OPTIMIZATION OF ELECTRICAL DISCHARGE MACHINING PARAMETERS USING ARTIFICIAL NEURAL NETWORK WITH DIFFERENT ELECTRODES

V.Balasubramaniam[1*], N.Baskar[2], C.Sathiya Narayanan[3]

[1*]Department of Mechanical Engineering, J.J College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India, 620 009, email: baluv_tce@yahooo.com.

[2]Department of Mechanical Engineering, Saranathan College of Engineering, Tiruchirappalli, Tamil Nadu, India, 620 012, e- mail: baskarnaresh@yahoo.co.in.

[3]Department of Production Engineering, National Institute of Technology, Tiruchirappalli, Tamil Nadu, India, 620 015, email: csathiya@nitt.edu

Abstract

Electrical Discharge Machining (EDM) is a time consuming process and the operating cost is high. Optimum machining conditions reduces the machining time in the EDM process and yield better performances. Electrode material is also having their significance in the performances. In this paper a work has been carried out with different electrode materials namely copper, brass and tungsten while EDM of Al-SiCp Metal Matrix Composite. Material Removal Rate (MRR), Electrode Wear Rate (EWR) and Circularity (CIR) are considered as the performance measures. Artificial Neural Network is used for optimization of the machining parameters such as current, pulse on time and flushing pressure. Investigations indicate that the current is the most significant parameter. Among the three electrodes copper yields better performances. Machining time is reduced with better performances.

Key words: EDM, MRR, ANN, Circularity

1 Introduction

EDM is an electro-thermal process, where electrical energy is used to generate spark and the material removal mainly occurs due to thermal energy of the spark. EDM is focused to machine difficult-to-machine materials and high strength materials [1]. EDM can also be used to machine difficult geometries. EDM is a well known process for machining composites [2]. In this process the metal is removing from the work piece due to erosion case by rapidly recurring spark discharge taking place between the tool and work piece. Material removal occurs due to instant vaporization of the material as well as due to melting. Thillaivanan. et al. [3] worked on Taguchi method and ANN for optimization machining parameters like current and feed. The resilient back propagation training algorithm is used to eliminate harmful effects of the magnitudes of the partial derivatives. Mohana et al. [1] investigated the effect of electrode rotation of machining Al-SiC composite. Also they optimized the cutting conditions polarity, current, electrode material, vol % SiC, pulse duration and rotation of electrode for maximizing MRR. Pellicer [2] et al. worked on electrode with different geometries to improve the basic performance measures for H13 steel. The results presented how to select suitable process parameters to predict geometrical features and surface roughness patters. Pandhee et al. [4] used NSGA-II to optimize the machining parameters in powder mixed EDM through response surface methodology. Ignacio Puertas et al. [5] optimized the EDM conditions for B_4C and WC-Co conductive ceramics for SR, EW and MRR. The main significant factors among the remaining factor were analyzed. Somashekhar et al. [6] reported the development of modeling and optimization for micro-electric discharge machining for MRR. Neural Network was developed using MATLAB programming and the trained network was simulated. Optimal neural network with 4-6-6-1 was found to give reasonably good prediction for the performance.

Dhavamani et al. [7] optimized machining parameters for MRR and SR. Multiple regression model was used to represent the relationship between the output performances and the machining parameters. The application multi-objective optimization which is based on a Taguchi method, increases the flexibility on selecting the optimal parameters of composite materials. Ramezan Ali et al. [8] worked on machining parameters optimization of EDM for SiC with Neural Network and Non-dominating Sorting Genetic Algorithm. 81 experiments have been conducted with different machining parameters for maximum MRR and minimum SR. Gopalakrishnan et al. [9] worked on Al 7075 with 0.5 wt% SiC nanoparticles prepared by ultrasonic cavitations method. The developed mathematical models of MRR, EWR and SR are fairly well fitted with experimental values with a 95% confidence level. Chiang et al. [10] analyzed the over cut variation through variance analysis of coupling effects in EDM process. A correlation coefficient was performed to determine the coupling effects of the dimensional variables of electrodes and spark holes. The results revealed that the coupling effect of dimensional variable is an important factor in the over cut variation. Sharma et al. [11] worked on Genetic Algorithm based approach for robust evaluation on Form Tolerances. Tolerance and data points were obtained from CMM. GA used here does not need any significant preprocessing for calculating the tolerances. Machining of high strength material, like composite and the need of the same rises in a parallel manner. While machining on EDM, very large amount of heat is generated and which will affect the surface of the machined hole of the materials. This phenomenon was an unavoidable event in EDM process. Since the machining cost is high in EDM finding optimal parameters which will give optimum performances is necessary task. Quality of its machined surface and productivity depend on the process parameters in any manufacturing process optimization of machining parameter is needed [6].

The above literature reveals that no work has been carried with electrode material as one of the parameters in Al-SiC MMC and ANN as modeling tool. Therefore the EDM process of machining Al-MMC with different electrode material as parameter against the performance like MRR, EWR and CIR is necessary.

Figure 1 Electrical Discharge Machine

Figure 2 Coordinate Measuring Machine

2. Artificial Neural Network

Recently the application of artificial intelligence is more in all the fields of engineering. An ANN is neural network consists of an interconnected group of artificial neurons. It has been developed as generalization of mathematical models of human cognition or neural biology. A model can be constructed very easily based on the given input, and the output is trained to accurately predict the process dynamics [6]. ANN have important role in the field of linear and nonlinear problems in engineering. Many EDM researchers worked in development of mathematical models for improving the performance measures in EDM process [3,4,6]. For this modeling and optimization are necessary. As the EDM process is high cost associated process, it is very important to form a model and optimizing the same is vital. Hence an attempt is made to model EDM processes through ANN approach based on Feed-forward back-propagation. In ANN network approach and the model can be constructed very easily based on the given input, and the output. .

3. Experimental Procedure

In this work it was planned to study the effect of machining parameters namely pulse current, pulse on time, flushing pressure and different electrode material. The response variables were namely MRR, EWR and Circularity. The machining parameters and their levels are arrived in the Table 1.

Table 1. Machining parameters and their levels.

Sl.No	Machining Parameters	Level 1	Level 2	Level 3
1	A	4	6	8
2	Pon	200	400	600
3	Pr	0.25	0.50	0.75
4	Em	Copper (1)	Brass (2)	Tungsten (3)

Machining was carried out using SPARKONIX die-sinking ED machine as shown in Figure 1. Based on weight loss the MRR and EWR were calculated. MRR, which is the ratio of difference between the weights of the work piece before and after machining with the time of machining, was found. EWR, which is the ratio of electrode weights before and after machining with the time, was found. The work piece and the electrode were weighed by SHIMAZU Electronic balance of capacity 220g with the readability of 0.001g. Circularity of the machined hole was measured by Coordinate Measuring Machine (CMM) supplied by CHECKMASTER as shown in Figure 2. The experiment was planned by DoE and L_9 orthogonal array has been derived for machining the work-piece. During machining positive polarity was for the work piece and the negative polarity for the electrode.

4. Results and Discussion

The network consists of an input layer, variable number of hidden neurons, and an output layer. The input layer receives information from the external source, which is subsequently modified by interconnecting weights between it and the adjacent hidden layers. For this work, four machining parameters and three performance measures are considered. So a model with 4 input layers 3 hidden layers and 3 output layers is found to suitable and it is shown in Figure 3.

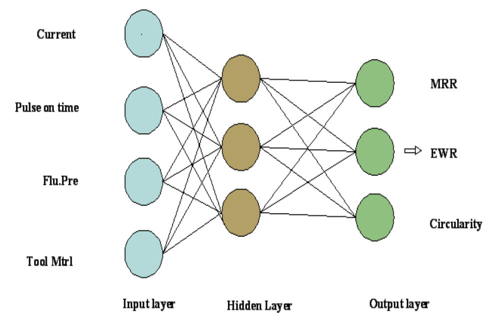

Figure 3. Architecture of ANN model

The input and output patterns sequentially presented to the network for training and various interconnections are adjusted using Feed-forward back-propagation

4.1 Prediction of performance measures

This work is aimed at establishing the correlation between input machining parameters such as Current (A), Pulse in time (Pon), Flushing pressure (Pr) and Electrode Material (Em) with performance measures namely MRR, EWR and CIR. Modeling of the EDM with Feed-forward back-propagation is having two stages namely training and testing of the network with experimental results. The trained data was tuned till the R^2 value reaching 0.9. Out of 9 experimental results 6 were trained and the 3 values were tested. Training parameters namely learning rate, momentum coefficients and epochs are 0.032, 0.9 and 10,000 respectively were achieved the R^2 value as 0.9. As a result, all the input parameters are equally important in the training of network.

4.2 Optimizing the Number of Hidden Nodes and Layers

Selection of number of hidden layers and number of neurons in the hidden layers is important in ANN. The optimum architecture is found through varying the number of neurons in the hidden layers using MATLAB. Error value is the numerical difference between the actual value of output and the value predicted by the trained network. The prediction error is expressed as for all the output performance evaluation. The ANN is trained with optimized number of nodes in the hidden layer.

4.3 Training and testing the data

Testing is carried through two stages. Initially it is tested with seen input data sets. In the second phase, the network is tested with unseen input data sets. Table 2.

shows the actual and predicted outcomes of the performance measures.

Table 2 ANN model outcomes for performances

MRR (g/min)		EWR (g/min)		CIR (mm)	
Actual	Predicted	Actual	Predicted	Actual	Predicted
0.1088	0.1098	0.0289	0.0297	0.032	0.031

5. Conclusion

In this study the MRR, EWR and CIR in the EDM process was predicted through Feed-forward back-propagation by extensive simulation. EDM performance was modeled using ANN.

1. The networks were successfully trained and tested using the experimental data.
2. Selection of various machining parameters namely current, pulse on time, flushing pressure and electrode material indicates that the ANN model is potential to predict the neural network architecture such as 4-3-3.
3. The network data helps to predict the optimum parameters for the maximum MRR, minimum EWR and minimum CIR viz MRR-0.1098 g/min, EWR- 0.0297 g/min and CIR- 0.031mm

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