Sborník vědeckých prací Vysoké školy báňské - Technické univerzity Ostrava
číslo 2, rok 2006, ročník LII, řada strojní
článek č. 1557

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MODELLING AND SIMULATION OF THE ELECTROCHEMICAL MACHINING USING NEURAL NETWORKS

MODELOVÁNÍ A SIMULACE ELEKTROCHEMICKÉHO OBRÁBĚNÍ POMOCÍ NEURONOVÝCH SÍTÍ

Abstract

The electrochemical machining (ECM) belongs to the unconventional machining methods. ECM is suitable for hard and extra hard materials used for cutting and moulding tools manufacturing and also for special forms machine part manufacturing used in aeronautics, prothesis and hydropneumatic machinery. ECM is a very complex process as the result of a set of electric, mechanics and chemical parameters. So the analytical modeling of the process is difficult. Due to the large number of measurements required, the artificial neural network very greatly simplifies the relationship between the input and the output parameters. The neural network was trained with a set of data containing very different machining parameter choices. This paper presents the results obtained for the prediction of some output parameters.

Abstrakt

Elektrochemické obrábění (ECM) patří mezi nekonveční metody obrábění. ECM je vhodné pro tvrdé a extra tvrdé materiály a používá se při výrobě řezacích a lisovaných nástrojů a taktéž pro speciální díly používané v aeronautice, tvorbě protéz a hydropneumatických strojů. ECM jako velmi komplexní proces je výsledkem sady elektrických, mechanických a chemických parametrů. Takže analytické modelování procesu je složité. Díky nutnosti provést velké množství měření, umělá nervová síť podstatně zjednodušuje vztahy mezi vstupními a výstupními parametry. Neuronová síť byla testována pomocí sady dat, které obsahují různé mechanické parametry. Tento příspěvek prezentuje výsledky získané pro odhad několika výstupních parametrů.

1 INTRODUCTION

The anodic dissolution of metals was already known in the previous century. But it was not until the 1960s that it came into use as a practical machining method. In non-traditional machining processes, electrochemical machining (ECM) has tremendous potential on account of versatility of its applications, and it is expected that it will be a promising, successful and commercially utilized machining process in the modern manufacturing industry [De Silva 1999, Lievestro 2004].

The ECM has some technological variants, such as electrochemical micromachining (EMM), electrochemical discharge machining (ECDM), electrochemical polishing (EP) and electrochemical grinding (ECG). The main characteristic of ECG is that the passive layer resulted from anodic dissolution is removed by an abrasive electrode wheel with artificial diamond in a metallic binder. It is known that ECG allows acceleration of stock removal, reduction of diamond consumption and improvement of machining quality and operational characteristics of produced parts and tools [Lyubimov 1998].

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2 EXPERIMENTAL DETAILS

The ECG input parameters are mechanical, electrical and chemical. As mechanical may be mentioned abrasive wheel rotation, relative speed between electrode and work piece, longitudinal feed rate, normal pressure abrasive electrode – work piece, machining area, work piece material. As electrical may be mentioned supplying source voltage, intensity of d.c., current density. Chemical parameters are relationship with electrolytes formula and concentration. As ECG output parameters may be mentioned stock removal, diamond consumption, machined surface quality and roundness of edges.

The goal of this research is to determine the influence of voltage U [V], contact pressure p [daN/cm^2], relative speed v [m/s], feed rate S [ds/min] and height of the contact surface h [mm] on stock removal Q [cm^3/min] and diamond consumption DC [cm^3/cm^3].

Because the process is very complex the analytical modelling of ECG is difficult. The neural network modelling was chosen because this methodology is an alternative to modelling physical and non-physical system with scientific or mathematical basis.

Experimental values for input and output parameters are shown in Table 1. The experiments were made based on multicriterial programmed method.

Table 1. Experimental data

U	p	v	S	h	Q	DC
5	4	18	8	8	0.0053	0.0023
11	4	18	8	4	0.0458	0.0017
5	8	18	8	4	0.0114	0.0039
11	8	18	8	8	0.0503	0.0034
5	4	34	8	4	0.0062	0.0018
11	4	34	8	8	0.0428	0.0016
5	8	34	8	8	0.0114	0.0038
11	8	34	8	4	0.0809	0.0026
5	4	18	16	4	0.0054	0.0031
11	4	18	16	8	0.0276	0.0026
5	8	18	16	8	0.0100	0.0047
11	8	18	16	4	0.0579	0.0033
5	4	34	16	8	0.0054	0.0028
11	4	34	16	4	0.0502	0.0014
5	8	34	16	4	0.0117	0.0039
11	8	34	16	8	0.0509	0.0036
2	6	26	12	6	0.0038	0.0038
14	6	26	12	6	0.1052	0.0016
8	2	26	12	6	0.0086	0.0016
8	10	26	12	6	0.0236	0.0041
8	6	10	12	6	0.0104	0.0040
8	6	42	12	6	0.0190	0.0018
8	6	26	4	6	0.0181	0.0018
8	6	26	20	6	0.0145	0.0027
8	6	26	12	2	0.0186	0.0016
8	6	26	12	10	0.0095	0.0035
8	6	26	12	6	0.0138	0.0025

3 NEURAL NETWORK MODELLING

Neural networks perform computation in a very different way than conventional computers. Neural networks are built from a large number of very simple processing elements, neurons that individually deal with pieces of a big problem. A processing element (PE) simply multiplies an input by a set of weights, and nonlinearly transforms the result into an output value. The principles of

computation at the neuron level are deceptively simple. The power of neural computation comes from the massive interconnection among the neurons and from the adaptive nature of the parameters (weights) that interconnect them [Galantucci 2000].

The neural network architecture which is most frequently used in data fitting and non linear approximation consists of three layers: input layer, hidden layer and output layer. In the input layer each neuron corresponds to an input parameter and in the output layer there is a neuron for each output parameter. In hidden layer, the number of neurons may vary. For neurons from hidden and output layers, the activation function and learning rule are chosen.

Multilayer feed forward neural networks offer a generous framework for modelling non linear phenomena whenever the physical insight fails in providing relevant information for the construction of a parameterized model, whose parameters play precise roles in capturing the essentials of studied behaviour. The neural network operates as a nonlinear mapping, parameterized by the weights and biases of its layers, which can be adjusted so as to fit experimental data, but without any physical meaning for the identified parameters. In

In order to compare alternative neural network models and to measure the performance of the network for a particular data set MSE, NMSE, AIC and MDL information criteria are used.

MSE (Mean Squared Error) calculates the mean of squaring the difference between the desired output and corresponding network output for each row from data set. The smaller the mean error is, the better the equation.

The NMSE (Normalised Mean Square Error) is an estimator of the overall deviations between predicted and measured values. It is defined as:

$$\mathrm{NMSE} = \frac{\mathrm{P}\cdot\mathrm{N}\cdot\mathrm{MSE}}{\sum_{j=0}^{p}\frac{\mathrm{N}\sum_{i=0}^{N}d_{ij}^2-\left(\sum_{i=0}^{N}d_{ij}^2\right)^2}{\mathrm{N}}}, \tag{1}$$

where:

P - the number of processing elements,

N - the number of exemplars in the data set,

d_{ij} - desired output for exemplar i at processing element j.

The NMSE generally shows the most striking differences among models. If a model has a very low NMSE, then it is well performing both in space and time. On the other hand, high NMSE values do not necessarily mean that a model is completely wrong. That case could be due to time and/or space shifting.

Akaike's information criterion (AIC) is used to measure the tradeoff between training performance and network size:

$$\mathrm{AIC(k)} = \mathrm{N}\ln(\mathrm{MSE}) + 2\mathrm{k}, \tag{2}$$

where:

k - the number of network weights,

N - the number of exemplars in the training set.

The goal is to minimize this term to produce a network with the best generalization. Rissanen's minimum description length (MDL) criterion is similar to the AIC in that it tries to combine the model's error with the number of degrees of freedom to determine the level of generalisation. It is defined as:

$$MDL(k) = N\ln(MSE) + 0.5k\ln(N), \quad (3)$$

4 RESULTS AND DISCUSSION

The neural network models were constructed to predict the stock removal and diamond consumption based on the experimental data from Table 1. In Table 2, there are presented the error criteria for training process of some different NNs topologies.

Cases 1 to 8 refer to multilayer perceptrons (MLPs) that are layered feedforward networks typically trained with static backpropagation. These networks require static pattern classification, are easy to use, can approximate any input/output map but they train slowly. In case 1, the NN has 1 hidden layer with 4 neurons, tanhsigmoid activation functions are considered for all layers, learning rule is momentum and 1000 epochs are considered for training. Case 2 is similar with case 1 excepting the number of epochs which is 5000. The activation function from case 2 becomes sigmoidian and case 3 is obtained. The difference between the 3rd and the 4th case is that in case 4 the hidden layer has 5 neurons. In case 5, the NN structure is like in case 4, but tanhsigmoid activation function is used.

The NNs from cases 6 to 8 have two hidden layers, each of them with 4 neurons momentum learning rule. In cases 6 and 7 the activation functions are tanhsigmoids and the number of epochs is 3000 respectively 5000. Case 8 is similar with case 7 excepting the activation function that is sigmoid.

Case 9 corresponds to a generalized feedforward network (GFN), which is a generalization of the MLP such that connections can jump over one or more layers. In theory, a MLP can solve any problem that a generalized feedforward network can solve but requires hundreds of times more training epochs than the generalized feedforward network containing the same number of processing elements. The GFN has 1 hidden layer, the transfer function is tanhaxon, momentum is the learning rule and the network was trained for 5000 epochs.

Table 2 Analysis of different NN topologies

Case	MSE	NMSE	R	AIC	MDL
1	0.0018	0.0076	0.9962	-102.2	-114
2	0.0004	0.0019	0.9989	-114.4	-130
3	0.0037	0.0628	0.9704	-82.76	-94
4	0.0036	0.0605	0.9719	-67.75	-82
5	0.0009	0.0037	0.9981	-105.3	-120
6	0.0024	0.0102	0.9953	-54.34	-73
7	0.007	0.0031	0.9982	-86.4	-105
8	0.023	0.39	0.72	6.95	-12
9	0.0044	0.0184	0.9909	-58.38	-74

For each case, the error criteria MSE, NMSE, AIC and MDL are performed in order to evaluate general performance of the NNs. In Table 2 R is the correlation coefficient. The best topology from those presented in Table 2 corresponds to 2nd case.

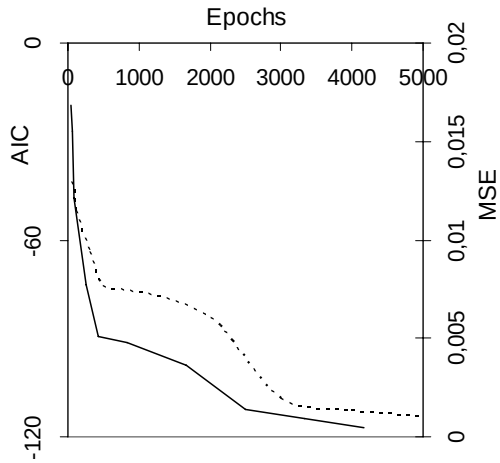

Fig. 1 AIC (.) and MSE (—) criteria vs. numbers of epochs

The testing data set has 32 different experiments and is used to test the performance of the network. Once the network has been trained, the weights are then frozen, the testing set is fed into the network, and the network output is compared with the desired output. The testing set is specified in the same manner as the validation set.

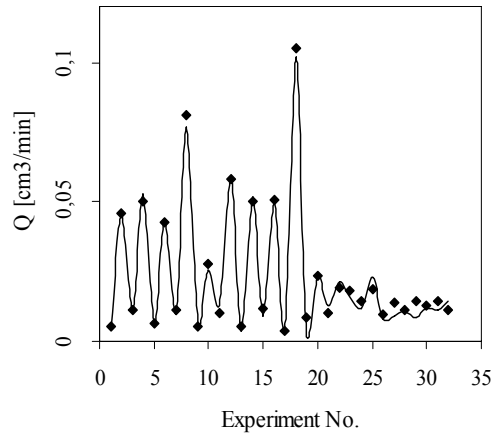

Fig. 2 Graph between experimental (♦) and predicted values for stock removal (—)

In figures 2 and 3 are shown the predicted and the experimental values of the two outputs of the neural network in the test process.

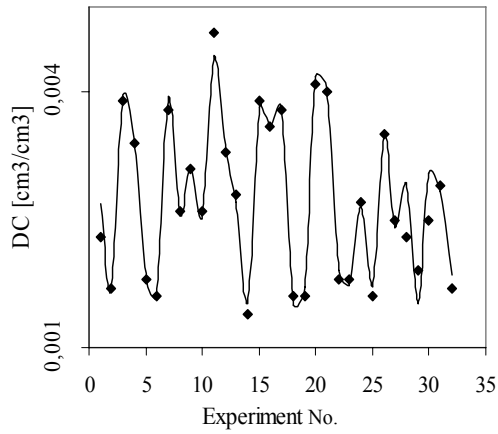

Fig. 3 Graph between experimental (♦) and predicted values for diamond consumption (—)

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Reviewer: doc. Ing. Lenka Landryová, CSc., VŠB – Technical University of Ostrava