Roughness (SR). The electric discharge machining is very difficult to determine the optimal machining parameters due to complex and stochastic characteristics of process. In the present study the machining qualities are MRR and SR which are conflicting in nature. MRR and SR reflect the productivity and accuracy of the product.

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the EDM parameters. The result obtained from simulation was authenticated with the target output awaiting the network error has congregated to threshold minimum. In\textsuperscript{2} aims to study the influence of parameters on EDM output measures by combine gray relational and orthogonal analysis. In\textsuperscript{3} experiments conducted based on L9 orthogonal array to experimental investigation and optimization of the electrical discharge machining of S-03 a novel special stainless steel. The gray relational analysis was used to optimize the multi-objective machining parameter, the results verified through a confirmation experiment. In\textsuperscript{4} experimental study of the Surface Roughness of three types of cryogenically treated titanium alloys by varying the eight input parameters and observed the peak current is most significant factor cryogenic treated as less significant factor in surface roughness and the experimental values are predicted in the ANN and error obtained by ANN is between 2.346\% to 0.006\%. In\textsuperscript{5} Work presents the influence of wire cut electrical discharge machining parameters on material removal rate and surface roughness of high strength armor steel using Taguchi technique. The Experimental results shows input parameters are significant variables to MRR and SR. The results validated through confirmation of experiments. In\textsuperscript{6} developed ANN model for EDM process and concluded that the total average prediction error of experimental results for machining qualities with that values predicted from the developed neural network model prediction was calculated as 4.4616\%. In\textsuperscript{7} a research work on effect of process variable on MRR, TWR and SR was examined for machining of SS 440C with Copper electrode in EDM process using ANN. It was observed that current and Gap voltage shows significance effect on MRR Surface Quality. In\textsuperscript{8} studied the performance of the EDM Machining parameters used as model input variables during the development of the models for Material Removal Rate; finally the modeled ANN was successfully used. In\textsuperscript{9} predicted the surface roughness in electrical discharge machining of SKD 11 Tool steel, and studied the influence of different EDM parameters. The proposed model can satisfactorily predict the surface roughness and ANN a valuable tool for the process planning of EDM Machining. In\textsuperscript{10} experiments conducted on Inconel 718 and ANN has been trained with the experimental data set using back propagation algorithm. Non-dominated sorting genetic algorithm employed to obtain pareto-optimal solutions. In\textsuperscript{11} carried out work on EDM with various levels of input parameters for obtaining optimum machining parameters and the developed ANN model using Radial basis function was validated through experimental data. In\textsuperscript{12} Design of experiments and ANN with back propagation learning method used for modeling and prediction of maximum and mean error with different architectures network. In\textsuperscript{13} addressed optimization of MRR in the EDM of Materials like Ti6Al4V, HE15, 15CDV6 considering different input variables. In developed model weights are selected with genetic algorithm. In\textsuperscript{14} ANN to model micro-EDM process and Genetic Algorithms were used to determine optimum process parameters. In\textsuperscript{15} presented an efficient and integrated approach for MRR evaluation using An Augmented Lagrange multiplier net work to determine the optimum machining parameters for maximum MRR. From the literature, it is observed that there is a little work done on machining of 17-4 Precipitation Hardening Stainless Steel with copper tungsten electrode using EDM machining. The objective of the present work is to develop artificial neural network model and prediction of output parameters such as MRR and SR for above said tool and work piece combination on EDM. Back propagation neural network algorithm using MATLAB programming a model is developed and the validity of the model is ascertained with the experimental studies.

2. Experimental Procedure

The experiments were conducted on precision die sink electric discharge machine (Askar Microns V3525). The machine has 8 current settings from 3A to 24A pulse on time and pulse off time each have 9 settings. The selected size of the work piece surfaces top and bottom are finished using high precision grinding machine. Bottom portion of tool polished with a very fine-grade emery sheet before each experiment. Machining was done with straight polarity for a machining time of the 10 minutes in a dielectric fluid EDM30 Gap voltage is 30 V and flushing pressure maintained constant. The input levels and number of experiments are decided based on the design of experiments. Process parameters and their levels are presented in Table 1. For accuracy and validity the experiments are repeated for three replications. At the end of each experiment, the work piece and tool were removed, washed, dried, and weighed using the digital electronic weighing balance 1mg accuracy to determine MRR using following equation(1).


\[ MRR = \frac{1000 \cdot (W_1 - W_2)}{T} \text{ mg/min}. \]  

(1)

Where

- \( W_1 \) = work piece weight before machining (mg)
- \( W_2 \) = work piece weight after machining (mg)
- \( T \) = Machining time (min)

Table 1. Process parameters and their levels.

| Sl. No. | Process parameters | Symbol | Level 1 | Level 2 | Level 3 |
|---------|-------------------|--------|---------|---------|---------|
| 1       | Discharge current (A) | A      | 9       | 12      | 15      |
| 2       | Pulse on time (µs) | B      | 50      | 100     | 200     |
| 3       | Pulse off time (µs) | C      | 20      | 50      | 100     |
| 4       | Lift time (µs) | D      | 10      | 20      | 50      |

The 17-4 PH steel work piece used in dies manufacturing and aerospace. The rectangular plate work piece with dimensions of 60mm X 50mm X 5 mm machined with Copper Tungsten electrode which had high wear resistance, good electrical conductivity and minimum tool wear. The chemical compositions of work material used in the experiments are shown in Table 2.

Table 2. Material composition.

| Element             | Concentration (% by wt) | Element             | Concentration (% by wt) |
|---------------------|-------------------------|---------------------|-------------------------|
| Carbon              | 0.07 max                | Chromium           | 15.00 – 17.05           |
| Manganese           | 1.00 max                | Nickel             | 3.00 – 5.00             |
| Phosphorus          | 0.040 max               | Copper             | 3.00 – 5.00             |
| Sulphur             | 0.030 max               | Columbium + Tantalum | 0.15 – 0.45          |
| Silicon             | 1.00 max                | Iron Balance       |                         |

3. ANN Model Development for MRR and SR

ANN model was developed with Experimental results which are used to predicting MRR and SR. In this work, four inputs variables current, pulse on time, pulse off time, lift time and two output variables are MRR, and SR are considered as the data of ANN model. In 27 experimental data set of which 18 data points were used for training the network and 9 data points were chosen randomly for testing the performance of the trained network. After successful completion of the network training stage, it was tested with the experimental data which are not present in the training data set. The input and output data is scaled between 0-1. The appropriate values of learning rate coefficient and momentum terms are choose based on results of trial and error. The important specifications of parameters that are required for modeling process are shown in Table 3.

Table 3. Parameter used in ANN.

| Parameter used in ANN. | Input | Parameter | Input |
|------------------------|-------|-----------|-------|
| No. of Hidden Layer    | 1     | Momentum Factor | 0.9   |
| No. of Input Neurons   | 4     | Tolerance  | 0.0010 |
| No. of Hidden Neurons  | 14    | Learning Coefficient | 0.6000 |
| No. of Output Neurons  | 2     | No. of Data Sets | 27    |
| Sigmoid Gain           | 1     | No. of Iterations | 6000  |

The MSE should be minimized which shows the performance of the network. MSE is calculated using equation (2).

\[ MSE = \frac{1}{Q} \sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q} \sum_{k=1}^{Q} [t(k) - y(k)]^2 \]

(2)

Where \( e(k) \) the error between the target and ANN output. \( t(k) \) target output, \( y(k) \) ANN output value and \( Q \) is the number of total data.

The comparison of both MRR and SR which obtained from the trained ANN model are given in Table 4. The error can be calculated using equation 2. It can be observed that the trained values and experimental values have very small deviation. The average error observed in MRR and SR as 4.14 and 2.42 respectively. The comparison of the trained data of ANN model with experimental data for MRR and SR are shown in Figure1 and 2. It is cleared that experimental data agree very close with trained ANN data.
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### Table 4. ANN trained values of MRR and SR with experimental results.

| Expt. No. | MRR (mg/min) | SR (µm) |
|-----------|--------------|---------|
|           | Expt.       | ANN     | Error | Deviation % | Expt. | ANN     | Error | Deviation % |
| 1         | 68.73        | 66.54   | 2.19  | 3.19        | 6.88  | 6.77   | 0.11  | 1.59   |
| 2         | 66.96        | 65.00   | 1.96  | 2.93        | 7.63  | 7.4    | 0.23  | 3.01   |
| 3         | 70.70        | 68.50   | 2.2   | 3.11        | 7.31  | 7.15   | 0.16  | 2.19   |
| 4         | 24.37        | 23.02   | 1.35  | 5.54        | 7.45  | 7.31   | 0.14  | 1.88   |
| 5         | 25.30        | 23.90   | 1.4   | 5.53        | 8.07  | 7.71   | 0.36  | 4.46   |
| 6         | 23.70        | 23.22   | 0.48  | 2.02        | 5.61  | 5.58   | 0.03  | 0.53   |
| 7         | 25.30        | 23.95   | 1.35  | 5.34        | 3.46  | 3.41   | 0.05  | 1.45   |
| 8         | 7.42         | 6.98    | 0.44  | 5.93        | 3.97  | 3.68   | 0.29  | 7.31   |
| 9         | 5.04         | 4.84    | 0.2   | 3.97        | 3.71  | 3.62   | 0.09  | 2.42   |
| 10        | 47.66        | 45.63   | 2.03  | 4.26        | 7.41  | 7.38   | 0.03  | 0.41   |
| 11        | 26.5         | 25.90   | 0.6   | 2.26        | 7.93  | 7.82   | 0.11  | 1.38   |
| 12        | 97.07        | 95.33   | 1.74  | 1.79        | 8.01  | 7.95   | 0.06  | 0.75   |
| 13        | 36.93        | 34.98   | 1.95  | 5.28        | 8.09  | 7.97   | 0.12  | 1.48   |
| 14        | 28.30        | 27.38   | 0.92  | 3.25        | 6.67  | 6.36   | 0.31  | 4.65   |
| 15        | 31.30        | 29.98   | 1.32  | 4.23        | 6.92  | 6.73   | 0.19  | 2.75   |
| 16        | 8.84         | 8.23    | 0.61  | 6.90        | 4.35  | 4.31   | 0.04  | 0.92   |
| 17        | 11.58        | 10.96   | 0.62  | 5.35        | 4.18  | 4.05   | 0.13  | 3.11   |
| 18        | 12.13        | 66.54   | 2.19  | 3.63        | 3.54  | 3.43   | 0.11  | 3.10   |

Average error in MRR (trained) 4.14
Average error in SR (trained) 2.42

### Table 5. ANN tested values of MRR and SR with experimental results.

| Expt. No. | MRR (mg/min) | SR (µm) |
|-----------|--------------|---------|
|           | Expt.       | ANN     | Error | Deviation % | Expt. | ANN     | Error | Deviation % |
| 1         | 123.6        | 120.4   | 3.2   | 2.58        | 9.79  | 9.55   | 0.24  | 2.45   |
| 2         | 189.27       | 186.79  | 2.48  | 1.31        | 9.32  | 9.19   | 0.13  | 1.39   |
| 3         | 162.8        | 159.97  | 2.83  | 1.74        | 10.55 | 10.28  | 0.27  | 2.55   |
| 4         | 54.96        | 52.15   | 2.81  | 5.11        | 7.23  | 7.17   | 0.06  | 0.83   |
| 5         | 45.27        | 44.16   | 1.11  | 2.45        | 8.24  | 8.1    | 0.14  | 1.69   |
| 6         | 39.77        | 38.54   | 1.23  | 3.09        | 10.12 | 9.99   | 0.13  | 1.28   |
| 7         | 15.4         | 14.96   | 0.44  | 2.85        | 3.69  | 3.51   | 0.18  | 4.87   |
| 8         | 14.03        | 13.66   | 0.37  | 2.63        | 4.89  | 4.82   | 0.07  | 1.43   |
| 9         | 16.03        | 14.72   | 1.31  | 8.17        | 4.89  | 4.71   | 0.18  | 3.68   |

Average error in MRR (tested) 3.32
Average error in SR (tested) 2.25
After the training the network tested with the experimental data that were not present in the training data set. The results obtained were compared using statistical methods given in Table 5. The mean deviations of the predicted and experimental results of both MRR and SR output parameters are very small. Figure 3 and 4 shows the comparison of measured and predicted data of the MRR for the training and testing stages, respectively. The comparison of measured and predicted data of the SR for the training and testing stages respectively are shown in Figure 5 and 6. The average error observed in MRR and SR as 3.32 and 2.25 respectively. From the results it is observed that there is very less deviation between predicted and experimental values of both MRR and SR.

Thus, the ANN model can give adequate predictions of the machining qualities for chosen levels of parameters and experimental model.

Figure 1. Comparison of predicted and experimental MRR (Trained).

Figure 2. Comparison of predicted and experimental SR (Trained).

Figure 3. Comparison of predicted ANN model with experimental results for MRR (trained).

Figure 4. Comparison of predicted ANN model with experimental results for SR (trained).

Figure 5. Comparison of predicted ANN model with experimental results for MRR (tested).
4. Conclusions

In the current work, the ANN model has been developed for EDM process for machining of 17-4 PH steel with copper tungsten electrode. The training and testing of ANN for input-output patterns has been carried out using the Neural Network Toolbox in MATLAB software package. From the experimental investigation, the following conclusions are derived:

In ANN model the mean deviation of the predicted and experimental results of MRR and SR are very small and good agreement between both training and testing data.

The average error observed in ANN model for MRR and SR as 3.32 and 2.25 respectively in testing stage. According to ANN model results the developed model produced the better prediction for MRR and SR compared to the Regression model. The developed ANN models can be used to estimate the results of EDM for given range of process parameter.

5. References

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