Algorithm of the tool condition monitoring system based on many neural networks

Algorytm diagnostyki zużycia ostrza oparty na wielu sieciach neuronowych

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Presented is a comparison of different methods of estimating tool wear – obtained for group of RBF neural networks, hierarchical methods and the standard time counting. The analysis of the signals from the machining process carried out for three different experiments, clearly demonstrating the effect of presented methods. The results obtained for group of RBF neural networks are similar to results obtained for hierarchical methods.

KEYWORDS: tool condition monitoring, RBF neural network

As the demand for productivity and quality increases, the degree of automation of machining is increasing as well. One of the elements of this automation is the cutting process monitoring system. The basic task of these systems is to diagnose the tool condition.

A cutting edge diagnostics algorithm based on a neural network team was built and tested. Its operation was compared with an algorithm based on a single neural network as well as with a hierarchical algorithm. The purpose of the study was to investigate whether an algorithm based on a neural network team can compete with a hierarchical algorithm built and refined in ITW PW within several national and European projects over the last dozen or so years. The hierarchical algorithm built on the principle of integrating estimates from individual measures has already exhausted its development potential. One of the development directions of tool wear diagnostic algorithms is neural network assemblies that could use synergies to estimate consumption on the basis of several measures at the same time.

Analysis of the problem

The most commonly used neural networks are used to integrate measures in tool wear diagnostics. It may be a perceptron with different number of hidden layers: 0 and 1 [3, 8], 1 [9-11], and 1, 2 and 3 [2] with backward propagation as a learning algorithm.

Other neural networks are also used, such as the self-organizing Kohonen network [6], the fuzzy logic network [7], the radial basis function network [4]. A review of such solutions can be found in the paper [1] - the author analyzes over 100 literature items. In addition to neural networks, fuzzy logic [12] can be used that can be supported by genetic algorithms [12]. A hierarchical algorithm was also used. The most popular network is a multilayer perceptron, but its optimization time (number of neurons, learning parameters and learning itself) is quite long. However, it has been shown that good results are achieved by using radial basis functions [4]. It has the advantage over the perceptron that its learning time is incomparably shorter. The whole process of optimizing network structure and parameters can be carried out in a few seconds. As a result, no additional production delays associated with the use of the cutting system are introduced.

Comparison of the efficacy of different neural networks in the diagnosis of tool wear can be found in [13]. Following networks were tested here:

- unidirectional network with one layer hidden taught by the method of reverse propagation,
- unidirectional network with one layer hidden taught by the quasi-Newton method,
- one-way network with one layer hidden taught by Levenberg-Marquardt method,
- one-way network with one layer concealed taught by conjugated gradient method,
- one-way network with one hidden layer taught by the Quick-Propagation method,
- one-way network with one hidden layer taught by the Delta-Bar-Delta method,
- network with radial basis functions taught by means of: K-means, explicit method,
- network with radial basis functions taught by K-means, Isotropic method,
- network with radial basis functions taught by K-means, Isotropic, pseudo-inverse, error propagation method,
- network with function extension of the taught by method of error propagation.

The results of this work also indicate that the Radial Basis Function (RBF) neural network has similar results to the MLP (MultiLayer Perceptron) network.

Publication [5] compares the hierarchical algorithm and RBF network. The result was superior to the algorithm. However, it was obtained on the basis of a single experimental study, which could have been a coincidence. These studies were repeated by the authors

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[15] using three distinctly different treatments (different treatments) for examining the experimental dependence of diagnostic signals on the tool condition. The results confirm the initial observation that a single neural network is much less effective as an algorithm for integrating multiple measures in a wear diagnostic system than a hierarchical one.

A serious problem with using a single neural network is the need to maintain a proper ratio of the number of network inputs (measurements used) to the number of teaching data (limited by the economic necessity of minimizing the number of life periods intended for teaching).

One solution to this problem is the initial fusion of measures by calculating the product of the quotient of sums, sums, etc. of individual measures [2]. This does not guarantee that the full information contained in the original measures will be used and a synergy effect will be used. Another solution is to determine the tool condition separately, based on a set of measures, and then integrate these partial responses. Such strategy was proposed in [14]. It consists of two parts:

- stage of the tool wear estimation separately for each sensor based on the measurement of the signals coming from them and the cutting parameters; this uses a single network with radial basis functions for each sensor;
- stage of integrating predictions from individual sensors into the final response of the system; This stage is done in the form of a set of fuzzy logic rules.

Experimental

When developing the wear diagnostics algorithm, text files with predetermined values were used, since it is very time-consuming to set up measurements from signal files, and to repeat the operation every time is unnecessary when testing a new version of the algorithm. During the previous work a software was created to generate text files with measures. The work contains only a very brief description of the algorithm, which determines the measure. For a more detailed description, see e.g. [15].

Three sets of experimental data were used to test the tool wear diagnostics strategy - each obtained from another machine tool and another machining task. Detailed information on these studies is given in the table. The files with diagnostic signals from these tests according to the described algorithm were measured and saved in text files.

Before initializing the measurement in automated diagnostic systems, pre-treatment of the signal and cutting detection are necessary. Taring is the removal of the sensor offset. The average of 120 ms of the following signals is calculated as soon as 40 ms after the start of the working feed and the value is subtracted from the signal for the duration of the feed. Then, from the 400 ms signal, the value of the moving standard deviation is determined and the signal is filtered using a Butterwoth II low pass filter with a cutoff frequency of 1 Hz at 10 kHz sampling. Both of these signals are compared with thresholds, the value of which is determined at the step of removing the constituent from the signal. The standard deviation of this signal is multiplied by:

- 3 for a method based on a standard deviation,
- 5 for the filter-based method.

TABLE. Study description

Name of the test	Turning Inconel 625	Drilling steel NC10	Turning steel 45
Workpiece	Inconel 625	steel NC10	steel 45
Machine tool	TKX 50N	Arrow 500	VENUS 450
Machining	Facing of the engine rotor housing	Drilling in the face of the cylinder	Longitudinal turning of the cylinder
Tool	RNGN 120700T01020 CC670	NWKa DIN 338 RN (Baildon) ⌀6	CNMG 120408 BP30A
Holder	CRSNL 3225P12 MN7	7625-40-20-63 firmy Bizon (Białystok)	PCLNR 3225P 12
Cutting parameters	a_p = 2,5 mm f = 0,2 mm/rev v_c = 220 m/min	f = 31,86 mm/min f_z = 0,06 mm/rev v_c = 10 m/min	a_p = 1,5 mm a_p = 2,0 mm f = 0,1 mm/rev v_c = 150 m/min
Sensors	Kistler 9017B	Kistler 9017B	Kistler 9601A31
	Kistler 8152B	Kistler 8152B	Kistler 78152B121
	PCB PIEZOTRONICS 356A16	PCB PIEZOTRONICS 356A16	–
Signals	AE_{rms}, V_y, V_z, F_x, F_y, F_z	AE_{rms}, V_x, V_y, V_z, F_x, F_y, F_z	AE_{rms}, F_x, F_y, F_z
Data acquisition	NI-PCI 6221 30 kS/s	NI-PCI 6221 30 kS/s	1 kS/s

Cutting is detected when the previously defined threshold (any of the two) is exceeded and must continue to run for a specified period of time (default 250 ms), which prevents false alarms from temporarily increasing the signal level.

Likewise, the cutting end detection is running in the same way, but the waveforms must fall below the thresholds to which they relate, and this state also needs to be at least 250 ms. If more than one diagnostic signal is sampled in the system so that the system finds that the cutting has been detected, it is sufficient to detect it on any of them. Due to interference with various system installations on the machine tools during the installation of the diagnostic system, it is determined for each signal which method to detect on the channel.

The next step in the measurement procedure is segmentation, that is, the selection of the signal segment representing the operation. In automated systems, segmentation must be carried out without operator intervention.

In the system described in this article, segmentation was a division of the signal during its acquisition into fragments of 1 second length. Prior to performing these procedures, it is essential to select segments that best represent the state of the blade during machining. It is preferable that the signal to measure the measurements comes from a signal recorded at stable cutting, accompanied by stable signals. The method of evaluating signal immutability (for segment B adjacent to segments A and C) is described by equation (1). The lower the immunity, the better the segment is suitable for diagnostics.

$$Fl_B = \left|\frac{RMS[A]}{RMS[B]} - 1\right| + \left|\frac{RMS[C]}{RMS[B]} - 1\right| \qquad (1)$$

where: *RMS* - value of the segment respectively: *A, B, C;* Fl_B - signal stability rating indicator.

To select the most stable segments, while maintaining their even distribution in the operation, they are grouped into six packages and each of them chooses the segment with the best rating. However, if you run the analysis on average every 6 seconds, you might find that with long machining operations common in the aviation industry, today's computers will have too little computing power and memory to handle such a task. The way to avoid this problem is to eliminate the excess number of segments, because the diagnosis of the level of natural wear and tear need not be conducted online.

Two elimination criteria were adopted. The first is the maximum number of segments in an operation. In the case of limiting the number of segments in an operation, the adjacent segments are sequentially grouped after the first object in the packets (so that each block contains as many segments as possible) corresponding to the constraint (maximum 20), then, the best segment is selected from each one.

Due to this selection of tools with a small number of shelf-life operations, the diagnostic system makes a diagnosis often during processing. Differently - for tools with a long shelf life, which are able to do many things - it is acceptable to estimate consumption much less often.

Signal from each selected segment is processed using the wavelet transform WP3 (all levels WP0 to WP3), the wavelet db2, and for each band are determined: energy, rms (effective value), mean value, standard deviation, modal value, threshold (for three different threshold values) and the dwell time above the threshold (for three different threshold values). In addition, Power Spectral Density (PSD) was determined, and energy was determined from the resulting signal.

Each measure is approximated by the second order polynomial. As a model quality indicator, the mean square (RMSE) was assumed:

$$RMSE = \sqrt{\frac{\sum_i^n (Y_i - A_i)^2}{n}} \qquad (2)$$

where: Y_i - value of measure in i-th operation, A_i - approximated value of measure in i-th operation, n - number of all operations.

The RMSE indicator depends on the value received by the measure. To be able to compare this indicator for different measures, they should be normalized to one range. The range [0; 1]. After the first shelf-life, this indicator is a measure of the "smoothness" of the measure, and after successive shelf life - a measure of repeatability. However, it may turn out that several measures have very similar milestones and - consequently - very similar values of the quality index. To eliminate this phenomenon as a measure of similarity, the correlation coefficient between the model and the measure of the signal was used.

Development of a blade wear diagnostic algorithm based on multiple neural networks

One of the most commonly used methods of determining the state of a tool in industrial practice is to count the blade operating time/number of operations performed on a given blade based on the cutting time/number of operations performed on a master blade (usually the first). This method, however, has serious limitations due to the random nature of blade life. Next, more advanced methods for estimating blade wear based on diagnostic signals, which are suitable for use in automated tool status diagnostics are presented.

Measure integration - hierarchical algorithm

For each selected measure, a model is created based on the third degree polynomial. The polynomial values are written to a 120-element array, the index of which corresponds to the portion of blade life that is used in percent. Estimating the wear using a hierarchical algorithm can be divided into two steps:

- **Step 1:** Searching for the model array of the measure for finding the nearest value to the result of the analyzed operation. One can search only above the previously obtained result. This prevents the indicated wear level from decreasing. Maximum n% of the initial point is searched, where n is the previous estimate of consumption, increased by twice the average increase in consumption per operation. This prevents very rapid increases in wear indicators, calculated on the basis of accidental indications. This also makes it possible to use non-monotonic measures.
- **Step 2:** Averaging the estimates obtained for each measure.

Integration of measures using multiple neural networks

A RBF network consisting of a layer of concealed radial neurons and a liner neuron output layer was used. Radial neurons with base function based on exponential function were used. Learning the RBF neural network consists of three steps: selecting radial function centers, selecting the radial function radius, and selecting the neuronal weight of the linear output layer.

The location of radial function centers is determined by the K-means method. The radial width is determined using the K-nearest method. The weight of the output layer is determined by the least squares method based on the comparison of the response of the learned radial layer algorithm and the value of the network response pattern. Radial neuron centers, their width and the weight of the linear neuron are selected in the learning process based on the learning data. Network learning parameters (which in the case of the RBF approximation method are the number of neurons, the number of neighbors, and the coefficient of radial function width) are selected on the basis of the network performance on the verification set.

The number of radial neurons is selected from the range 2 ÷ 15 with step 1, the number of neighbors - from the interval 1 ÷ 5 with step 1, and the width factor - from the interval 0.6 ÷ 2 with the step 0.2. In the case of blade wear diagnostics, the learning and verifying set is created from the data that teaches the blade life expectancy by assigning to each other a sample.

The network is built for each designated segment. If, during surveillance, the next network response is less than the previous estimate of system consumption, the estimate does not change. All selected measures are divided into groups of K measures where K can be freely adjusted. For each measure set a separate neural network is created, which is optimized on the learning and verification sets (based on these measures). In surveillance mode, the response of each network is compared to the last estimate of consumption. If it is smaller, the wear value is set to the last estimate. If the growth rate of response exceeds double the rate of growth of wear during the teaching period, then the response of the network is doubled of the increase in wear from the training periods.

Analysis of the effectiveness of different tool condition estimation methods based on own research

Before analyzing the effectiveness of the various tool condition estimation methods, we conducted a study to determine the optimal repeatability threshold. The experiments consisted of conducting a series of experiments in search of the smallest RMSE, which used different methods of estimating blade wear (timekeeping, hierarchical algorithms, neural networks) for three different threshold values (8, 15, 25). As a result of the study, it was found that the optimal repeatability threshold (statistically the smallest RMSE) was obtained for a threshold of 15.

The results of blade estimation using various methods (timekeeping, hierarchical algorithm and two-measure network) for three different experiments are summarized in the figure. The graphs represent the estimated portion of the blade life span (*ΔT%*) as a function of the actual portion of the blade life span for individual cutting blades. The graph also shows the RMSE (*T*) value, which is a measure of the effectiveness of the algorithm - the closer it is to the unity, the better the estimate of the wear.

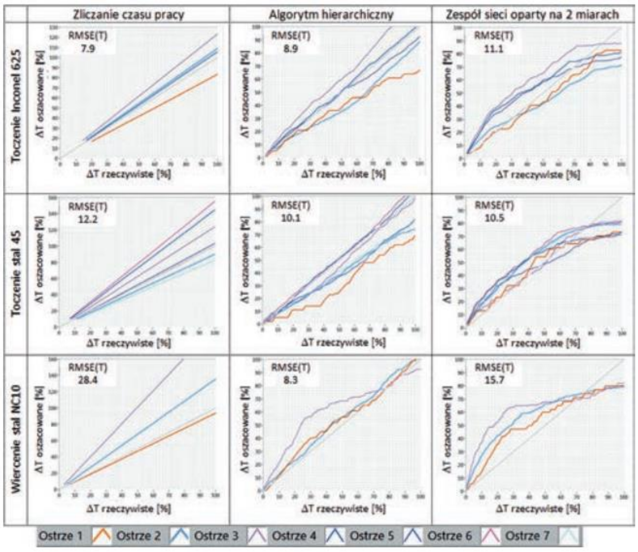

Fig. Results of blade wear estimation using various methods (time counting work, hierarchical algorithm, and a network of measures based on two measures) for three different experiments

For two of the three studies, better results of counting the time worked were achieved from a hierarchical algorithm and network. Statistically, however, the best results were obtained for the hierarchical algorithm. The results of the network team can be considered comparable. The quality rating of RMSE may not be the most appropriate. Counting working time has the highest error where it is most important to make the error as small as possible – i.e. at the end of the shelf life. A low error in the first part of the period with the RMSE quality indicator favors this solution. The error for the network set is also large at the end of the period. However, the scattering of estimated values alone is small, giving you the opportunity to improve the algorithm's efficiency after eliminating systematic errors.

Conclusions

The tool condition monitoring system based on the RBF neural network assembly produces results similar to the hierarchical algorithm. There is, however, a systematic error that underestimates the estimates in the most important end-of-life period of the tool. After eliminating this error and taking into account the concentration of the results, it can be assumed that the network complex would be a better solution than the hierarchical algorithm. The network-based algorithm also has the potential to develop a new method for selecting measures dedicated to neural networks.

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