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Estimation of Machining Performances in WEDM of Aluminium based Metal Matrix Composite Material using ANN

Gurupavan H R[a]*, Devegowda T M[a], Ravindra H V[a], Ugrasen G[b]

[a]Department of Mechanical Engineering, P.E.S. College of Engineering, Mandya, INDIA
b Department of Mechanical Engineering, B.M.S. College of Engineering, Bangalore, INDIA

Abstract

The present work is to estimate surface roughness, accuracy, volumetric material removal rate and electrode wear based on the machining parameters like pulse-on, pulse-off, current and bed speed. The experimental work consists of machining of aluminum silicon nitride composite material using Wire EDM (WEDM). The experiment will be carried out by varying the machining parameters. Surface roughness, accuracy and electrode wear will be measured using surfcom flex and micrometer. Experimental analysis will be carried out to study the variation of the performance parameters viz., surface roughness, accuracy, volumetric material removal rate and electrode wear for various machining conditions. Then, to estimate the surface roughness, accuracy, volumetric MRR and electrode wear by using sophisticated diagnosing method like Artificial Neural Network (ANN).

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Keywords: WEDM; MMC; ANN

1. Introduction

WEDM is a widely accepted non-traditional material removal process used to manufacture components with intricate shapes and profiles irrespective of hardness. WEDM has evolved as a simple means of making tools and dies to the best alternative of producing micro-scale parts with the highest degree of dimensional accuracy and

* Corresponding author. Tel.: +91-8232-220043; fax: +91-8232-222075.
E-mail address: gpavan1989@gmail.com

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surface finish. Molybdenum wire is used in limited applications which require very high tensile strength to provide a reasonable load carrying capacity in small diameter wire. The effect of process parameters on the responses is to be investigated experimentally in WEDM. An attempt has been made to estimate machining responses out using sophisticated diagnosing method like ANN. In the past, many researchers have developed the model and its application in process optimization of machining performances using artificial neural network in WEDM. Taguchi's technique is used for optimization. The control factors are pulse-on, pulse-off, current and bed speed. Three response variables namely accuracy, surface roughness and VMRR were considered. It is observed that neural network trained with 70% of the data gives good prediction results [1]. ANN was used for analyzing the material removal of µ-EDM to establish the parameter optimization model. When experimental and network model results are compared for the performance considered. Then, genetic algorithms (GAs) have been employed to determine optimum process parameters for any desired output value of machining characteristics. The well-trained neural network model is shown to be effective in estimating the MRR and is improved using optimized machining parameters [2]. The machinability characteristic of aluminum silicon carbide composite on EDM is carried out. Discharge current, pulse duration, duty cycle, flushing pressure, weight fraction of silicon carbide in the composite and mesh size are selected responses. MRR, tool wear rate, surface roughness and circularity are measured responses. Classical Taguchi method is used for optimization of single parameter. Hybrid approach combining Principal Component Analysis (PCA) and fuzzy inference system is coupled with Taguchi method for multiple parameters [3]. The intelligent modeling and multi-characteristics optimization of dry WEDM process while machining of Al–SiC metal matrix composite. Experiments were designed and conducted based on L_{27} Taguchi's orthogonal array to study the effect of pulse on time, pulse off time, gap voltage, discharge current, wire tension and wire feed on cutting velocity and surface roughness. In order to correlate relationship between process inputs and responses, an Adaptive Neuro-Fuzzy Inference System (ANFIS) has been employed to predict the process characteristics based on experimental observation. The optimal results which are obtained through ANFIS-ABC have been verified by confirmatory experiment to show the efficiency of proposed method [4]. Parametric study of dry WEDM process of cemented tungsten carbide was conducted. Central composite rotatable method was employed to design experiments based on RSM. To increase the predictability of the process, intelligent models have been developed based on BPNN and accuracy of these models was compared with mathematical models based on Root Mean Square Error (RMSE) and Prediction Error Percent (PEP). The results indicated that the developed BPNN models have higher accuracy rather than mathematical models due to lower values of RMSE and PEP [5].

2. Experimental Work

The experiments were performed on CONCORD DK7720C four axes CNC WED machine. The WED machine has several special features. Unlike other WED machines, it uses the reusable wire technology. i.e., wire can't be thrown out once used; instead it is reused adopting the re-looping wire technology. The experimental set-up for the data acquisition is illustrated in the Fig. 1. The gap between wire and work piece is 0.02 mm and is constantly maintained by a computer controlled positioning system. Molybdenum wire having diameter of 0.18 mm was used as an electrode. The control factors and fixed parameters selected are as listed in Table 1. The control factors were chosen based on review of literature and experts. In this study, four machining parameters were used as control factors and each parameter was designed to have three levels denoted I, II and III as shown in Table 1. Machining was carried out on Al-5% wt Si_3N_4.

Table 1. Machining settings

Control Factors/Level		Level		
		I	II	III
A	Pulse –on	20	24	28
B	Pulse-off	5	6	7
C	Current	4	5	6
D	Bed speed	30	35	40

Fig. 1. Experimental Set-up

3. Results and Discussions

3.1. Artificial Neural Network

ANN is an interconnected group of artificial neurons that uses a mathematical model or computational models for information processing based on a connectionist approach to computation. ANN is an information processing paradigm that is inspired by procedure in the biological nervous system. Neural networks are non-linear mapping systems that consist of simple processors which are called neurons, linked by weighed connections. Each neuron has inputs and generates an output that can be seen as the reflection of local information that is stored in connections. The output signal of a neuron is fed to other neurons as input signals via interconnections. The neuron has a bias b, which is summed with the weighted inputs to form the net input n.

$$n = w1,1p1 + w1,2\, p2 + \ldots + w1,R\, pR + b \tag{1}$$

Various input to the neurons are represented by '*Xn*'. Each of these inputs is multiplied by a connection weighed, represented by '*Wn*' and added to the bias 'φ' to compute activation '*an*' which is converted into the output '*On*' via transfer function. Various input to the neurons are represented by '*Xn*'. Each of these inputs is multiplied by a connection weighed, represented by '*Wn*' and added to the bias '*φ*' to compute activation '*an*' which is converted into the output '*On*' via transfer function.

$$an = Wn\, XnT + \varphi \tag{2}$$

$$On = f\,(an) \tag{3}$$

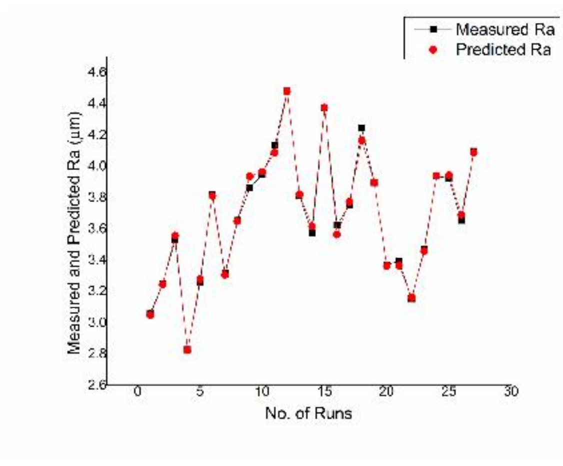

Fig. 2: Measured and predicted roughness

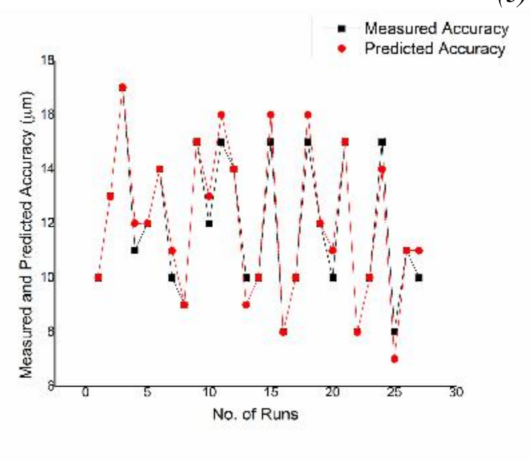

Fig. 3: Measured and predicted accuracy

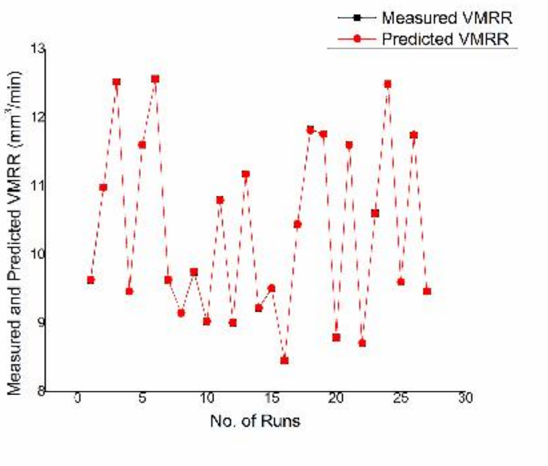

Fig. 4: Measured and predicted VMRR

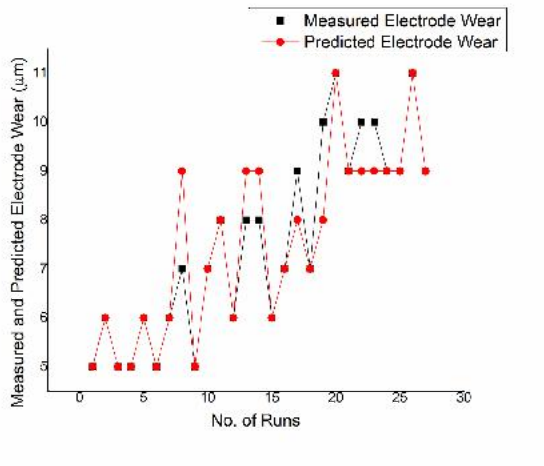

Fig. 5: Measured and predicted electrode wear

Fig. 2 shows the comparison of experimentally measured surface roughness values and predicted values using ANN. It is clearly observed that measured surface roughness is correlating well with the predicted surface roughness values. Fig. 3 shows the comparison of experimentally measured accuracy values and predicted values using ANN. It is clearly observed that measured accuracy is correlating well with the predicted values. Fig. 4 shows the comparison of experimentally measured VMRR values and predicted values using ANN. It is clearly observed that measured VMRR is correlating well with the predicted VMRR values. Further, it is also observed that ANN prediction shows a similar trend in all the runs studied. Fig. 5 shows the comparison of experimentally measured electrode wear values and predicted values using ANN. It is clearly observed that measured electrode wear is correlating well with the predicted electrode wear values.

4. Conclusion

The experimental studies were performed on a CONCORD DK7720C four axis CNC WEDM for Al6061 alloy and Al6061-6%wt. Si_3N_4 composite material using molybdenum wire for various machining conditions. Taguchi's L_{27} orthogonal array was selected to conduct the experiments. ANN was used to predict performance parameters. Back propagation feed forward neural network (BPNN) and Levenberg–Marquardt algorithm (LMA) are used to build and train the network. It was observed that neural network trained with 70% of the data in training set gives good prediction results and it was correlating well with the measured one.

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