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Application of artificial intelligence to diagnose tool wear during milling

Zastosowanie sztucznej inteligencji do diagnozowania zużycia narzędzia w procesie frezowania

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The paper contains a research about an ability to use an artificial intelligence in tool condition monitoring process online. There was a parolee why developing a system which set a machine able to get a decision them self is advisable. Besides, there was described an ability to use an artificial intelligence, and limits to use the technology. In conducted experimental researchers there was discover an influence neural network's structure on learning process (learning time-consuming and ability to make a knowledge an abstract).
KEYWORDS: milling, neural networks, TCM

The development of technology entails an increase in expectations both for the quality of products offered by producers and for work safety. Optimizing production costs while increasing the diversity of products requires the use of information technology in the production process. Therefore, it is advisable to work on systems that enable the automation of the production process. To achieve this, it is necessary to develop a series of diagnostic system solutions that will be able to detect critical events and determine the degree of wear of machine parts and cutting tools.

Work on TCM (tool condition monitoring) systems for monitoring the condition of the tool during technological processes (milling, turning, grinding) has been carried out for many years [1, 2]. Nevertheless, there are still no effective solutions that could be used on an industrial scale.

The diagnostic system can not influence the process [3]. In practice, it is only possible to measure indirect processing parameters, most commonly vibrations, acoustic emission, cutting force or spindle torque.

The main obstacle in the development of diagnostic systems and supervising milling processes is a large number of factors that affect the same diagnostic signals. This creates problems with correlating the values of signals with recognized faults. For this reason, in practice, simplified models are used, which, however, do not allow to predict all possible signal values. Existing databases with experimentally tested parameter values often contain too little information about the processes in which the emergency conditions occurred. In addition, such databases are expensive to create, and access to them is limited [4].

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The increase in computing power of computers opens up new possibilities for the development of artificial intelligence. Systems based on this technology are gaining more and more popularity because they come to the aid when developing algorithms based on a mathematical object model is difficult or impossible due to the complexity of the phenomenon model.

The use of a neural network in diagnosing an object allows for taking into account many correlations between various technological parameters and the state of the object and a diagnostic signal. The functioning of artificial intelligence shows that the network in the learning process should develop such weighting factors so that signals that do not provide information about the object's status are omitted [5].

This technology has limitations in spite of its unquestionable advantages. There are no clear rules that would allow you to design a working neural network. The learning process itself is long-lasting and it is difficult to assess whether (and how many iterations) it will be successful. The time required for the learning process depends on the network structure and the amount of input information, as well as on the random factor.

From this point of view, it is important to examine the influence of the neural network structure on the learning process and the ability of the network to generalize the knowledge used to recognize the state of the tool - this was the purpose of this work. Generalization of knowledge is important due to the variety of treatments performed in the milling process. The neural network should recognize the universal characteristics of vibrations occurring due to the tool wear. This is crucial when using artificial intelligence in the TCM system.

Test conditions

The assumptions assume that the diagnostic signal will be vibrations from the piezoelectric sensor placed on the workpiece, which is practical. Firstly, an experienced operator is able to assess the condition of a tool using a hearing protection, which allows one to suppose that the neuron will also be able to determine this state based on the vibrations of the object. Secondly, the vibration measurement does not require the use of a specially adapted machine and - thirdly - does not interfere with the machining process.

The analysis of vibrations as a function of time is inconvenient, therefore as an input to the neural network an amplitude-phase characteristic was used, calculated by fast Fourier transform [6]. Due to the fact that the resulting vibrations depend on the technological parameters of the process [7], the input data included: cutting width, depth of cut, feed per tooth, number of blades, spindle revolutions.

The designed neural network is assumed to have one output neuron. The value 0 of this neuron means usable and the value 1 - tool used.

For the sake of simplifying the experiment and reducing the time of testing, it was assumed that only one technological parameter will be changed: the depth of cut. It was assumed that the vibrations would be repeated in cycles and that the input data would be vibration from a 1 s time window (to average vibrations occurring during the process). The diagram of the tool diagnosis methodology is shown in fig. 1.

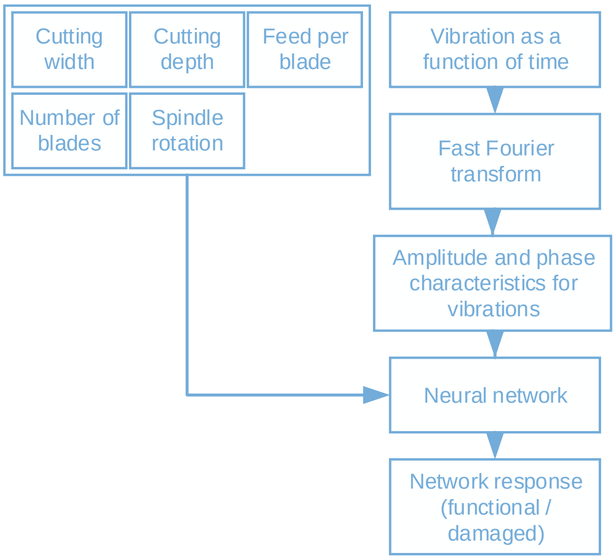

Fig. 1. Block diagram of the tool state diagnosis method

Vibration model

At the first stage of the research, a vibration model was created based on literature studies [7]. This model takes into account qualitative relations between the parameters of the milling process and the frequency and amplitude of vibrations (tab. I).

In this phase of research, the neural network easily learned to recognize the state of the tool. As a result of experimental tests, it was found that increasing the number of neurons in the hidden layer causes:

- increasing the average network error (fig. 2),
- reducing the number of iterations needed to learn by the tool recognition network (fig. 3),
- an increase in the network's tendency to memorize patterns while reducing the tendency to generalize knowledge (fig. 4).

TABLE I. Effect of vibration in cutting process

Parameter	Vibration frequency	Amplitude of vibrations
Cutting speed	Increase	Decrease
Feedrate	No change	Increase
Cutting depth	No change	Increase
Cutting width	No change	Increase
Tool wear	Increase	Increase

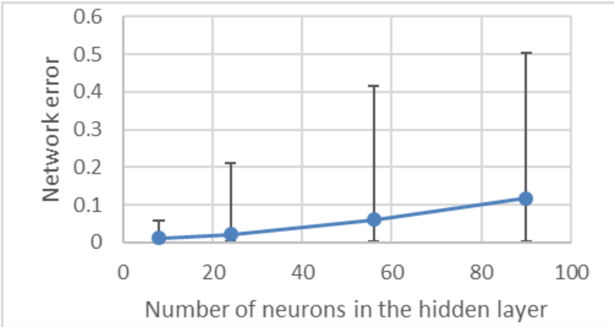

Fig. 2. Graph of the change in the mean error value of the neural network

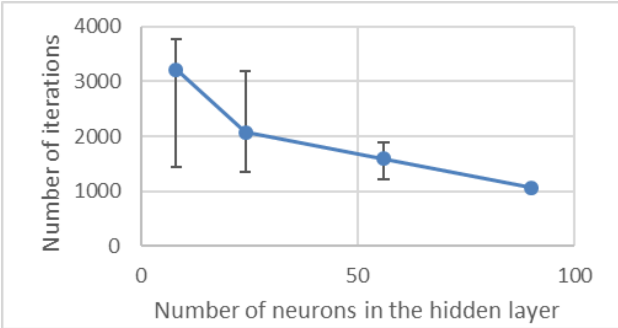

Fig. 3. Graph of the average number of iterations required to complete the neural network learning process

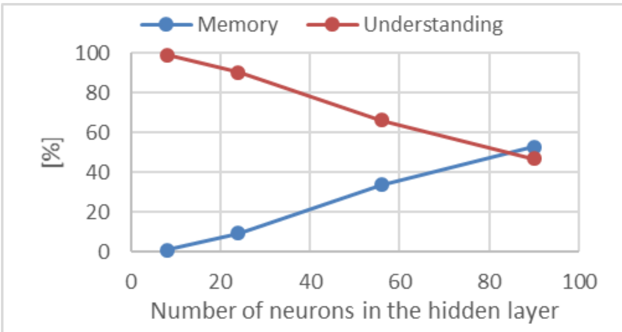

Fig. 4. Graph of the impact of the number of neurons in the hidden layer on the network's ability to generalize knowledge

Experimental research

The second stage of the research included the performance of vibration measurements during the milling process. Also in this case, the variable cutting parameter was the depth of cut. The measurements were made using a carbide monolithic milling cutter with a diameter of 10 mm. Two milling cutters were used in the experiment: new and used. The data was not subject to filtration. The data set consisted of 12 characteristics: six for the sharp tool and six for the used tool. This allowed us to test three different cutting depths. Double measurement with the same technological parameters allowed to obtain information on interferences occurring in the signal. In addition, 10 measurements were made that served as test data for the neural network.

During the research, the milling process was carried out with the following technological parameters:

- cutting depth a_p = 0.7; 0.5; 0.4; 0.2 mm;
- cutting width a_e = 3 mm;
- feed f = 200 mm/min;
- revolutions with a value of 3500 rpm.

Many attempts have been made to successfully teach the neural network to recognize the wear of the cutter. Experience has shown that a neural network with one hidden layer does not have enough intelligence potential to solve this problem. In addition, the use of data with a resolution of 1 Hz is too time-consuming.

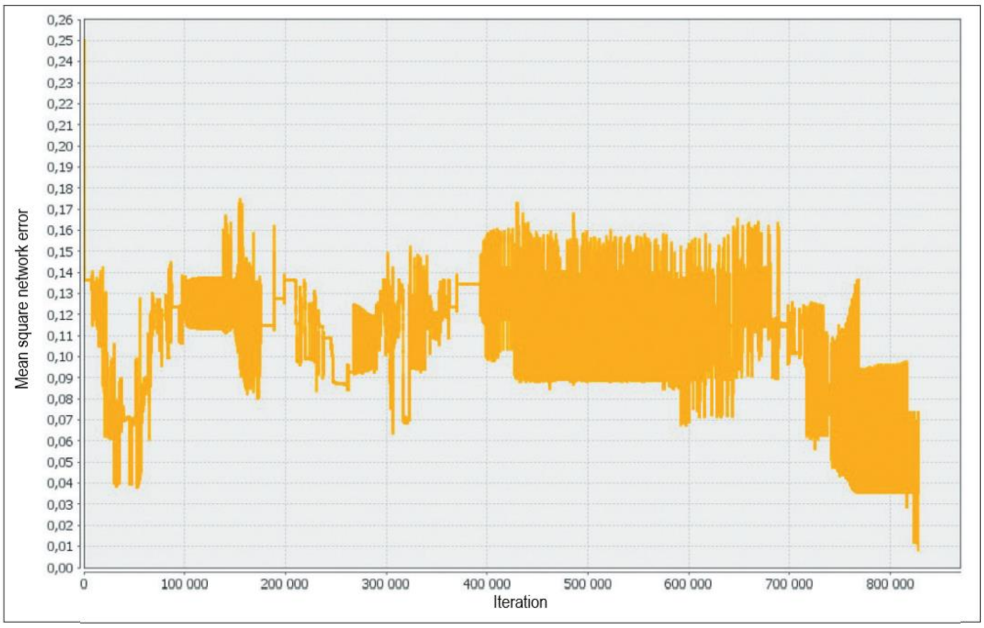

Fig. 5. Diagram of the mean square error of the neural network during learning

TABLE II. Test results for training data

No.	Network response	Expected result	Error
1	0,1528	0	0,1528
2	0,1528	0	0,1528
3	0,0196	0	0,0196
4	0,1528	0	0,1528
5	0,841	0	0,841
6	0,9982	1	−0,0018
7	0,841	1	−0,159
8	0,841	1	−0,159
9	0,9972	1	−0,0028
10	0,841	1	−0,159
11	0,9972	1	−0,0028
12	0,9972	1	−0,0028
13	0,9972	1	−0,0028
Average error			0,00730

TABLE III. Test results for a cutting depth of 0.4 mm

Lp.	Network response	Expected result	Error
1	0,1528	0	0,1528
2	0,1528	0	0,1528
3	0,1528	0	0,1528
4	0,9982	1	−0,0018
5	0,9982	1	−0,0018
6	0,9982	1	−0,0018
Average error			0,0116

After these failures, data processing was performed. First, units were converted from m/s^2 to dB. Next, the arithmetic mean of noise measurements from CNC machine tools was calculated and included in the characteristics of the examples for teaching the neural network. The last step was to reduce the input data resolution to 100 Hz. After this data was prepared, attempts were made to teach the neuron network. A network with one hidden layer was still unable to find the right solution to the problem. A positive result was provided by a neural network with two hidden layers: the first one consisted of 120 neurons and one bias neuron, and the other - from 20 neurons and one bias neuron. A graph showing the change in the network error along with subsequent iterations is shown in fig. 5.

During this test, the network learning coefficient was 0.2, while the maximum permissible medium-square error of the network - 0.01. The number of iterations performed by the network during the learning process was 827 494 and as a result the network reached an error of 0.008.

The last task was to determine the nature of the network's learning. This parameter determines whether the network memorizes the patterns and recognizes them later, or generalizes the knowledge. For this purpose, a test was carried out with the parameter a_p = 0.4 mm. A cutting depth of 0.4 mm was not given in the training data. After two tests - one with the same data used in the learning process and one with a_p = 0.4 mm - the results given in tab. I, II and III were obtained (red color means incorrect network diagnostics as to the condition of the tool).

Conclusions

The performed research indicates that the neural network can be used in the process of diagnosing the condition of the tool. The key elements determining the origin of the learning process are the number and quality of input parameters. Further research in this respect should include increasing the diversity of input data.

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