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CBN TOOL LIFE PREDICTION BY ARTIFICAL NEURAL NETWORK

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For economic application of CBN tools it is important to know how the tool life changes as a function of the most important technological parameters (cutting speed, feed rate, depth of cut and work piece diameter). These technological parameters have significant effects on the productivity of machining. The extended Taylor equation takes the effects of feed rate, depth of cut into account besides the cutting speed, but this equation is not valid in the whole range of cutting speed. Beyond the publicated tool life equations in the professional articles, the tool life can be determined by Artificial Neural Network (ANN). ANNs have huge flexibility and can handle different number of inputs thus they are suitable for determining tool life as a function of several cutting parameters.

Keywords: Tool life, Artifical Neural Network

Introduction

Cubic boron-nitride was synthesized by R. H. Wentorf in 1957. It was first produced in industrial sizes in 1968. CBN tools with definite tool edge geometry have been produced since 1970's. Due to coating processes (PVD, CVD) have appeared later the various (TiN, TiAlN, TiCN) coated cutting tools. CBN is the second hardness material after diamond. Due to its great hardness and heat resistance, CBN is suitable for machining hardened steel (>55 HRC). Nowadays the hard turning is used more widely in finish machining instead of/besides grinding. Hard turning has several benefits over grinding: higher flexibility, machining complex work pieces in one clamping, no need for coolant liquid, easy automation and better material removal rate [1]. The providing of required strict dimensional- and shape accuracy of the work piece demand high quality in cutting tools. It is a basic demand from these cutting tools to provide the quality and accuracy expectations of work piece beside long tool life.

Nowadays the numerical methods are widely used to solve several different problems in engineering science. One of these numerical methods is that of the least squares, which is used to function approximation. Due to the available mathematical softwares the Artificial Neural Networks (ANNs) can be applied to approximate different types of functions using the method of least squares. The bases of ANNs were laid down by McCulloch and Pitts in 1943 [2]. Nowadays ANNs are widely used to evaluate various experimental results. In this study, ANN was created and simulated to determine tool life in case of different cutting speeds, work piece diameters, constant feed rate and depth of cut.

Artificial Neural Network

A model of a neuron

ANNs consist of a set of hierarchically organised neurons. The neurons do the same operations parallel. Each neuron in a network is connected to a certain number of neurons, and this is usually a one-way relationship. *Fig. 1* shows the structure of a neuron [3].

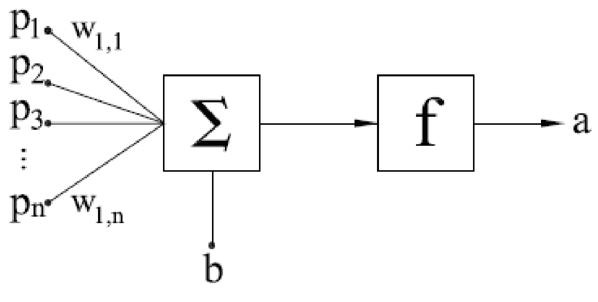


Figure 1: The architecture of a neuron

The $p_1, p_2, p_3, \ldots, p_n$ inputs are connected to the neuron by w_{1n} weights. Furthermore there is an additive part b which is called bias. Eq. (1) shows how a neuron works.

$$a = f\left(\sum_{i=1}^{n} w_{1,n} p_n + b\right) \tag{1}$$

The function f is the activation function of neuron. Usually it is a sigmoid type function such as tangent sigmoid, which is shown by Eq. (2).

$$f(x) = \frac{2}{1 + e^{-2 \cdot (x)}} - 1 \qquad (2)$$

Multi-layered ANNs

A neural network consists of three different layers at least. The first is called the input layer. This layer contains those neurons which transfer the input signal to the network. The second is the hidden layer. The neurons which carry out the real processing belong to this layer. A network has one or more hidden layers. The third (or last) layer is the output layer. The neurons in this layer transfer the information to the outside. The tasks of these neurons are same as that of the neurons in the hidden layer. The structure of a multi-layered feed-forward neural network is shown by *Fig. 2* [3].

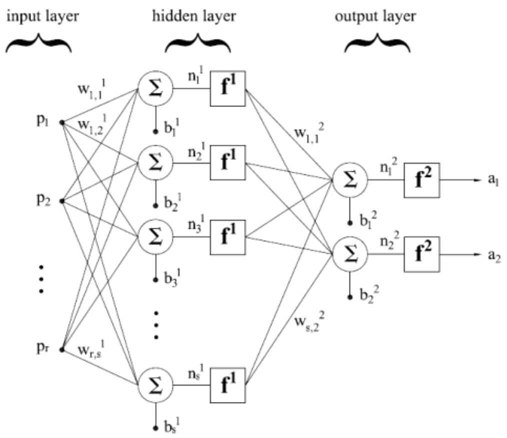


Figure 2: Structure of a multi-layered neural network

Multi-layered feed forward neural networks can be used for function fitting. These networks are using back-propagation training algorithm. During the training, the network changes the values of weights and biases according to the error function. The aim of ANN training is to minimize the error function E, which is shown by Eq. (3) [4].

$$E = \frac{1}{2} \sum_{i=1}^{n} \left\| a_i - t_i \right\|^2 \qquad (3)$$

where:

a_i – the i-th output value,

t_i – the i-th target value,

n – number of outputs,

E – the mean square error.

The i-th net input of k+1-th layer can be calculated by Eq. (4)

$$n_i^{k+1} = \sum_{j=1}^{s} w_{i,j}^{k+1} a_j^k + b_i^{k+1} \qquad (4)$$

where:

n_i^{k+1} – the i-th net input of k+1-th layer,

w_{ij}^{k+1} – the weight between the j-th neuron of previous layer and the i-th neuron of subsequent layer,

a_j^k – the j-th output of k-th layer,

b_i^{k+1} – the i-th bias of k+1-th layer.

The i-th output of k+1-th layer can be calculated by Eq. (5).

$$a_i^{k+1} = f^{k+1}(n_i^{k+1}) \qquad (5)$$

where:

f^{k+1} – the activation function of k+1-th layer.

Before training the network is initialized by random weights and biases. Each weights and biases are updated during training using Eq. (6) which is known as the back-propagation delta rule [4].

$$\Delta w_{ij}^{k+1} = -\alpha \frac{\partial E}{\partial w_{ij}^{k+1}} = -\alpha a_i^k \delta_j^{k+1} \qquad (6)$$

where:

α – the learning rate, which defines the step length of each iteration in the negative gradient direction,

δ_j^{k+1} – the backpropagated error at the j-th neuron in the k+1-th layer,

a_i^k – the i-th output of k+1 layer.

The value of δ_j^{k+1} is different, depending on that, whether the k+1-th layers is an output layer or a hidden layer. If the k+1-th layer is an output layer [4]:

$$\delta_j^{k+1} = a_j^{k+1}(1 - a_j^{k+1})(a_j^{k+1} - t_j) \qquad (7)$$

If the k+1-th layer is a hidden layer [4]:

$$\delta_j^{k+1} = a_j^{k+1}(1 - a_j^{k+1}) \sum_{i=1}^{m} w_{ij}^{k+2} \delta_i^{k+2} \qquad (8)$$

Determining tool life by Artifical Neural Network

In this paper the experimental data set given in [5,6] is used to design a neural network model which predicts tool life according to given range of feed rate, depth of cut, workpiece diameter and cutting speed. The applied technological parameters, which were used for training is shown in *Table 1*.

The ANN used for modelling tool life is a two layered feed-forward network with 35 neurons in the hidden layer and 1 neuron in the output layer. The network was made using Matlab R2009 software. The activation function in hidden layer is a sigmoid type and in the output layer it is linear. The network was trained with 108 data points according to Table 1 and simulated with 27 data points. A data point contains the feed rate, the depth of cut, the workpiece diameter and the cutting speed. The applied cutting parameters to simulate ANN were the following:

- depth of cut a_p=0.15 mm,
- feed rate f= 0.05 mm/rev.,
- cutting speed v_c=11–120 m/min,
- workpiece diameter d= 45, 75, 100 mm.

Table 1: Technological parameters for training the network

Feed rate f mm/rev.	Depth of cut a_p mm	Workpiece diameter d mm	Cutting speed v_c m/min
0.025	0.10	45	11,20,29,40,50,68,92,105,120
0.125	0.10		
0.050	0.15		
0.250	0.25		
0.025	0.10	75	
0.125	0.10		
0.050	0.15		
0.250	0.25		
0.025	0.10	100	
0.125	0.10		
0.050	0.15		
0.250	0.25		

The back-propagation learning algorithm has been used with ‘trainlm’ training function. This training function is based on Levenberg-Marquardt nonlinear least squares method.

As a result of the simulation the calculated tool life and the deviations between measured and calculated tool life are summarized in *Table 2*.

It can be seen, the maximal deviation between measured and calculated tool life is 58%, but it occurs at very small value thus it is not significant.

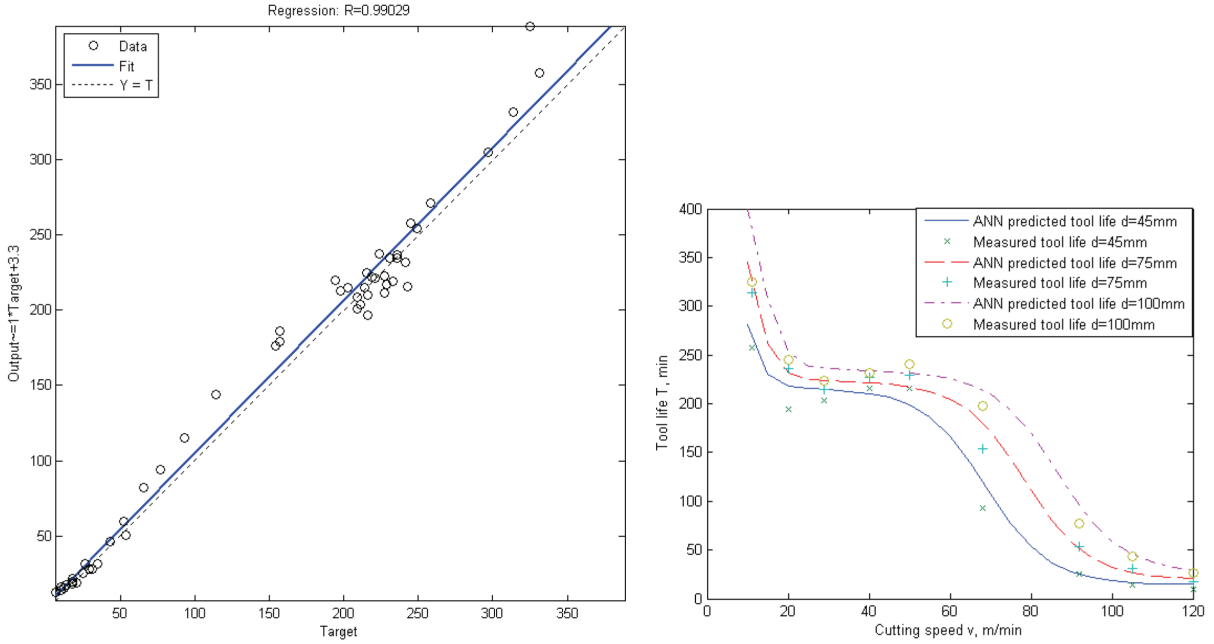
Fig. 3 shows the results of simulation. The correlation R between the outputs of ANN and the measured tool life values can be seen in Fig. 3a. The simulated data set is different in feed rate and depth of cut from the data set of training.

The value of correlation R=0.99029 is very close to 1 which means a good fitting of calculated values to measured values. Fig. 3b shows the tool life curves at different workpiece diameters and constant feed rate and depth of cut.

Table 2: The calculated tool life values and deviations between measured and calculated tool life values

v_c m/min	Workpiece diameter, mm											
	45				75				100			
	f, mm/rev.		a, mm		f, mm/rev.		a, mm		f, mm/rev.		a, mm	
	0.05		0.15		0.05		0.15		0.05		0.15	
	T_m	T_{ANN}	E	E%	T_m	T_{ANN}	E	E%	T_m	T_{ANN}	E	E%
11	258	270.93	-12.93	5.0	314	331.59	-17.59	5.6	325	388.56	-63.56	19,5
20	194	219.61	-25.61	13.2	236	234.51	1.48	0.6	245	257.66	-12.66	5,1
29	203	215.17	-12.17	6.0	215	225.07	-10.07	4.6	224	237.51	-13.51	6,0
40	216	210.20	5.79	2.6	227	222.42	4.57	2.0	231	234.70	-3.70	1,6
50	216	196.57	19.42	8.9	229	217.37	11.62	5.0	241	231.89	9.10	3,7
68	93	114.99	-21.99	23.6	154	176.66	-22.66	14.7	198	212.98	-14.98	7,5
92	25	25.43	-0.43	1.7	54	50.57	3.42	6.3	77	94.14	-17.14	22,2
105	14	17.80	-3.80	27.1	31	27.89	3.10	10,0	43	46.66	-3.66	8,5
120	10	15.80	-5.80	58,0	18	21.77	-3.77	20.9	26	31.49	-5.49	21,1

T_m – Measured tool life
T_{ANN} – ANN predicted tool life
E – deviation between measured and ANN predicted tool life
E% – deviation in %



a) The correlation between ANN results and measured tool life values

b) The measured and simulated tool life values at different workpiece diameters (f=0.05 mm/rev, a_p=0.15 mm)

Figure 3: The results of ANN simulation

It can be seen on Fig. 3b that the characteristics of tool life curves predicted by ANN are similar to curves by specified in [6]. In [7, 8] professional articles Kundrak et al. was a new generalized tool life equation used [5].This equation is valid in the whole range of the cutting speed. The effect of changing of the workpiece diameter on tool life was published Kundrak et al. in [6]. According to this at small workpiece diameter the changing of the direction of chip flow vector is steeper than in case of greater diameters. Therefore the tool life is decreased at small workpiece diameters.

Summary

The aim of this paper was to determine the tool life of CBN cutting tools using Artifical Neural Network. The inputs of ANN were feed rate, depth of cut, workpiece diameter and cutting speed. These parameters have huge influence on tool life of CBN cutting tool. The predicted tool life by ANN shows good agreement with experimental results of [6].

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