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EVALUATION OF INTELLIGENT ANALYSIS METHODS INSTRUMENT CONDITIONS

Abstract. This article provides an overview of modern data mining methods used to monitor and diagnose the condition of the cutting tool.

When operating metal-cutting machines, the issues of increasing reliability, productivity, accuracy of work, improving the quality of manufacturing parts, as well as the level of automation remain relevant. All these factors depend to one degree or another on the condition of the cutting tool on the machine during processing. Cutting tools play an important role in industrial production, where the accuracy and efficiency of material processing are crucial. To ensure the smooth operation of mechanical equipment, systems for monitoring and diagnosing the condition of cutting tools become an integral part of production processes.

Machining accuracy is the most important characteristic of any technological equipment, for example, a numerically controlled machine tool (CNC). As you know, increasing the accuracy of manufacturing parts increases the service life of machines and equipment. They cannot function normally with insufficient manufacturing accuracy of its components due to dynamic loads arising during operation, which cause accelerated wear of the equipment and its further destruction. The causes of processing errors on metal-cutting machines are associated with inaccuracy, deformations and wear of machines, devices and tools, as well as directly with deformations of workpieces processed on machines under the action of cutting forces, heating, errors in the measurement process and others.

For CNC machines performing processing in automatic mode, the requirements for the quality of the tool as a parameter determining the accuracy of processing are significantly increasing. It is unacceptable to treat the problem of processing accuracy insufficiently carefully in the conditions of computerized production, built according to the principle of «deserted work».

One of the promising ways to improve the quality of processing is to create and apply intelligent control systems for technological equipment that ensure the manufacture of parts taking into account the technical characteristics and condition of the machine, cutting tool, workpiece and information and measurement subsystem. Production systems should be equipped with intelligent modules in order to improve the quality of processing, increase the efficiency and reliability of production processes. In the field of diagnostics and control of the cutting process, such systems will also have the highest level of execution of the quality of the technological process.

Keywords. Tool, accuracy, wear, diagnostics, neural network.

Introduction.

The problem of diagnosing the condition of the cutting tool, with an assessment of its wear, remains relevant for many years. The issues of diagnostics and assessment of the condition of the tool have become more relevant, in connection with the computerization of machine systems and the equipping of production with multi-operational CNC machining centers. Since in the conditions of flexible automated production, metalworking processes in most cases assumed an automatic character, operators were removed directly from the working machines. In this regard, the problem of intelligent control of the state of processing centers and their components has become relevant.

Production systems should be equipped with intelligent modules in order to improve the quality of processing, increase the efficiency and reliability of production processes. In the field of diagnostics and control of the cutting process, such systems will also have the highest level of execution of the quality of the technological process.

The purpose of this article is to review the existing methods of intelligent analysis of systems for monitoring and diagnosing the condition of cutting tools.

Materials and methods.

In the modern world, it is necessary to use automated systems for monitoring and controlling the state of the cutting tool, with minimal human involvement.

The neural network has the ability to learn based on the input-output ratio, and also allows you to provide simpler solutions for complex management tasks. The neural network, unlike traditional adaptive control methods, does not use complex mathematical devices. Sigmoid activation functions of a neural network make it possible to implement nonlinear mappings and make networks suitable for solving nonlinear control problems.

The study was carried out with the involvement of the regression analysis apparatus, by evaluating existing methods of intelligent analysis of diagnostics of the state of the cutting tool.

Results.

In the approach to tool condition monitoring using the adaptive neuro-fuzzy inference system «ANFIS» in the paper the authors introduce the concept of the utilization factor of the installed sensor [1]. This coefficient is a function of the number of operational characteristics used by a particular sensor, the total number of sensor characteristics in the system and the number of physical sensor signals. The authors prove that the application of the installed sensor utilization factor is very effective in accounting for the reduction in instrument condition monitoring costs. This is especially noticeable when sensors that do not produce sufficiently useful signals are removed from the system. The cost analysis is calculated using the variable cost of the system: sensor replacement and installation costs.

The proposed approach consists of two main steps: first, a tool wear model was developed based on the ANFIS (Adaptive Network-based Fuzzy Inference System) module. A dataset obtained from real tests conducted during machining on a Heller milling machine equipped with a Kistler force sensor was used. The trained ANFIS tool wear model was subsequently run in conjunction with a neural network to estimate the tool wear state. Figure 1 shows the basic architecture of the proposed system.

It is a typical tool condition monitoring system that utilizes a sensor to collect cutting force signals during milling operations using a data storage module. The signal processing module analyzes the cutting process signals to extract characteristics sensitive to tool wear, which will be used as input values in a data evaluation based decision making system. The main purpose of the system is to compare the input features for the current tool state, i.e. to determine the total tool wear.

A multilayer perseptron neural network with error back propagation algorithm [1] is used as a solution for system learnability, noise suppression and parallel processing operations capability.

In developing the model, the authors adopted two different types of membership functions to analyze in training the ANFIS module and compared their differences with respect to the speed and accuracy of tool wear prediction by back face. After training the evaluation unit, its performance was tested under different cutting conditions. The performance of this method was found to be satisfactory for back face wear estimation, within 5% as average error percentage.

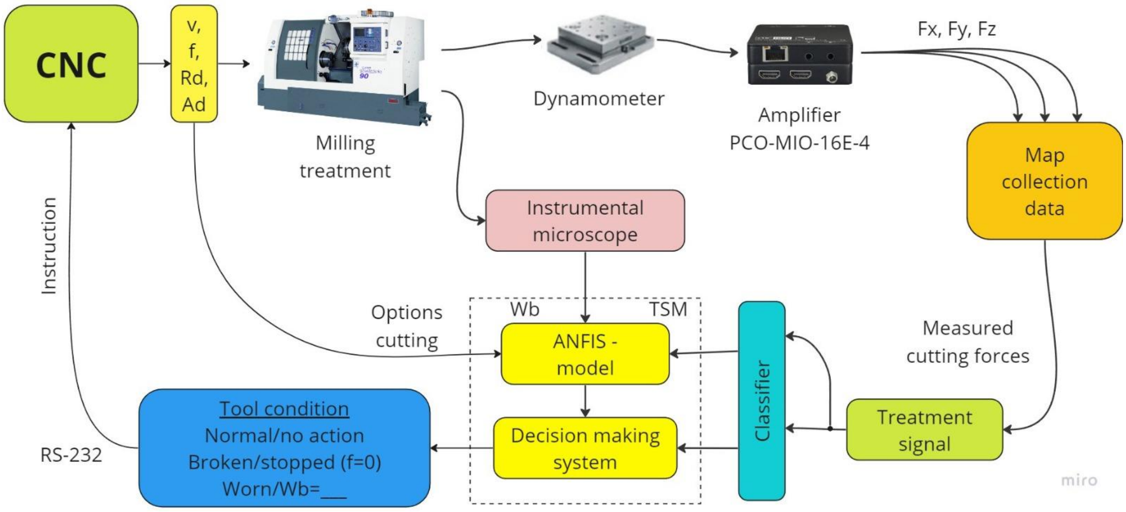

Figure 1 - System Architecture

The structure of the fuzzy logic inference system is a network that maps inputs through input membership functions and their associated parameters, and then, through output membership functions and their associated parameters, label the outputs. Figure 2 shows the architecture of ANFIS fuzzy rules, in the case of assuming a triangular membership function. The architecture presented in the figure consists of 31 fuzzy rules.

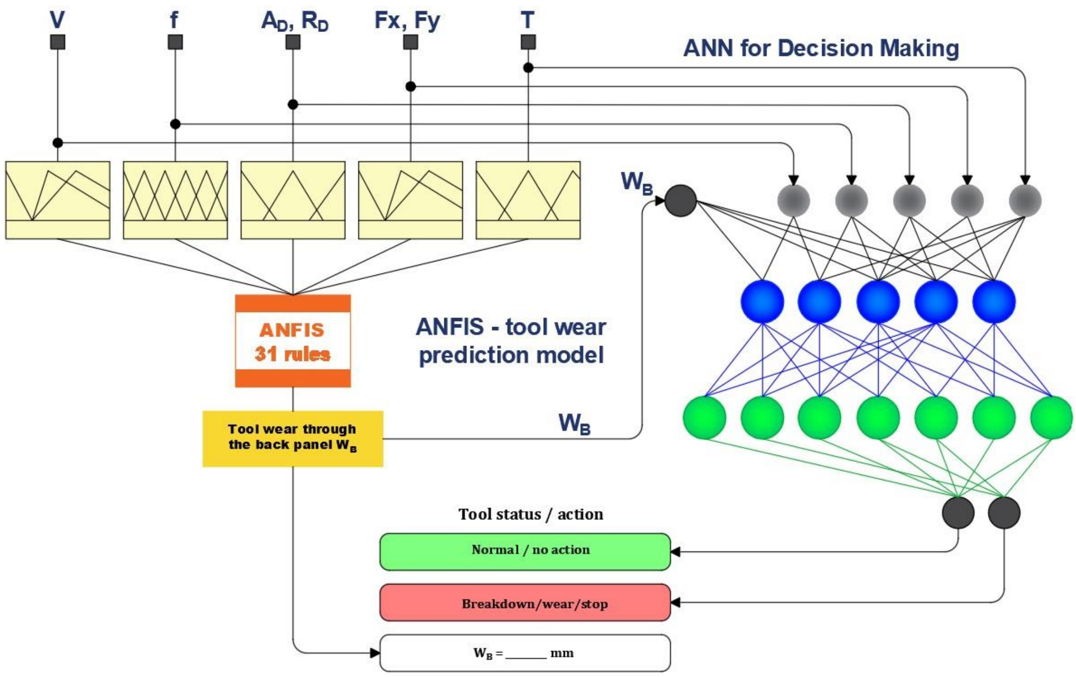

Figure 2 - Components of the tool condition monitoring system in the process of evaluation and decision making by an artificial neural network (ANN): V - cutting speed, m/min, f - feed, mm/min; A_D, R_D - axial and radial cutting depths, mm; Fx, Fy - cutting forces, T - cutting time, min

Experiments were conducted for all combinations of selected cutting parameters and tool wear [1]. The following cutting regime parameters were set: four feed rate levels (f_1 = 0.05; f_2 =

0.25; f_3 = 0.35; f_4 = 0.45 mm/tooth), four spindle speed levels (n_1 = 200; n_2 = 360; n_3 = 340 and n_4 = 480 min^{-1}) and three radial/axial depth of cut levels (R_{D1} = 1d, R_{D2} = 0.5d, R_{D3} = 0.25d; A_{D1} = 2, A_{D2} = 4, A_{D3} = 8 mm; d = 16 mm). Parameters such as cutting tool diameter, angle of inclination, etc. are taken as constants. The accuracy of the training set data was 98.1% and the accuracy of the tested data was 94.9%. The output node value of the back propagation neural network was observed as 0.01 for normal cutting condition and 0.99 for worn tool.
When the outputs of the neural network outputs fix the mark of 0.9 (tool breakage), the network sends «Tool worn» signal to the computer. When both outputs of the neural network have values below 0.9, the network sends the signal «Tool usable».

When the neural network outputs fix the mark 0.9 (tool breakage), the network sends the signal «Tool is worn out» to the computer. When both outputs of the neural network have values below 0.9, the network sends the signal «Tool usable».

Figure 3 a) and b) represent the cutting force signals for normal and worn tool. The developed neuro-fuzzy decision-making system includes fixed limits for tool breakage detection. The limits are: L1 (tool crack), L2 (tool fracture), L3 (tool wear) and L4 (no tool constraints)

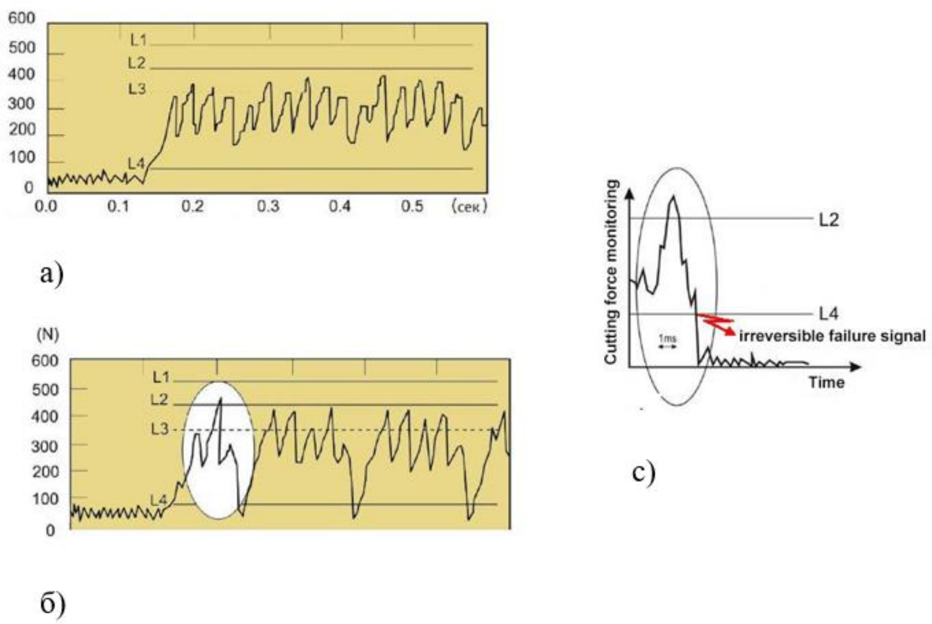

Figure 3 - Axial force of: a) normal and b) worn tool in real-time tool condition monitoring, c) indication of tool breakage with respect to force distribution limits.

The method outlined in [2] demonstrates the utilization of Mel-frequency cepstral coefficients for online assessment of cutting tool condition. Figure 4 illustrates the process of extracting these coefficients [3]. This involves defining parameters like the number of filters (Nf), sampling frequency (fHZ), amplitude of filter frequencies, and the filter set configuration (triangular or quadrilateral). Subsequently, the calculation of mel-frequency cepstral coefficients involves utilizing the inverse discrete cosine transform:

$$MFCC_i = \sqrt{\frac{2}{N_f}} \sum_{j=1}^{N} m_j \cos\left(\frac{\pi i}{N_f}(j - 0{,}5)\right) . \quad (1)$$

As a result, a seven-digit vector was obtained, where each digit corresponds to one parameter. The coefficients were calculated using the VoiceBox: SpeechProcessingToolbox block of the MatLab software package [3].

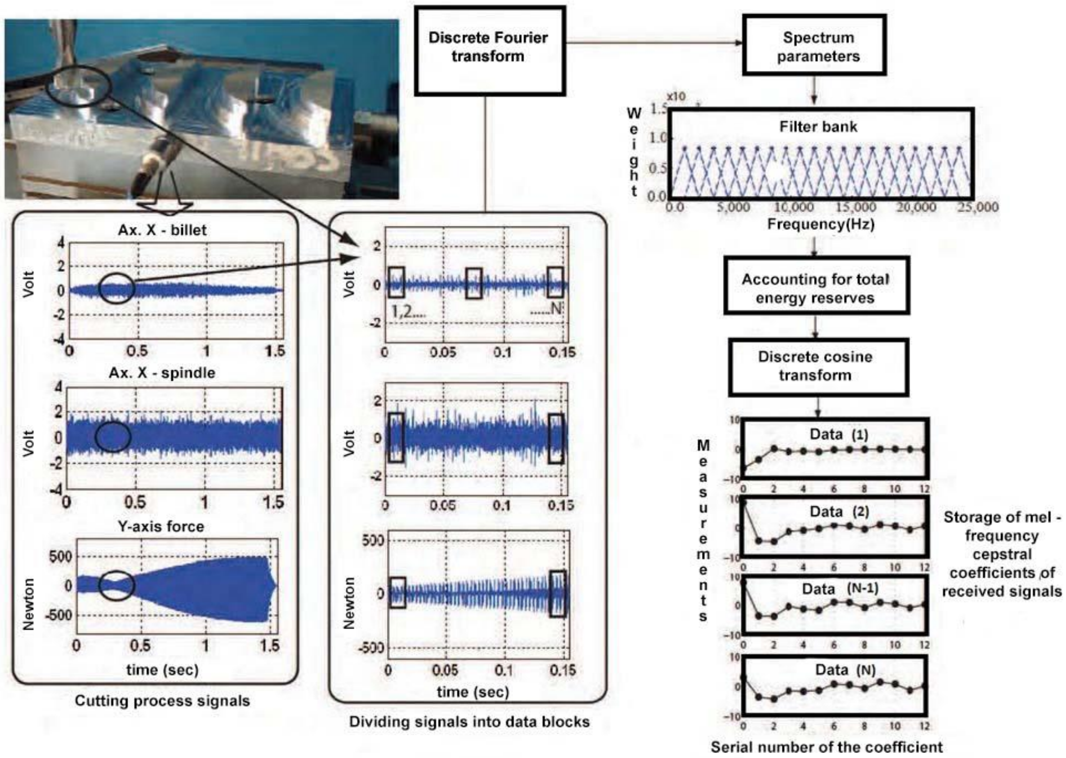

Figure 4 - Procedure for extraction of mel-frequency cepstral coefficients

To assess the cutting tool wear condition against traditional methods, a simulation of the diagnostic process was conducted employing an artificial neural network (ANN) model. The proposed system consists of twelve input neurons, one invisible layer consisting of twelve neurons, and one final neuron. As shown in Figure 5, the input neurons of the ANN model contain: data on tooth feed rate, tool size, radial therapeutic cutting, workpiece material strength, curvature, and the seven-bit MHCC vector.

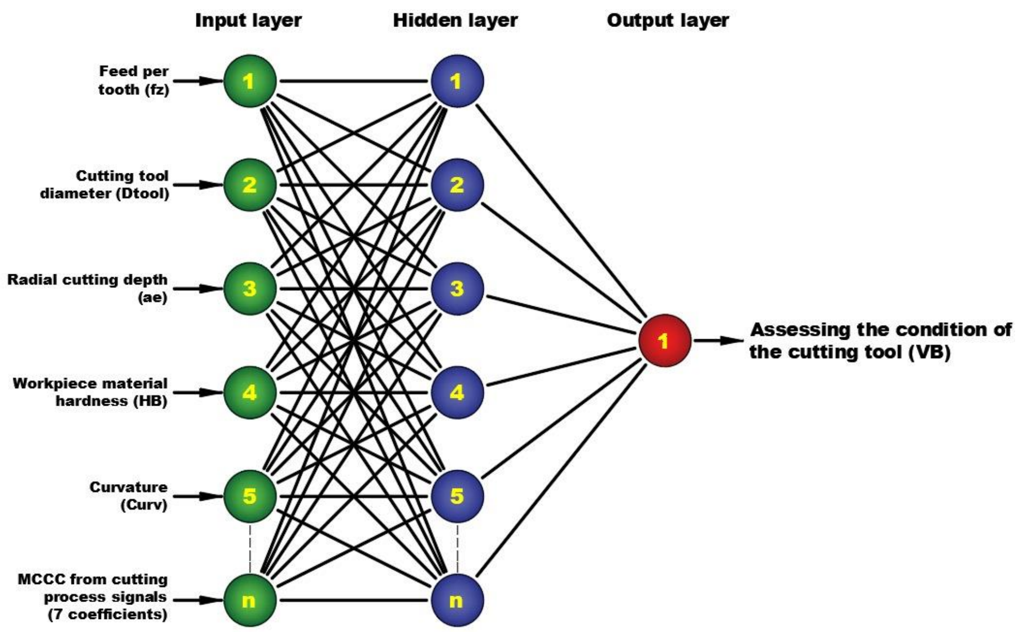

Figure 5 - An artificial neural network applied for real-time monitoring and assessment of cutting tool status

The ANN model was linked directly to the «tanh» (hyperbolic tangent) activation function and was trained using the backpropagation of error technique. For analysis purposes, the input information (fz, Dtool, ae, HB, Curv and MHCC vector) was determined between [-1, 1] using the input data matching tool. Normalization was applied to the entire range of experimental data to eliminate possible numerical instability. For data normalization, the mean value (μ) and the standard deviation (σ) in the following equation:

$$f_x = \frac{x-\mu}{\sigma} = \text{x} . \quad (2)$$

The bipolar sigmoidality method was used as the second normalizing method. This particular technique was used because the minimum and maximum values were unknown in real time. The nonlinear transformation prevented most values from clumping into the same ranges and also compressed the large samples of values obtained. The bipolar sigmoidal method was applied with the following equation:

$$f(\bar{x}) = \frac{1-e^{(-\bar{x})}}{1+e^{(-\bar{x})}} . \quad (3)$$

In relation to the output neuron (cutting tool state), these values were localized between normalized tool wear and worn tool state (Table 1).

Table 1 - Mapping of tool wear obtained from the ANN model relative to tool wear in the cutting process

Cutting tool wear condition	Normalized wear condition cutting tool
New	from +0,66 to +1,00
Slightly worn	from 0,0 to +0,66
Significantly worn	from -0,66 to 0,0
Critically worn	from -1,00 to -0,66

Diagnostics of cutting tools wear and prediction of their residual durability in real-time machining on CNC machines.

On the world market there are many diagnostic systems of leading manufacturers such as Montronix Gmb H, ARTIS, PROMETEC Gmb H, WILL-BURT, Eddyfi and others. The analysis and research of works allowed to reveal the following aspects, on which the attention of foreign experts is focused: the lack of solutions in the field of predicting the residual durability of cutting tools in the on-line mode; the frequent impossibility of flexible change of the diagnostic algorithm without changing the parameters of the system itself.

The dissertation work [5] is devoted to the solution of these issues. The author, on the basis of the analysis of the state of the issue, sets himself the task of building a model of functioning of the toolkit for diagnosing the state of residual resistance of the cutting tool in real time, as well as the development of algorithms for the construction of key components of the system.

It is also noted that during the performance of the work the author has defined diagnostic features, built a model of functioning of the toolkit diagnosing in real time the cutting tool and predicting its residual durability.

The author also provides a model of the developed system (Figure 6):

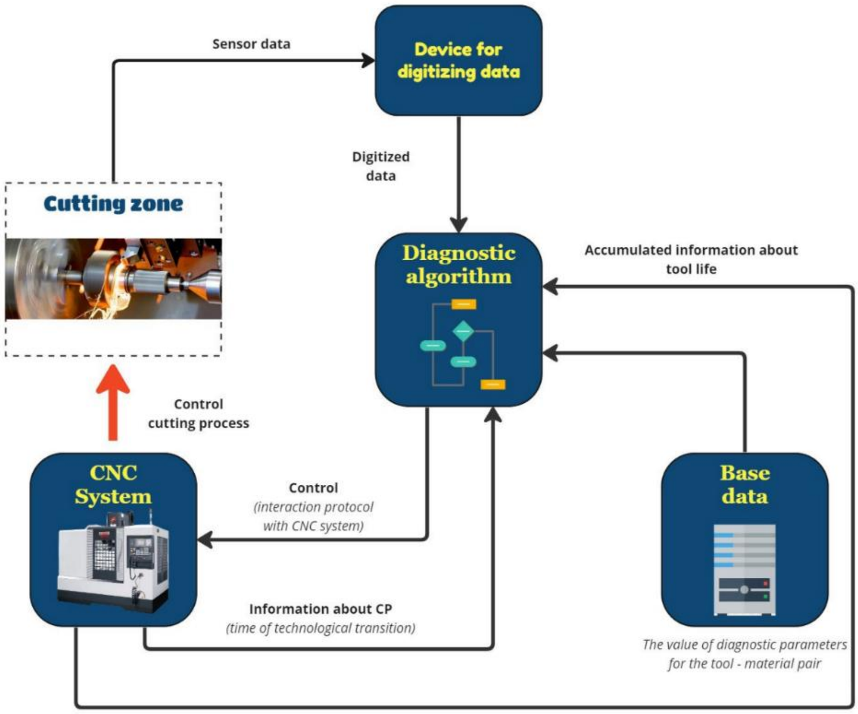

Figure 6 - Model of functioning of the diagnostic and forecasting toolkit.

Discussion.

The values representing the results of the artificial neural network model were calculated using ten different data sets selected in random order. The training and testing processes were realized using MatLab software package. The achieved outcomes pertain to 8 distinct ANN models, each sharing an identical structure but differing in their MFCC vectors. Mel-frequency cepstral coefficients were computed for various sources of signals from the metalworking process, including accelerometers, cutting forces, and acoustic emission. Table 2 displays the outcomes derived from different signals utilized in diagnosing the cutting process. These values represent the averages across ten datasets. The initial two columns delineate the performance based on accelerometers placed on the workpiece, the subsequent pair of columns represent accelerometers situated on the spindle, and the final two columns correspond to the AE acoustic emission sensors.

Table 2 - ANN models submitted for training and testing datasets

Data sets	Billet		Spindle		Cutting force, axis X	Cutting force, axis Y	AE-spindle	AE-billet
	Accelerometer - X	Accelerometer - Y	Accelerometer - X	Accelerometer - Y				
Training	90,2%	94,5%	97,8%	98,7%	94,2%	97,6%	99,9%	99,2%
Testing	31,3%	33,8%	40,4%	47,2%	48,5%	48,0%	89,9%	69,7%

The calculations are based on the reference values contained in the database. The commands generated by the diagnostic algorithm are sent to the CNC system for controlling the machine tool actuators [6].

The dissertation work [6] is also devoted to the issues of revealing the regularities of cutting tool wear. The author introduces such a value as the remaining service life:

$$\mathrm{T_{ост}} \leq [\mathrm{T_{ост}}] \ ,$$
(3)

where $\mathrm{T_{ост}}$ is the remaining serviceability resource, $[\mathrm{T_{ост}}]$ is the maximum allowable value of the remaining serviceability resource.

$$\mathrm{T_{ост}} = \mathrm{T_{р}} - \sum_{i=1}^{n} \tau_i , \quad (4)$$

where $T_{\text{р}}$ - cutting time before the cutting tool change, τi - cutting time when the tool performs the *i*-th technological transition.

The author notes that for maximum productivity it is desirable that $\tau i = [T_{\text{ost}}]$, then for the time T_p an integer number of parts is processed, the assigned resource is fully produced, and failure during the cutting operation is also prevented.

Also in [7], a universal coefficient *A* is introduced, which determines the dependence of the time to failure on the cutting speed:

$$V_{\text{рез}} = \frac{A}{T^m} \ , \quad (5)$$

where m is an indicator of the degree of influence of cutting speed on the time until failure.

The average time to failure (mathematical expectation) $\bar{T} = mT$ is taken as time *T*. From this point of view the author puts forward a proposal to estimate the cutting parameters as hypothetical diagnostic signs of the tool state by the criterion $\mathrm{H} = {}^{1}/_{\sigma}$, which is inversely proportional to the value of the standard deviation.

With reliable diagnosis of the inoperable condition of the cutting tool

At reliable diagnostics of inoperable state of the cutting tool the expectation expectation *mh*' increases approaching to the value *[h]* as the scattering *h'* decre 251ases. The measured value of the failure criterion [6] is taken as the value of h'. A smaller value of mh' relative to *[h]* leads to a decrease in the expectation of operation time to failure *mT*.

Conclusion.

At this time, the increasing attention of scientists is often focused on the application of neuro-fuzzy tool condition management systems, which are able to provide ease of operation when using, for example, simple fixed state limits to detect tool breakage. Despite the significant amount of research on this topic, the relevance of continuing research work in the direction of the problem of diagnosing the condition of cutting tools does not weaken, due to the demand and constant increase in the importance of research results in the field of machine-building production.

Application of methods and algorithms of intelligent machine control will allow to form estimates of the state of the machining system and the current state of the cutting tool, as well as, if necessary, to make corrections to the control program in order to increase the durability period of the cutting tool. This opens up the possibilities of a modern approach to the problem of tool condition diagnostics on the basis of self-learning and intelligent adjustment of the machine control system in the process of machining.

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ҚҰРАЛДЫҢ КҮЙІН ИНТЕЛЛЕКТУАЛДЫ ТАЛДАУ ӘДІСТЕРІН БАҒАЛАУ

Аңдатпа. Бұл мақалада кескіш құралдың күйін бақылау және диагностикалау үшін қолданылатын деректерді өндірудің заманауи әдістеріне шолу жасалады.

Металл кесетін станоктарды пайдалану кезінде сенімділікті, өнімділікті, жұмыс дәлдігін арттыру, бөлшектерді дайындау сапасын, сондай-ақ автоматтандыру деңгейін арттыру мәселелері өзекті болып қала береді. Осы факторлардың барлығы өңдеу процесінде машинадағы кескіш құралдың күйіне белгілі бір дәрежеде байланысты. Кесу құралы материалдарды өңдеудің дәлдігі мен тиімділігі шешуші болып табылатын өнеркәсіптік өндіріс салаларында маңызды рөл атқарады. Механикалық жабдықтың үздіксіз жұмысын қамтамасыз ету үшін кескіш құралдың жай-күйін бақылау және диагностикалау жүйелері өндірістік процестердің ажырамас бөлігіне айналады.

Өңдеу дәлдігі кез келген технологиялық жабдықтың маңызды сипаттамасы болып табылады, мысалы, сандық басқарылатын металл кескіш машина (СББ). Бөлшектердің дәлдігін арттыру машиналар мен жабдықтардың қызмет ету мерзімін ұзартатыны белгілі. Олар жұмыс процесінде пайда болатын динамикалық жүктемелерге байланысты оның құрамдас бөліктерін өндірудің жеткілікті дәлдігі болмаған кезде қалыпты жұмыс істей алмайды, бұл жабдықтың тез тозуына және одан әрі бұзылуына әкеледі. Металл кесетін станоктарда өңдеу қателіктерінің пайда болу себептері станоктардың, құрылғылар мен

құралдардың дәлсіздігімен, деформацияларымен және тозуымен, сондай-ақ кесу, қыздыру күштерінің әсерінен станоктарда жұмыс істейтін дайындамалардың деформацияларымен, өлшеу процесінде қателіктермен және т. б. байланысты.

Автоматты режимде өңдеуді жүзеге асыратын СББ машиналары үшін өңдеу дәлдігін анықтайтын параметр ретінде құралдың сапасына қойылатын талаптар айтарлықтай артады. «Қаңылтыр» принципі бойынша құрылған компьютерленген өндіріс жағдайында дәл өңдеу мәселесін мұқият қарастыруға болмайды.

Өңдеу сапасын арттырудың перспективалық жолдарының бірі - станоктың, кескіш құралдың, дайындаманың және ақпараттық-өлшеу ішкі жүйесінің техникалық сипаттамалары мен күйін ескере отырып, бөлшектерді дайындауды қамтамасыз ететін технологиялық жабдықты басқарудың интеллектуалды жүйелерін құру және қолдану. Өндірістік жүйелер өңдеу сапасын арттыру, өндірістік процестердің тиімділігі мен сенімділігін арттыру мақсатында интеллектуалды модульдермен жабдықталуы керек. Кесу процесін диагностикалау және бақылау саласында мұндай жүйелер Технологиялық процестің сапасын орындаудың ең жоғары деңгейіне ие болады.

Түйінді сөздер. Құрал, дәлдік, тозу, диагностика, нейрондық желі.

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ОЦЕНКА МЕТОДОВ ИНТЕЛЛЕКТУАЛЬНОГО АНАЛИЗА СОСТОЯНИЯ ИНСТРУМЕНТА

Аннотация. В данной статье представлен обзор современных методов интеллектуального анализа данных, используемых для мониторинга и диагностики состояния режущего инструмента.

При эксплуатации металлорежущих станков остаются актуальными вопросы повышения надежности, производительности, точности работы, повышения качества изготовления деталей, а также уровня автоматизации. Все эти факторы в той или иной степени зависят от состояния режущего инструмента на станке в процессе обработки. Режущий инструмент играет важную роль в сферах промышленного производства, где точность и эффективность обработки материалов имеют решающее значение. Для обеспечения бесперебойной работы механического оборудования, системы мониторинга и диагностики состояния режущего инструмента становятся неотъемлемой частью производственных процессов.

Точность обработки является важнейшей характеристикой любого технологического оборудования, например, металлорежущего станка с числовым программным управлением (ЧПУ). Как известно, повышение точности изготовления деталей увеличивает срок службы машин и оборудования. Они не могут нормально функционировать при недостаточной точности изготовления его составляющих частей в

связи с возникающими в процессе работы динамическими нагрузками, которые вызывают ускоренный износ оборудования и его дальнейшее разрушение. Причины возникновения погрешностей обработки на металлорежущих станках связаны с неточностью, деформациями и износом станков, приспособлений и инструментов, а также непосредственно с деформациями обрабатываемых на станках заготовок под действием усилий резания, нагрева, погрешности в процессе измерения и др.

Для станков с ЧПУ, выполняющих обработку в автоматическом режиме, значительно возрастают требования к качеству инструмента как параметра, определяющего точность обработки. Недопустимо недостаточно тщательно относиться к проблеме точности обработки в условиях компьютеризированного производства, построенного по принципу «безлюдной работы».

Один из перспективных путей повышения качества обработки заключается в создании и применении интеллектуальных систем управления технологическим оборудованием, обеспечивающих изготовление деталей с учётом технических характеристик и состояния станка, режущего инструмента, заготовки и информационно-измерительной подсистемы. Производственные системы должны быть оснащены интеллектуальными модулями, в целях повышения качества выполнения обработки, повышения эффективности и надежности производственных процессов. В области диагностики и контроля процесса резания такие системы также будут иметь наиболее высокий уровень исполнения качества технологического процесса.

Ключевые слова. инструмент, точность, износ, диагностика, нейросеть.

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