International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

# Predicting Material Removal Rate using an Artificial Intelligence Approach

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***Abstract*-In view of improvement in electric discharge machining (EDM) process performance, optimization of process parameters assumes significant importance. EDM process performance *i.e.* material removal rate (MRR) can be improved significantly by selecting optimal combination(s) of input parameters. EDM is capable of making complex cuts on difficult-to-cut materials. In the present work an Artificial Intelligence tool i.e. ANFIS tool has been used to model EDM process. ANFIS model of EDM process is developed by training of ANFIS with the experimental data taken from published work. Through experiment the capability of ANFIS for prediction has been verified. Through the work presented, it was shown that models developed in this paper using ANFIS technique could be used to effectively address these issues. Low Root Mean Square Error (RMSE) has been obtained, both for training and testing datasets.**

***Key Words: EDM, RMSE, ANFIS, MRR.***

## 1. Introduction

In view of improvement in electric discharge machining (EDM) process performance, optimization of process parameters assumes significant importance. EDM process performance (*i.e.* material removal rate, surface finish and tool wear rate) can be improved significantly by selecting optimal combination(s) of input parameters. EDM is capable of making complex cuts on difficult-to-cut materials [1,2]. The higher degree of accuracy and fine surface quality irrespective of the hardness of the work material make this process valuable. The selection of favourable machining conditions is one of the most important aspects of EDM process owing to the characteristically lower material removal rates. Full potential of the process has yet not been exploited due to its complicated discharge mechanism. Due to very complex nature of EDM process [2,3], selection of favourable parameters by traditional methods is not satisfactory with specific regard to material removal rate and surface finish. This is why researchers are inclined to employ mathematical techniques to optimize the process parameters for the best yield of cutting performance in EDM. To employ the mathematical techniques, it is essential to understand and model the process mathematically that can establish the relationship between input(s) and output(s).

Many empirical, statistical and regression techniques have been used by researchers for modelling EDM process [3]. Use of statistical techniques for modelling EDM process is limited because curve fitting becomes difficult in non-linear systems when number of inputs is high. The role of regression techniques is also limited because of the presence of noise in the system variables of the EDM process. It is seen that ANN has the capability of modeling the given system and efficiently measuring the EDM performance. In order to tackle the above problem various techniques has been used for modeling the input variables with the output ones and then comparing the performance. Various techniques so far used for MRR analysis include Mathematical modeling, curvilinear regression equations, linear regression equations, response surface methodology, etc.

The rest of the paper is organized as follows: Section II describes the Literature Review. Section III deals with data used, IV the methodology part of work done, followed by results and discussions in section V. In the end, based on the discussion various conclusions are drawn and the future scope for the present work is discussed.

## 2. Literature Review:

A brief review of the works carried out in this direction has been discussed. Literature review is mainly focused on experimental investigations, process modeling and parametric optimization. On the basis of literature review, some gaps have been identified and efforts are intended to fill the gaps through this work. [3] made an effort to develop model of material removal rate (MRR) for Ti-5Al-2.5Sn material using Artificial Neural Network (ANN). [4] used die electric EDM process using neuro solution package for the development of MRR optimization model using multiperceptron neural network. [5] experimentally collected data using EDM process and then used ANN technique for the development of MRR prediction model using raw data. They achieved low percentage error. This clearly demonstrated the prediction capability of ANN. [6] used Al-SiC composite material for EDM process and used asymmetric model for MRR modeling. [7] used Al/ SiC-graphite Hybrid Metal Composites (HMCs) material for EDM process drilling. They studied the effect of EDM process parameters on MRR using ANN modeling technique.

## 3. Dataset Used:

In the present work, the experimental data for predicting MRR using EDM process has been taken from the published paper [3]. Axial point central composite design was used for designing the experiment using response surface design method. A number of experiments were carried out according to the design of experiment (DOE) to investigate the influence of various machining factors on EDM process. Variables such as peak current, pulse on time, pulse off time and servo voltage were used to determine their effect on material removal rate. Table 1 given below lists the values of the parameters used for model development.

**Table-1 Machining Parameters and their Levels**

| S.no | Parameters | Units | Notations | Level 1 | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|---|---|---|---|
| 1 | Peak Current | amp | $I_p$ | 1 | 8 | 15 | 22 | 29 |
| 2 | Pulse On Time | micro-sec | $T_{on}$ | 10 | 95 | 180 | 265 | 350 |
| 3 | Pulse Off Time | micro-sec | $T_{off}$ | 60 | 120 | 180 | 240 | 300 |
| 4 | Servo Voltage | volts | $S_v$ | 75 | 85 | 95 | 105 | 115 |

**4. ANFIS Model Development**

ANFIS [9,10,11] is a judicious integration of FIS and ANN, capable of learning, high-level thinking and reasoning and it combines the benefits of these two techniques into a single capsule. Identification of the rule base is the key of a FIS. To generate a FIS using ANFIS [10,11], it is significant to choose proper parameter, inclusive of the number of membership functions (MFs) for each individual antecedent variables. It is also important to select proper parameters for learning and refining process, including the initial step size (ss). For FIS identification subtractive clustering rule extraction method has been used, for initial ANFIS parameter identification [8]. MATLAB Fuzzy Logic Toolbox [12] has been used for ANFIS simulation. However, the parameters of the subtractive clustering algorithm still need to be specified. The clustering radius is very important parameter in the subtractive clustering algorithm and is optimally determined through a trial and error procedure. For other parameters default values are used in the subtractive clustering algorithm. Gaussian membership functions are used for each fuzzy set in the fuzzy system. Hybrid learning algorithm has been used for determining the Gaussian membership function parameters. The number of epochs used for ANIFS training is set to 500.

In MATLAB [12], Sugeno type FIS structure, making use of subtractive clustering algorithm is generated using *genfis2* command. This has been done because of only one output variable. This *genfis2* command extracts a set of rules for ANFIS which is further used for data performance. This subtractive clustering algorithm is used by the command subclust. This initially determines the number of rules and antecedent membership functions. Then it uses least square estimate to find out the rules consequent equations. The parameters used in the model for training ANFIS are given in Table 2 and the rule extraction method used are given in Table 3. Table 4 summerizes the results of types and values of model parameters used for training ANFIS.

**Table.2 Parameters used in all the models for training ANFIS**

| | |
|---|---|
| Rule extraction method used | Subtractive clustering |
| Input MF type | Gaussian membership (‘gaussmf’) |
| Input partitioning | variable |
| Output MF Type | Linear |
| Number of output MFs | one |
| Training algorithm | Hybrid learning |
| Training epoch number | 20 TO 200 |
| Initial step size | 0.01 |

**Table 3 Rule extraction method used for training ANFIS**

| Rule Extraction Method | Type |
|---|---|
| And method | ‘prod’ |
| Or method | ‘probor’ |
| Defuzzy method | ‘wtever’ |
| Implication method | ‘prod’ |
| Aggregation method | ‘max’ |

**Table 4 Types and values of parameters used for training ANFIS model**

| | |
|---|---|
| No. of nodes | 157 |
| No. of linear parameters | 75 |
| No. of non-linear parameters | 120 |
| Total no. of parameters | 195 |
| No. of training data pairs | 20 |
| No. of testing data pairs | 12 |
| No. of fuzzy rules | 15 |

**5. Results and Discussions:**

ANFIS model having four input variables are trained and tested by ANFIS method and their performances compared and evaluated based on training and testing data. The best fit model structure is determined according to criteria of performance evaluation. The performances of the ANFIS model are shown in ***Fig. 1 & 2*** below and their RMSE values both for training and testing data are shown in Table 5 below**.** Fig. 3 is the graphical representation of the RMSE values for various model development stages, both for training and testing data. The low RMSE value obtained during testing phase clearly shows that the model so developed has been able to address the issue, i.e. it has performed well for predicting the Material Removal Rate (MRR) during the machining process.

**Table 5:- RMSE Values for Datasets after using ANFIS**

| Model Development Stages | | RMSE | |
|---|---|---|---|
| | | Trg. Data | Chk. Data |
| 1 | System generated using ANFIS | 0.0018 | 0.1160 |
| 2 | Optimised Output value | 0.0018 | 0.0979 |
| 3 | Testing the overfitting | 0.0018 | 0.0949 |

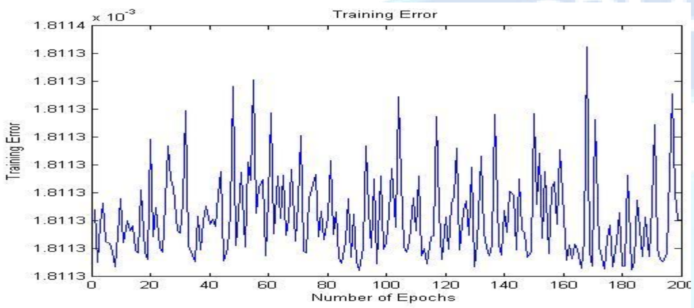


**Fig.:- 1 RMSE Plot of Training Datasets during ANFIS Training**

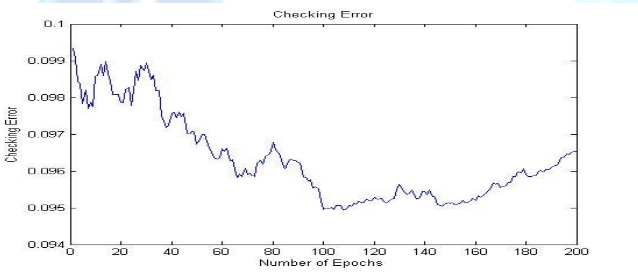


**Fig.:- 2 RMSE Plot of Testing Datasets during ANFIS Training**

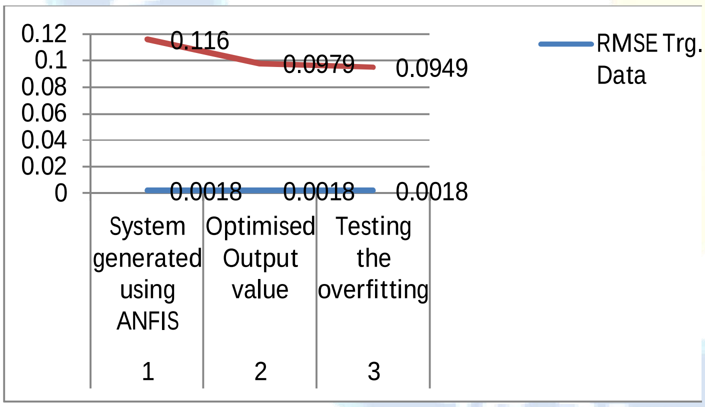


**Fig. 3: Plot of RMSE Values for Training and Testing Data**

Further from the analysis of the RMSE values as given in table 5 and as also from the corresponding graph given in fig.3 above, both for training and testing data sets, it is clear that the ANFIS model has been able to perform better for both training and testing datasets. From the perusal of Fig.3 it is evident that during the various stages of model development the RMSE values for testing datasets has shown improvement, whereas the RMSE values for training datasets has remained the same. Further it is seen that during testing the over-fitting of the model the RMSE value has improved for test data, clearly showing that the model so developed has not over-fitted, i.e. during training phase the model has not been subjected to too much learning.

## 6. Conclusion:

In the present chapter, applicability and capability of ANFIS techniques for Material Removal Rate prediction prediction has been investigated. It is inferred that ANFIS have fast computational capability, can take care of noisy data and are rugged. Due to the presence of non-linearity in the data, it is an efficient quantitative tool to predict MRR.

The initial parameter identification of ANFIS has been done using the subtractive clustering method. Gaussian membership functions are used for each fuzzy set in the fuzzy system. Subtractive clustering algorithm has been used for determining membership function numbers and fuzzy rules for ANFIS. Hybrid learning algorithm has been used for determining the Gaussian membership function parameters. Each ANFIS has been trained initially for 20 epochs in order to test the optimization capability of ANFIS and further for 200 epochs to test the over-fitting of the model. .

From the result analysis it is seen that the MRR prediction model developed using ANFIS technique has very well performed. The RMSE value obtained from ANFIS model during training phase is 0.0018, whereas during testing phase it is 0.0949. This again depicts the predictive capability of ANFIS technique.

## References

[1] Steve Krar, “Electrical Discharge Machining”, Basic Theory.

[2] E.P.Guitrau, “Basic Theory – Electrical Discharge Machining”, Technical Article, EDM Today, May-June 1991 Issue, pp. 22-34.

[3] M.m. Rahman, md. Ashikur rahman khan, k. Kadirgama, rosli a. Bakar, (2014) “Prediction of Material Removal Rate for Ti-5Al-2.5Sn in EDM using Multi-Layered Perceptron Neural Network Technique”, Recent Researches in Neural Networks, Fuzzy Systems, Evolutionary Computing and Automation, pp. 17-23.

[3] G Krishna Mohana Rao, G Ranga Janardhana, D. Hanumantha Rao and M. Srinivasa Rao(2008), “ Development Of Hybrid Model And Optimization Of Metal Removal Rate In Electric Discharge Machining Using Artificial Neural Networks And Genetic Algorithm”, ARPN Journal of Engineering and Applied Sciences, ARPN Journal of Engineering and Applied Sciences, pp. 19-30.

[4] Azli Yahya, Trias Andromeda, Ameruddin Baharom, Arif Abd Rahim and Nazriah Mahmud, (2011), “Material Removal Rate Prediction of Electrical Discharge Machining Process Using Artificial Neural Network”, Journal of Mechanics Engineering and Automation 1 (2011) 298-302.

[5] U. K. Vishwakarma , A. Dvivedi and P. Kumar, (2012), "FEA Modeling of Material Removal Rate in Electrical Discharge Machining of Al6063/SiC Composites", World Academy of Science, Engineering and Technology Vol:6 2012-03-24.
[6] Yanamandala Raghuram Chowdary, C.Yuvaraj, K. Prahlada Rao, B. Durgaprasad, {2012), " Neural Network for Prediction of EDM of Al/Sic-Graphite Particulate Reinforced Hybrid Composites", International Journal of Emerging Technology and Advanced Engineering, Volume 2, Issue 12, pp.730-739.
[7] Chiu, S., (1994), "Fuzzy Model Identification based on cluster estimation", Journal of Intelligent and Fuzzy Systems, 2 (3), pp 267–278.
[8] Jang, J-S. R., (1992), "Neuro-Fuzzy Modeling: Architecture, Analyses and Applications", P.hd. Thesis.
Jang, J-S. R., (1993), "ANFIS-Adaptive-Network Based Fuzzy Inference System", IEEE Transactions on Systems, Man and Cybernatics, 23(3), pp 665-685.
[9] Jang, J-S. R., SUN, C.-T., (1995), "Neuro-fuzzy modeling and control", Proceedings IEEE,. 83 (3), pp 378–406.
[10] "Fuzzy Logic Toolbox", MATLAB version R2013a.