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TOOL WEAR MONITORING WITH THE APPLICATION OF NEURAL NETWORKS

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ABSTRACT
The paper presents the results of developing a tool wear monitoring system for hard turning in laboratory conditions, using modern artificial intelligence methods as neural networks (NN). One of the most dominant factors influencing the reliability of turning process is tool condition; thus, systems for monitoring tool conditions have been developed both in practice and in laboratory conditions. The paper shows researches connected to the selection of methods and strategies for determining tool wear condition after turning on the basis of set laboratory system model. Tool monitoring is performed by indirect method on the basis of cutting force as one of best determiners of tool condition in the on-line working regime, combined with one of artificial intelligence method, i.e. neural networks. The paper also presents the topology of the neural network used for training.
Keywords: *tool wear, turning, neural networks*

1. INTRODUCTION
Modern production principles impose cost decrease as an imperative that can be realized in the following: increasing cutting conditions, decreasing machining time and decreasing the number of reject pieces. The condition of machining tool has a large influence on rejects decrease and production stagnation, which then directly influences the geometry, surface and structure of the manufactured part.
Adequate and timely tool change presents a very important component with every machining procedure, including turning, for which a monitoring system is developed and trained. Many authors have considered parameters influencing the tool wear process for hard turning. For example, Scheffer et all [3] believe that two basic parameters influencing the reliability of turning process are: cutting speed and the value of force appearing in turning. The researches conducted on this topic have shown that, from the point of optimal tool life duration, large variations in cutting speed and force are not permitted.
Based on conducted researches, it is known that flank wear band directly influences the quality of manufactured surface, and that for the plate break, dominant influence is the one of the crater wear band created by diffusion chemical reaction in the machining process. Researches conducted on this theme presented that various methods have been used for tool break and collision monitoring in relation to tool wear monitoring [3, 4, 6].

2. OVERVIEW OF THE LABORATORY MONITORING SYSTEM MODEL
Tool monitoring system model can basically be observed through four segments combined in a unity connected by feedback with the machine operating unit (Figure 1).

Special system segments are the following:

- sensor part
- part for data acquisition, processing, and analysis
- part for training neural networks
- part for result presentation

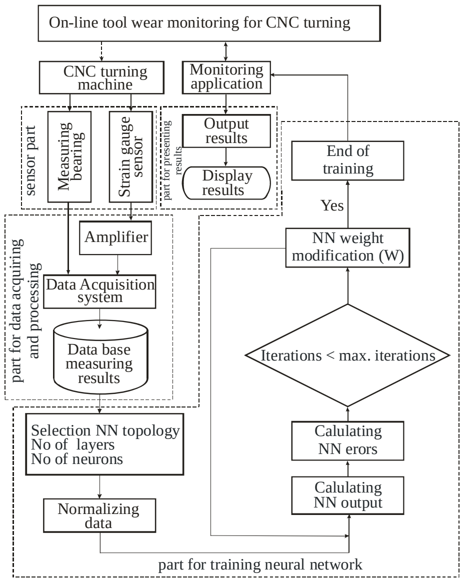

Figure 1. Algorithm of the developed tool monitoring system based on neural networks [1]

Sensor part of the system comprises of two sensors: PROMESS' measuring bearing placed in the front bearing of the main machine tool spindle, and the second sensor – working on the measuring bands – and placed on the turning knife handle and designed to measure forces appearing on the tool.

System part for data acquisition, processing, and analysis contains standard A/D cart ED 300, which enables programming sampling speed and input data types.

Neural network applied in the system is a multilayer perceptron network with one direction signal flow (feed-forward topology); more about it will be said later in the paper.

The system is designed by software to acquire and process information in on-line working regime and to operate hardware components work, so it can perform monitoring of machining process and tool wear on the basis of set limitations.

3. NEURAL NETWORK FOR TOOL WEAR MONITORING

3.1 Pre-processing and training set

As already observed, neural network possesses three inputs, those being: forces registered by measuring bands on turning knife handle, forces from promess sensor, and cutting speed. Using these three values, neural network on its output performs a value assessment of flank wear band VB in the same time moment.

To have more efficient training, all values in the training group are previously normalized. Normalization is performed in such a way that every input and output value over the training group has its middle value equal to zero, and standard deviation reduced to unit value. For *i*-th value of input vector from promess variable FR, promess normalized value is presented by the expression:

$$\hat{p}_i = \frac{p_i - p_{sr}}{s_p}. \tag{1}$$

where

$$p_{sr} = \frac{1}{N}\sum_{i=1}^{N} p_i. \tag{2}$$

middle value

$$s_p = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(p_i - p_{sr})^2} \qquad (3)$$

standard deviation of the input vector of promess variable defined over the whole training group (N = 30900).

Prior to the training process, besides data normalization, it is necessary to perform the neural network topology selection, for which it is important to determine the following [1]:

- Selecting adequate learning algorithm in order to correctly train the network,
- Selecting the values of certain parameters in multilayer architecture MLP, and
- Selecting the values for algorithm parameters for feed forward learning.

Since the values of output variable VB depend exclusively on current values of input variables, multilayer perceptron network with one direction signal flow (feed forward topology) has been selected for network topology.

$$y(net_i) = \frac{2}{1+e^{-net_i}} - 1. \qquad (4)$$

where

$$net_i = \sum_{j=1}^{M} w_{ji} x_j - b_i, \qquad (5)$$

sum of input values in the network multiplied with appropriate weight neuron coefficients (w_{ji}) [7].

Used network has three layers: input, hidden, and output, as shown in Figure 2, presenting the satisfactory number of layers for the observed problem, and considering the fact that multilayer perceptron with one hidden layer can by arbitrary accuracy ε > 0 uniformly approximate any real continual function on the real final axis.

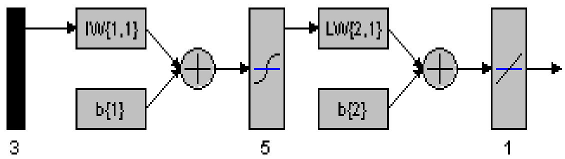

Figure 2. Neural network topology

In the input, as well as in the output layer, number of neurons is determined by the number of inputs, that is of outputs, and thus input layer contains three neurons corresponding to input variables (FR tool, FR promess, V), and output layer contains one neuron whose output provides the value of the estimated value of flank wear band VB.

Number of neurons in the hidden layer is determined by experiments comparing the performances of networks with different number of neurons in the hidden layer. During the experiment, networks with two to seven neurons in the hidden layer are tested. All experimental neural network topologies are trained with the same training group, so the performances of each topology could be estimated as objectively as possible. For selecting the final topology, general direction has been used stating that the total number of neurons in neural network should be as small as possible, hence increasing generalization capacity of the network and avoiding the appearance of overfitting. Figure 3 presents the behaviour of weight coefficients during network training.

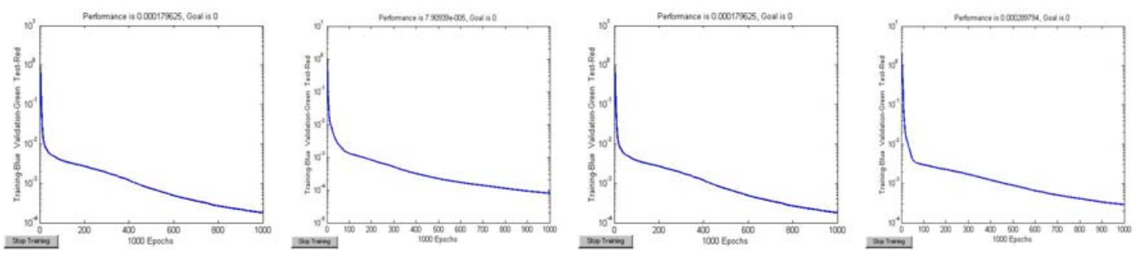

Figure 3. Alteration of average square error during neural network training

Training NNs has been performed with resilient modification of the main back-propagation algorithm designed for NNs with squashing activation functions, i.e., functions that compress infinite input area into final output interval (like sigmoid function).

4. RESULTS

The selected model has been valuated as a relatively reliable method for tool wear monitoring for hard turning. During this research, several different network configurations have been used and investigated for their application in tool wear monitoring for hard turning.

Tool wear (VB) is measured after each machining action and the value for one passing is linearly placed in the table. Wear measurements were performed using Tool microscope with 30x zoom. The look of a plate at the end of lifetime is presented in Figure 4. Figure 5 presents the correspondence between the model of the estimated value of the trained neural network and the real value obtained by measuring during the machining process.

Figure 4. Picture of a tool insert

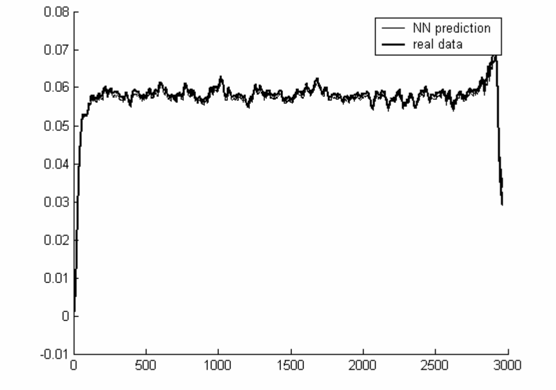

Figure 5. Accurate and estimated value of a neural network

5. CONCLUSION

The paper has shown that NNs can be used for effective wear monitoring during hard turning in laboratory conditions, with previously set limitations. After considering numerous possible settings for a wear monitoring model, the one providing optimal results for the selected number of network layers and neurons has been chosen. The set model can relatively easy be upgraded by a dynamic neural network, which presents one of relatively new research directions in this field.

6. REFERENCES

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