MODELING OF MATERIAL REMOVAL RATE IN EDM USING NEURAL FUZZY SYSTEMS

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Abstract: Material removal rate is an important performance measure in EDM process. Modeling approach material removal rate which uses artificial intelligence tools is described in this paper. The objective of this study is to design an adaptive neuro-fuzzy inference system (ANFIS) for prediction of material removal rate in EDM. The input parameters of model are discharge current, pulse duration and output parameter is material removal rate. The results indicate that the ANFIS modeling technique can be effectively used for the prediction of material removal rate in machining of manganese-vanadium tool steel.

Key words: EDM, material removal rate, ANFIS.

1. INTRODUCTION

Electrical discharge machining (EDM) is one of the most extensively used non-conventional material removal processes. Its unique feature of using thermal energy to machine electrically conductive parts regardless of hardness has been its distinctive advantage in the manufacture of mould, die, automotive, aerospace and surgical components. In addition, EDM does not make direct contact between the electrode and the workpiece eliminating mechanical stresses, chatter and vibration problems during machining [1, 2]. EDM is used for machining complex geometry workpieces and difficult-to-machine materials, for which conventional methods are not applicable.

The machining of difficult-to-cut materials is an important issue in the field of manufacturing. Materials with unique metallurgical properties, such as tungsten carbide, titanium, vanadium based alloys and other super-alloys, have been developed to meet the demands of extreme applications. The material like manganese-vanadium tool steel is finding increased application in many fields now-a-days. They have excellent properties such as high strength, high specific strength, high damping and low thermal expansion compared with the simple steels. The material removal rate (MMR) these materials are very low and other limitations in machining parameters and workpiece shapes are imposed. Manganese-vanadium tool steel is very hard steel, typically in the range of HRC over 60.

Material removal rate is an important performance measure and several researchers explored several ways to improve it. The material removal rate can be controlled and improved by controlling process parameters. The amount of energy applied during machining is controlled by peak current and pulse duration [3]. Longer pulse duration results in higher material removal resulting in broader and deeper crater formation. Material removal rate is highly affected by types of dielectric and method of flushing. Flushing is a useful procedure to remove debris from discharge zone even if it is difficult to avoid concentration gradient and inaccuracy [4, 5]. The influence of flushing on MRR and electrode wear has been studied by mathematical models and experimentally and many flushing methods have been proposed [6].

In the present work, the first parameter affecting the MRR is discharge current and second is impulse duration. An attempt has been made to develop the intelligent model for predicting material removal rate using adaptive-neuro-fuzzy-inference-system (ANFIS) mathematical method. The process parameters taken in to consideration were the discharge current ($I_d$) and pulse duration ($t_i$). The model predicted values and measured values were fairly close to each other. Model validation is the process by which the input vectors from input/output data sets on which the fuzzy-inference-system (FIS) was not trained, are presented to the trained ANFIS model, to see how well the ANFIS model predicts the corresponding data set output values. The data which not used for training the model have been successfully predicted. Their propinquity to each other indicates the developed model can be effectively used to predict the MMR in EDM process.
2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Fuzzy inference system (FIS) is a rule based system consisting of three components. These are:

- a rule-base, containing fuzzy if-then rules,
- a data-base, defining the Membership Functions (MF) and
- an inference system that combines the fuzzy rules and produces the system results.

The main problem with fuzzy logic is that there is no systematic procedure to define the membership function parameters. ANFIS eliminates the basic problem in fuzzy system design, defining the membership function parameters and design of fuzzy if-then rules, by effectively using the learning capability of neural network for automatic fuzzy rule generation and parameter optimization [7]. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system whose membership function parameters are tuned (adjusted) using either a back-propagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data they are modeling.

A network type structure of ANFIS is similar to a neural network. The entire system architecture consists of five layers, namely, the fuzzy layer and total output layer. Five network layers are used by ANFIS to perform the following fuzzy inference steps:

**Input nodes – layer 1:**

The general structure of ANFIS with two inputs x and y and one output z is shown in figure 1. Example of model with two rules as follows:

Rule 1: If x is A 1 and y is B 1 then z 1 = p 1 x + q 1 y + r 1

Rule 2: If x is A 2 and y is B 2 then z 2 = p 2 x + q 2 y + r 2

where A 1, A 2 and B 1 and B 2 are fuzzy sets of input premise variables x and y respectively.

Each node in this layer generates membership grades of the crisp inputs and each node’s output. An example of a node function is the generalized Gaussian membership function:

\[
O_i^1 = \mu_{A_i}(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}
\]  

(1)

where \(x\), \(c\) and \(\sigma\) is the parameter set.

**Rule nodes - layer 2:**

The outputs of this layer called firing strengths, are the products of the corresponding degrees obtained from the layer 1.

\[
O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1, 2
\]  

(2)

where \(\mu_A\) and \(\mu_B\) are the membership functions for \(A_i\) and \(B_i\) linguistic labels, respectively. Where \(w_i\) is output weight of each neuron.

**Average nodes - layer 3:**

The i-th node calculates the ratio of the i-th rule’s firing strength to the total of all firing strengths. The firing strength in this layer is normalized \(\bar{w}_i\) as:

\[
\bar{O}_i^3 = \frac{w_i}{\sum w_i} \quad i = 1, 2
\]  

(3)

**Consequent nodes - layer 4:**

Every node in this layer is with a node function \(w_{f_i}\) where \(w_i\) is the output of layer 3 and \([p_i, q_i, r_i] \) is the parameter set. These parameters are referred to as consequent parameters.

\[
\bar{O}_i^4 = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1, 2
\]  

(4)

**Output nodes - layer 5:**

This layer is called as the output nodes. The single node in this layer computes the overall output as the summation of contributions from each rule.

\[
\bar{O}_i^5 = f(x, y) = \sum_i \bar{w}_i f_i = \bar{w}_1 f_1 + \bar{w}_2 f_2 \sum_i w_i
\]  

(5)

![Fig. 1. Basic ANFIS architecture](image)

The details and mathematical background for these algorithms can be found in [8].

3. DESIGN OF EXPERIMENTS

Experimental investigation was conducted on an EDM machine tool FUMEC – CNC 2 F in South Korea. The work material used in the experiment was manganese-vanadium tool steel, ASTM A681 (0,9% C, 2% Mn, and 0,2% V), hardness 62 HRC. The tool was made of electrolytic copper with 99,9% purity and 20×10 mm cross-section. The dielectric was petroleum. Due to small eroding surface and depth, natural flushing was used.

The machining conditions included variable discharge current and pulse duration. The range of the discharge current was \(I_e = 1÷50\) A (current density \(0,5÷25\) A/cm²), while the pulse duration was chosen from the interval \(t_i = 1÷100\) μs to accommodate the chosen current. The rest of the parameters of electric impulse were held constant, according to the manufacturer’s recommendations (open gap voltage \(U_o = 100\) V, duty factor \(r = 0,8\) and positive tool electrode polarity).
The experiments were conducted according to the specified experiment plan. Input parameters were varied and the resulting machining parameters of EDM process were monitored and recorded.

Material removal rate (ratio of removed material volume and the effective machining time) was measured indirectly, by monitoring the machining time for the set eroding depth. The depth and time of eroding were monitored using the machine tool CNC control unit [9].

4. ANFIS RESULTS AND DISCUSSION

Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (Figure 2) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method.

For this model, main parameters for the experiments are discharge current $I_e$, pulse duration $t_i$ (input data set) and material removal rate $MMR$ (output data set).

The training dataset and testing dataset are obtained from experiments. The input/output dataset was divided randomly into two categories: training dataset, consisting 24 of the input/output dataset and test data set (unknown to model), which consists 4 of data. Table 1 compare the predicted values and experimental data of material removal rate after training by ANFIS with triangular membership function.

Training process is accomplished by using Mat Lab 6.0. In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used. The number and type of membership functions, method optimization hybrid or back propagation, and number epoch were changed. Then the best adaptive network architecture was determined. The training epoch for each network is 500, hybrid method optimization, the best results given 4 membership functions triangular type (Table 2). When the network training was successfully finished, the ANFIS was tested with validation data.

Figure 3 exhibits the 3D surface profile obtained during neuro-fuzzy modeling and shows the influence of the machining parameters (discharge current and pulse duration) on the material removal rate. In this work parameters which improves resulting in higher MRR are discharge current (30-40 A) and pulse duration (40-60 µs) as shown figure 3.
Figure 4 describe the comparison of experimental and ANFIS results for the material removal rate, respectively. It proved that the method used in this paper is feasible and could be used to predict the MMR in an acceptable error rate for EDM. The compared lines seem to be close to each other indicating with good agreement.

5. CONCLUSION

In this paper an ANFIS is used to estimate material removal rate in EDM. Table 1 shows the compared values obtained by experiment and estimated by ANFIS model. The average deviation of the training data is 3.92 %, average deviation of the checking data is 2.41%, while the average deviation data which unknown to the model is 6.72%. Research showed that ANFIS model gives accurate prediction on material removal rate. The ANFIS predicted material removal rate values show a good comparison with those obtained experimentally. It is evidence that the fuzzy logic technique can be help to better prediction of the experimental data.

The material removal rate can be controlled and improved by controlling process parameters. In this work the first parameter affecting the MRR is discharge current and second parameter is pulse duration. At values discharge current (30-40 A) and pulse duration (40-60 µs) the best results are achieved MMR. This values improves material removal rate and in future work should be define influences these parameters on tool wear and surface quality.

6. REFERENCES


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