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Prediction of wear and surface roughness in electro-discharge diamond grinding

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Abstract

The present work focuses on prediction of wheel wear and surface roughness using two techniques, namely design of experiments and neural network. Effect of process parameters, such as pulse current, duty ratio, wheel speed and grain size on output responses, namely, wheel wear and surface roughness of high speed steel (HSS) were investigated experimentally.

Keywords: Electro-discharge diamond grinding; DOE; Artificial neural network

1. Introduction

Electro-discharge diamond grinding (EDDG) is a hybrid machining process (HMP) which integrates diamond grinding and electrical discharge machining (EDM) for machining electrically conducting hard-to-machine materials.

In EDDG, the electrical spark is utilized to thermally soften the work-material on a microscopic scale to facilitate grinding and reduce grinding forces [1].

Thermal modeling of EDM process [2] has indicated that the fraction of molten material which is physically not removed but re-deposited on the parent material surface could be as high as 80%. The recast layer and the heat affected material immediately beneath contains numerous micro cracks which degrades the fatigue strength of the material. In EDDG, the crack-infested layer can be ground off appropriately selecting the grit size of abrasives used in the wheel.

Koshy et al. [3,4] proposed a mechanism of material removal in EDDG and studied the effect of current and pulse-on time on the material removal rate and grinding forces. Choudhury et al. [5] did experimental work on EDDG to find the effect of current, voltage pulse-on time and duty factor on material removal rate and grinding forces. Wang et al. [6] focused in the truing effects of EDM and the micro-geomorphic analysis of fine grain super abrasive grinding wheel surface after EDM dressing. Jain and Mote [7] carried out experimentation to investigate the temperature of the workpiece and specific energy during EDDG. Specific energy in EDDG was compared with that of EDM.

EDM of composite materials containing electrically non-conducting phases possess a few problems. The non-conducting material particles hamper the process stability and impede the material removal process [8]. These problems are taken care of in EDDG. Material removal rate is enhanced as the abrasive grains remove the non-conducting material particles expending little effort, with the spark discharge having thermally softened the surrounding binding material.

The present work comprises experimental investigation and modeling of wheel wear and surface roughness during electro-discharge diamond grinding process by using two techniques, namely design of experiment (DOE) and artificial neural network (ANN).

2. Prediction techniques

Underlying mechanism of complex electro-discharge diamond grinding process is not thoroughly understood and therefore the unknown process function has to be approximated with an appropriate empirical model. *Central rotatable composite design of experiment* has been adopted in the present work.

The use of artificial neural network, besides design of experiment, provides added benefits such as non-parametric input–output mapping, nonlinearity and adaptivity, for modeling of process. Therefore, in the current work both the techniques, namely ANN and DOE were used.

The development of the back-propagation algorithm represents a landmark in the history of neural networks.

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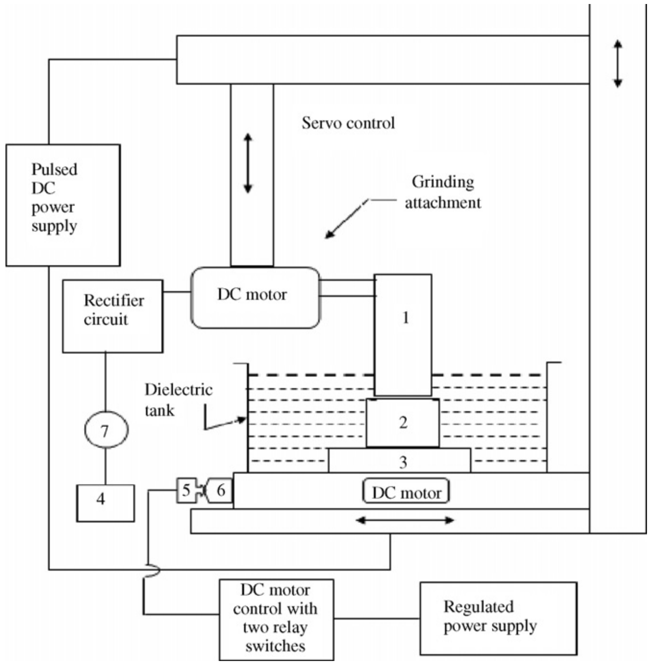

Fig. 1. Schematic diagram of the experimental set-up. (1) Metal bonded grinding wheel, (2) HSS workpiece, (3) fixture, (4) AC mains, (5) micro switch, (6) lever attached to machine table and (7) variac.

Back-propagation neural network is usually referred to as feed forwarded, multi-layered network with a number of hidden layers trained with a gradient descent technique [9]. It is important to note that the second order modification to back-propagation improves the speed of convergence of synaptic weights to the closest local minimum. The use of *hybrid learning algorithm* where one starts with incremental backprop and then switches to conjugate gradient-based backprop for final convergence phase, appears to be the fastest method for training moderate-sized feedforward neural networks (up to several hundred weights). This hybrid method has its roots in a technique from numerical analysis known as *Levenberg–Marquardt optimization* [10].

3. Experimentation

Experiments were carried out in surface grinding mode on a die-sinking type spark erosion machine equipped with a solid-state power supply. The negatively charged metal bonded diamond-grinding wheel was used in the experiment (Fig. 1).

Thirty-one experiments were carried out as per *central rotatable composite design* to obtain wheel wear rate and surface roughness (Ra) values for different combinations of machining parameters. Wheel wear rate was calculated in term of weight loss of wheel for corresponding machining time (1 h). A digital balance was used for weight measurement. Surface roughness of workpiece was measured using a surface analyzer.

4. Results and discussion

The empirical models for wheel wear rate (WWR) and surface roughness (SR) were obtained as follows:

$$\begin{aligned} \mathrm{WWR} = {} & 1.0168 + 0.3044i + 0.1251r + 0.1285n - 0.0786g \\ & + 0.0587i^2 + 0.0143r^2 - 0.0119n^2 + 0.0031g^2 \\ & + 0.0021ir + 0.0019in - 0.0004ig - 0.0018rn \\ & - 0.0012rg + 0.0012ng \end{aligned} \tag{1}$$

$$\begin{aligned} \mathrm{SR} = {} & 1.9086 + 0.2388i + 0.2136r - 0.3888n - 0.2778g \\ & + 0.0917i^2 - 0.0421r^2 - 0.0583n^2 - 0.0783g^2 \\ & + 0.0008ir + 0.0055in - 0.0005ig + 0.0048rn \\ & - 0.0042rg + 0.0082ng \end{aligned} \tag{2}$$

where, i, r, n and g are coded variables of current (I), duty ratio (R), wheel speed (N) and average grit number (G), respectively.

4.1. Artificial neural network modeling

Uniformly distributed 100 random data for input variables were generated for training and 20 data for validation of the ANN. The corresponding values of output responses were calculated using empirical models (Eqs. (1) and (2)).

The learning behaviour of the networks with different topological characteristics was studied and the one with architecture of 4–12–2 (4 input neurons, 12 hidden neurons and 2 output neurons) and 0.50 *learning rate* and 0.40 *momentum constant* was selected. Training of the neural network was performed with a mean square error (MSE) of 1.46536×10^{-5} and allowable error for each data point as 5% in 1000 iterations.

Maximum error for WWR and SR in training phase was 0.0125 and 0.0224% respectively. Hence it can be concluded that neural network model was properly trained for the allowable ranges of input parameters.

In validation phase, for WWR maximum error was 2.11% with an average error of 0.52% and for SR maximum error was 4.1% with an average error of 0.60%. This illustrates the ability of neural network to predict the WWR and SR within the allowable error for the input parameters other than those used in training phase.

Thus, it is apparent that the ANN model can be reliably used for prediction of output responses such as wheel wear rate and surface roughness in close conformity to the actual experimental data.

4.2. Parametric analysis

Using the regression Eqs. (1) and (2), best fitted response curves were drawn which give information about how the input parameters (pulse current, duty factor, wheel speed and grit number) affect the process responses (wheel wear rate and surface roughness).

Fig. 2 shows that the wheel wear rate increases with increasing current since at higher current more erosion of metal bond of wheel will take place and more grains will be pulled out. Discharge energy being proportional to duty ratio, extent of grain pull-out would increase with increasing duty factor, and hence, the WWR also increases with duty ratio.

It is clear from Fig. 2 that wheel wear rate also increases with duty ratio within working range of current from 1 to 20 A. Since discharge energy is proportional to duty ratio, extent of