Intelligent Platform for CNC Machines Based on the E-mind Machine Concept

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Abstract: his article covers the actual issues that rise up the trend of computerized integrated production. The large number of machining tools for production of a specific workpieces requires a principally new approach to the control of such production. In such type of industrial information, monitoring and control systems replace the human operator. Therefore machining systems state monitoring becomes essential today in control of the machining operations. The concept for E-Mind Machine intelligent platform for the CNC machining tools is presented in this paper and the detailed information on its structure and components is given.

Keywords: E-Mind Machine; CNC; multifunctional machine tools; tool monitoring; machine tool state; knowledge systems.

1. Introduction.

In addition to traditional research directions, such as increasing the geometric, kinematic, dynamic accuracy of machines, minimizing the influence of temperature deformations, etc., more attention is paid to providing high quality processing by introducing intelligent control systems (ICS) based on various methods of data mining, expert systems, and neuron-fuzzy systems. The machine, equipped with such intellectual tools, becomes a technological object endowed with self-organization, which allows achieving better processing quality, in comparison with traditional approaches. The basis for constructing possible conclusions in the performance of decision-making functions is the inherent experience and experience accumulated by the intelligent control system in the process of operation.

One of the areas of intellectualization of control is the formation of knowledge of the machine about its state, the features of dynamic, thermal phenomena, as well as the specifics of the processes that occur during the processing of workpieces. The basis for creating such a system of knowledge can serve as the development of intellectual documentation of machines based on generally accepted world approaches to the electronic documentation of science-intensive products.

This approach is based on the unified accounting and analysis of existing data on the technological facility, which are inherited characteristics of the traditional technical documentation of the machine, as well as dynamic data representing operational data of the machine, obtained from various hardware and software monitoring of the state of the technological facility during processing. A key feature of the approach is the intelligent analysis of the inherited and operational characteristics of the machine and processing and the derivation of non-trivial solutions based on them. The originality of the information shell approach lies in the use of modern documentation capabilities, while the difference

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from the known approaches is due to the use of the electronic technical documentation system with a subsystem of data mining and synthesis of machine management solutions. These features are directly used to improve the precision of the workpiece.

For the first time a knowledge system of the machine in the form of a set of databases and knowledge bases was created and software was implemented as an information and control module. This allows to take into account the specificity of technological equipment, to perform a unified accounting of data on its condition and to analyze data obtained during operation.

The set of factors, or the observed input influences $X^*(t)$, affecting the general error $Y^*(t)$, depending on the possibility of obtaining knowledge of them can be represented as a set (1) from the "inherited" set H and the "operative" sets O:

$$\begin{cases} X^* = (X^*_h, X^*_o), \\ X^*_h = (x^h_1, x^h_2,\dots,x^h_m); \\ X^*_o = (x^o_1,x^o_2,\dots,x^o_n). \end{cases} \qquad (1)$$

The inherited set X^*_h means the collection of m factors, knowledge of which is obtained with the acceptance or test measurements, and the set of n factors, measured directly during processing, is assigned to the operational set X^*_o. One of the reasons for dividing the factors into inherited and operational factors is the limited ability to obtain operational information from control devices directly in the processing the workpiece. Operational factors include, for example, displacement errors, inaccuracy of the smallest nominal displacements of the working element with successive discrete movements, drive errors, changes in the working stroke during machining.

In the own knowledge system of the machine, in addition to the data base, the error factors include sets of decision rules for various processing situations, processing types and required parameters for the accuracy of the finished workpiece. Situation assessment and decision making are performed by a multi-level ICS. The program for the synthesis of solutions by the number and parameters of passes is determined on the basis of inherited and operational data and knowledge. The functions of this management system include predicting the accuracy of processing, making decisions and action programs, comparing forecasts with the results of workpiece processing and accumulating knowledge.

2. E-Mind Machine concept.

The module is based on decision making in the manufacture of a product taking into account the emerging concrete situation and implements the following sequence of actions:

1. Assessment of the situation by the behavior of the control object, the process technology and the result of the process (possibly by stages);
2. Correction of the criteria bases and terminal conditions;
3. Simulation and re-planning of the program of movements;
4. Correction of the method for regulating the movements of working organs.

The creation of an intelligent machine module - e-Mind Machine in the CNC Unit or among the supporting services in the form of an on-board intelligent control system is an important step towards the formation of a single operating, programming and maintenance environment for multi-operation machines and other process equipment at various enterprises and from various manufacturers.

The basis of the intelligent platform of the e-Mind Machine module is the knowledge system, which includes a set of the following blocks: Processing, Machine state, Tool, Workpiece and Information exchange (**Figure 1**) [1]. The developed approach creates the possibility of controlling multi-operational machines by direct correction in the CNC Unit due to information and intelligent support on the basis of its own knowledge base about the state of the elements of the machine system [2-3].

3. Processing block.

Knowledge system uses various methods of data mining, including fuzzy sets, fuzzy logic and neural network algorithms [4]. The most important unit of the module is the Processing. The task of improving the technological quality of the machine (productivity and precision of machining), which solves, necessitates the planning of control operations for the product states $C_p(U)$ and for subtasks in the state space of the technological system (TS) [5]. The expedient transformation of situations is inextricably linked with the change in the states of the TS, the transitions between which are determined by the permissible control actions that multi-operational machines possess.

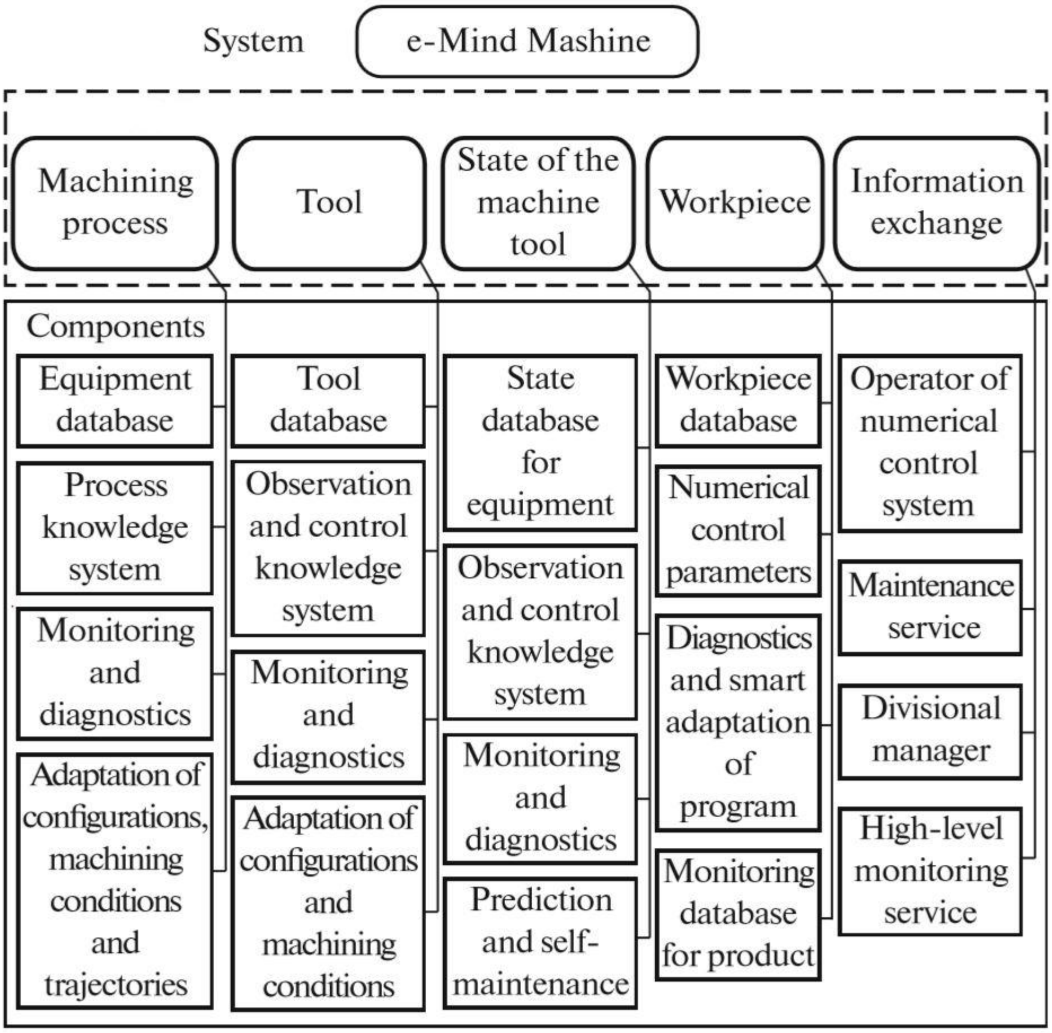


Figure 1. Structure of the e-Mind Machine module

If it is necessary to use the methods of intellectual control of the knowledge system, a search is made for a set of control solutions that ensure the conversion of a hypothetically identified state space (based on expert representations, inherited and operational parameters of the knowledge system) to a given result. This search (2) is carried out based on an analysis of knowledge about the functional capabilities of a particular machine as an individual:

$$C_p^* C_p\ (\mathrm{u}, \mathrm{U}, C_{pg}, C\ _p\ ) : C_p^* \Rightarrow C_{pg} \quad (2)$$

where Cp* is the hypothetically identified class of product states; Cpg, Cp - the target state and the total set of product states; U, u - the set of control actions and synthesized control.

This approach allows us to formulate some plausible hypothesis about the organization of expedient behavior of the TS [6].

Microprocessor systems for automatic monitoring, diagnostics and information management on the state of equipment are being created at advanced enterprises for working in production conditions.

The problem of developing a conceptual approach was not only the implementation of traditional rules for maintenance and repair of production equipment, but also automated autonomous control of its technical state.

The following wording of the concept of autonomous control is proposed for the technical state of machine tools: an independent automated control that performs targeted signaling and influence a particular machine component to maintain or restore its operability by means of special tools based on an assessment of its condition, role and connection with other devices of the system.

One of the variants of the methodology of the approach to the analysis of processes in objects and to the synthesis of solutions for autonomous control are the methods of artificial intelligence and intellectual control, including fuzzy sets theory and fuzzy logic.

The fuzzy causality of the assumptions and conclusions on the procedure for managing the state (3) is represented in the form

$R^* = A \rightarrow B,$ (3)

where A and B are the phase spaces of the observed and target / desired state as a whole.

The process of obtaining the result of fuzzy inference on control Y using the observable data X on the technical state and knowledge of $A \rightarrow B$ (4) is represented as:

$У = X \times R^* = X \times (A \rightarrow B)$ (4)

In the general case, the control of the state of the controlled object in the representations of fuzzy sets (5) has the form:

$Y = R(X)$(5)

$X = \{X_1, X_2, \ldots, X_n\}$ – set of observed data of input state variables.

$Y = \{Y_1, Y_2, \ldots, Y_m\}$ – set of control parameter vectors by the set of adjustable parameters in components and devices for automatic maintenance of the operability of the controlled object in general, as well as commands for performing the corresponding actions by the operator;

R is a fuzzy transition / transformation operator in machine control system.

On the basis of the resulted generalized representations the structure of system and function of independent management by a technical condition of machine tools with CNC are designed.

4. Machine state block.

The Machine state is the following important module of the E-Mind Machine concept. In the structure of the system of autonomous control of the state of the machine, the signals from the state sensors of the devices and the signals to the actuators of these devices come through the distributed control nodes by the technical state of the devices of the machine. These nodes are connected to the central node of the autonomous control of the central control unit of the system of autonomous control of the state of the machine, which performs the processing of signals about the state, assessment of states, making decisions on expedient actions to maintain the operability. In addition, each node performs signaling functions, visualization of device states, monitoring of state changes, criticality analysis, archiving, communication with the CNC Unit and external services of the computing system. The information connection of the machine through the computation system with external equipment maintenance and repair services and control structures is provided in accordance with the capabilities of e-Mind Machine [7].

A generalized assessment of the effectiveness of the autonomous control of the EAC (efficiency autonomous control) state in accordance with ISO 13381-1: 2004 [8] of a device or machine is generally represented using the following criteria (**Figure 2**):

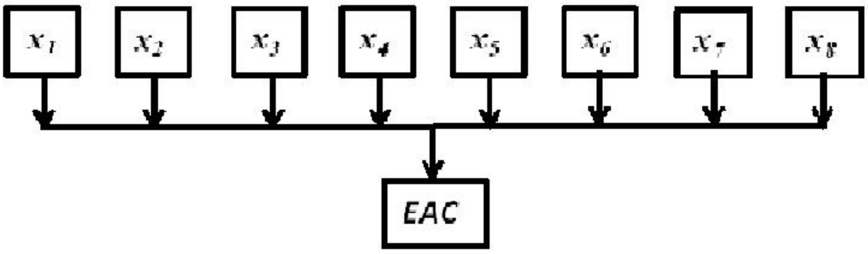


Figure 2. Evaluation of the effectiveness of autonomous control of technical condition

x_1 - the effectiveness of monitoring states, including the assessment of the weight / importance of technological violations;

x_2 - assessment of the degree of degradation of the state, incl. by gamma-percentage resource or proximity to the boundary condition;

x_3 - costs for restoration of operability by the operator;

x_4 - the cost of restoration of serviceability by PTP services;

x_5 - the level of autonomy of the device or machine as a whole;

x_6 - the level of equipped with means / devices for automated troubleshooting (correction of states);

x_7 - reliability of the systems of autonomous state control;

x_8 - the cost of systems for autonomous state control.

The method of estimating EAC using a neural network with 8 inputs (**Figure 3**) was used. As the learning algorithm, the Levenberg-Marquardtas algorithm was chosen to estimate the root-mean-square error of the deviations of the derivative outputs of the network from the standards. This algorithm provides rapid network training.

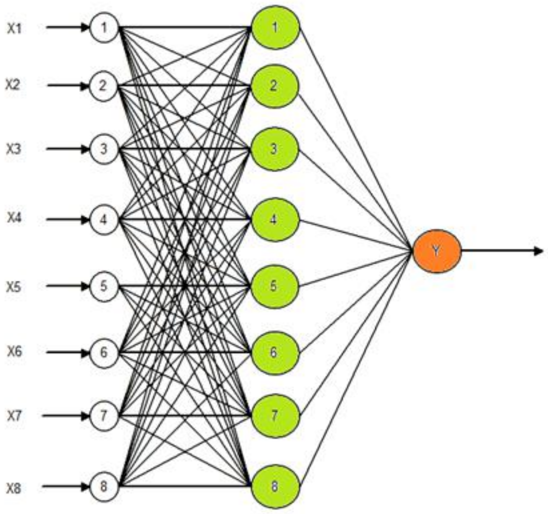


Figure 3 - Structure of a neural network for assessing the autonomy of state control.

The results of the assessment of the effectiveness of the autonomy of control by the technical condition will help to develop recommendations for the retrofitting of the machine by means of implementing the technical state management system, improving the reliability of the machine and optimizing costs, while achieving the required level of autonomy.

To perform the procedures and obtain the results of diagnostics of operational data, the submission of commands to the appropriate machine modules, a system for identifying the tool state based on the analysis of the acoustic emission signal is proposed. The identification system structure shown in **Figure 4.**

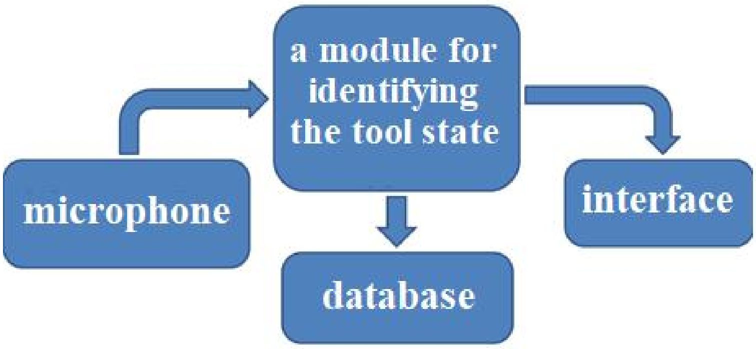


Figure 4. The tool state identification system structure

5. Tool block.

The other important module of E-Mind Machine concept is Tool. To obtain information about the tool state of a multi-operation machine in real time, the technique of streaming and frame-by-frame signal processing used. Sampling frequency selected in accordance with the research [9], the dependences between the oscillation frequency and the sources of the vibration spectrum dominant frequencies are presented in Table 1.

Oscillation frequency	Source of the dominant frequency of the spectrum of oscillations
70 – 90 Hz	workpiece – subsystem of the machine table
395 – 405 Hz	spindle – cutting tool
10 – 12 kHz	holder in two different harmonics
15 – 16 kHz	tool cutting part

Table 1. Dependence of the spectrum frequency harmonics of vibro-acoustic oscillations from the source

The experimental research was carried out in the same way as [10-11] on the multi-operation machine Okuma MB-46 VAE. The multi-operation machine was additionally equipped with a PC with database software and a knowledge system of the «e-Mind Machine» module. Recording is performed using a microphone with a sampling frequency of 20 kHz and a frame size of 20 kHz., which is one of the components of the electronic measuring system Navi Machining of the multi-operation machine Okuma MB-46 VAE.

The input signal is represented as a special property vector. The system uses the classical approach of cepstral coefficients, the algorithm of calculation of which could be divided into 3 stages:

1. Calculation of the spectral power density.

The dependency (6) is used:

$$\hat{S}_d(a,k) = \left|\sum_{j=0}^{N-1} w(j)s(a,j)e^{-\frac{2\pi ik}{N}}\right|^2, \qquad (6)$$

where:

$k \in \{0, 1, \ldots, K-1\}$ – frequency interval number;

N – frame length;

$s(a,j)$ – sound signal in the time domain;

$w(j)$ – window function in the time domain.

Graphically, the function of the power spectrum density shown in **Figure 5.**

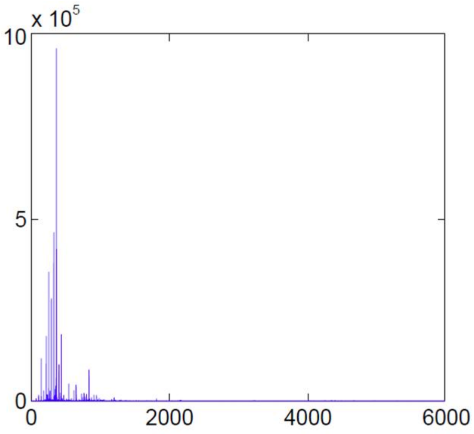


Figure 5. Spectrum power density of the frame signal

2. Calculation of signal energy in the mel-filter windows.

Each mel-filter is a triangular window function that allows to estimate the energy of the spectral components over a certain frequency range and thereby obtain a mel-coefficient.

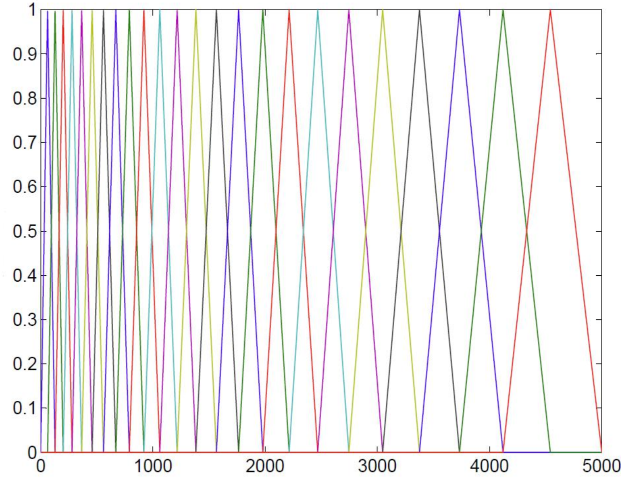


Figure 6. Mel-filters

The number of mel-coefficients is assumed equal to 24, and the frequency range being analyzed is 0 ÷ 5000 Hz. The greater the order number of the mel-coefficient, the wider the base of the filter, the division of the frequency range into the ranges processed by the filters occurs on the mel-scale.

You can convert the value of the sound frequency (Hz) into a height value (mel) (7) using the following relationship:

$m = 1127 * \ln(1 + f/700)$;(7)

To construct 24 triangular filters, 26 reference points were required, evenly distributed over the entire range of mel values (8). The inverse transformation performed in accordance with the expression:

$f = 700(e^{m/1127} - 1)$;(8)

Knowing the values of the reference points, we can construct triangular mel-filters, guided by the following dependencies (9):

$H_m(k) = \begin{cases} f(m)-f(m-1) \\ f(m+1)-k \end{cases}$,(9)

The energy of the signal entering each of the filter windows (10) was calculated:

$$S(m) = ln\left(\sum_{k=0}^{N-1} \hat{S}_d(a,k)H_{\mathrm{m}}(k)\right), \quad 0 \leq m < M \qquad (10)$$

The resulting set of values is the mel-frequency spectral coefficients. Graphically they are presented in **Figure 7.**

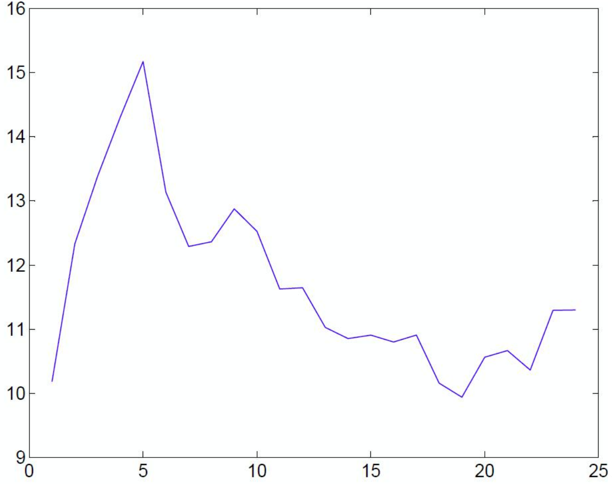


Figure 7. Mel-frequency spectral coefficients

To reduce the number of output parameters and decorrelation of the components, the last stage of calculating the cepstral coefficients performed.

3. Calculation of cepstral coefficients of the signal.

To obtain from the mel-frequency cepstral spectral coefficients, it is necessary to use a discrete cosine transformation (11):

$$c(n) = w(n) \sum_{m=1}^{M} S(m) \cos\left(\frac{\pi(n-1)(m-0{,}5)}{M}\right), \quad n = 1, 2, \dots N \qquad (11)$$

where:

m – is the number of filters;

n – is the number of cepstrum;

$$w(n) = \begin{cases} \frac{1}{\sqrt{N}} & n = 1 \\ \sqrt{\frac{2}{N}} & 2 \le k \le N \end{cases}. \qquad (12)$$

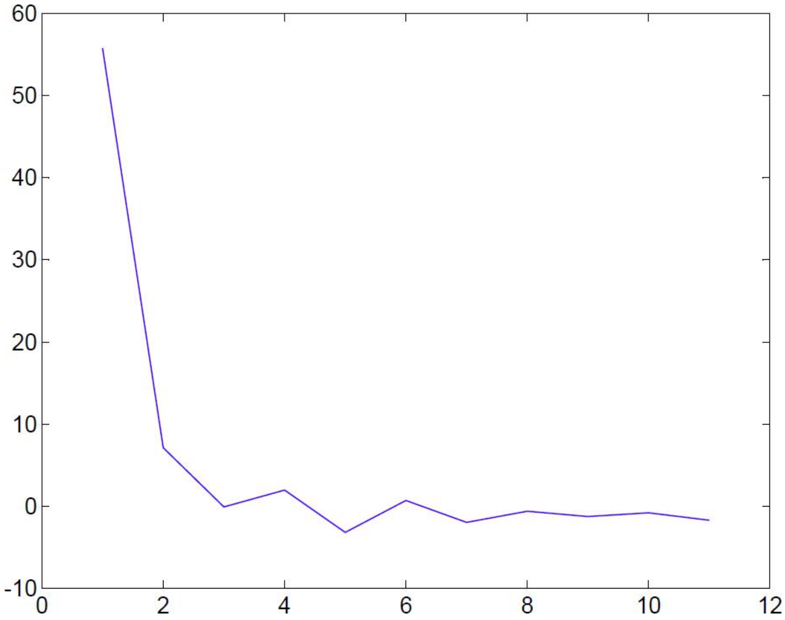


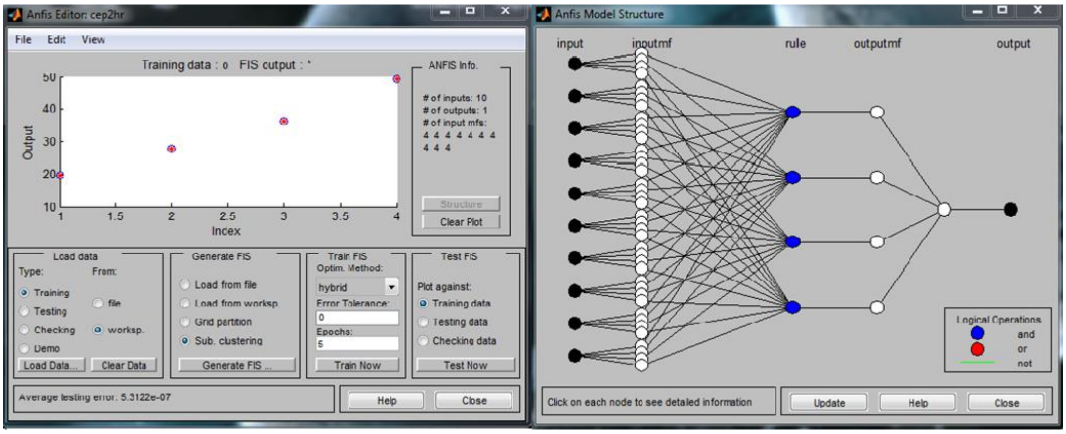
Figure 8. mel-frequency cepstral coefficients

The cepstral coefficients of the acoustic emission signal for each tool calculated at time points of 10, 25, 40 and 55 minutes. The average values of the cepstrum relative to the radial tool wear is shown in Table. 2.

Time, min.	10	25	40	55
Cepstral coefficients	9.5717	7.8478	6.7801	9.2595
	-1.9867	-8.2481	-7.5451	-7.5367
	2.105	4.5492	8.0612	10.594
	-5.9512	-6.9184	-7.3038	-8.8302
	0.94537	2.5981	4.6	5.5711
	-4.1483	-3.6609	-5.5595	-6.3928
	-0.58857	-0.056524	-0.66557	1.2965
	-3.1204	-4.2262	-4.3054	-6.1083
	-0.81463	1.535	2.6373	3.185
	-3.0483	-2.9674	-4.4281	-5.2095
Radial wear, micron	19,6	27,87	36,33	49,27

Table. 2. Values of the cepstrum relative to the radial cutting tool wear.

Identification of the cepstral coefficients values to the radial tool wear carried out using the adaptive neuro-fuzzy inference system (ANFIS) (**Figure 9**), where the cepsters values correspond to the radial wear value. The training sample is a matrix, each line of which is an input-output pair. The last column of the matrix corresponds to the vector of output values - the values of radial wear, and all the other columns - to the input data - the values of the cepstral coefficients.



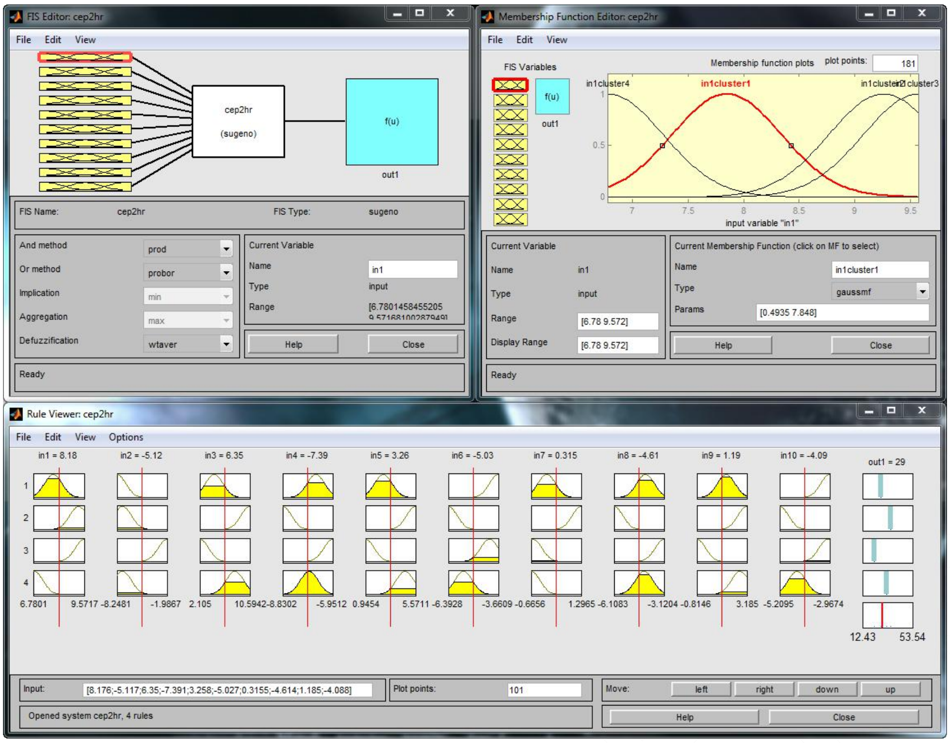
# of inputs: 10
# of outputs: 1
# of input mfs:
4 4 4 4 4 4 4
4 4 4

Type: ● Training ○ Testing ○ Checking ○ Demo
From: ○ file ● worksp.
○ Load from file ○ Load from worksp ○ Grid partition ● Sub. clustering
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 5
Plot against: ● Training data ○ Testing data ○ Checking data
Average testing error: 5.3122e-07
Click on each node to see detailed information

Figure 9. Adaptive Neuro-Fuzzy Inference System (ANFIS)

As an initial system of fuzzy inference, whose membership functions will be tuned using ANFIS, a fuzzy first-order Sugeno model with four rules is synthesized, using subtractive clustering. To train the model, a hybrid optimization method is used, using the method of back propagation of the error (steepest descent method) to configure the membership functions of the input variables and the least squares method to find the coefficients of the linear functions linking the inputs and outputs in each rule.

The resulting tuned fuzzy logic output system (**Figure 10**) is used to estimate tool radial wear.



FIS Name: cep2hr

FIS Type: sugeno

And method: prod

Or method: probor

Implication: min

Aggregation: max

Defuzzification: wtaver

Current Variable

Name: in1

Type: input

Range: [6.7801458455205 9.571681002879491]

Ready

plot points: 181

Current Variable

Name: in1

Type: input

Range: [6.78 9.572]

Display Range: [6.78 9.572]

Current Membership Function (click on MF to select)

Name: in1cluster1

Type: gaussmf

Params: [0.4935 7.848]

Ready

in1 = 8.18, in2 = -5.12, in3 = 6.35, in4 = -7.39, in5 = 3.26, in6 = -5.03, in7 = 0.315, in8 = -4.61, in9 = 1.19, in10 = -4.09, out1 = 29

6.7801 9.5717 -8.2481 -1.9867 2.105 10.5942-8.8302 -5.9512 0.9454 5.5711 -6.3928 -3.6609 -0.6656 1.2965 -6.1083 -3.1204 -0.8146 3.185 -5.2095 -2.9674

12.43 53.54

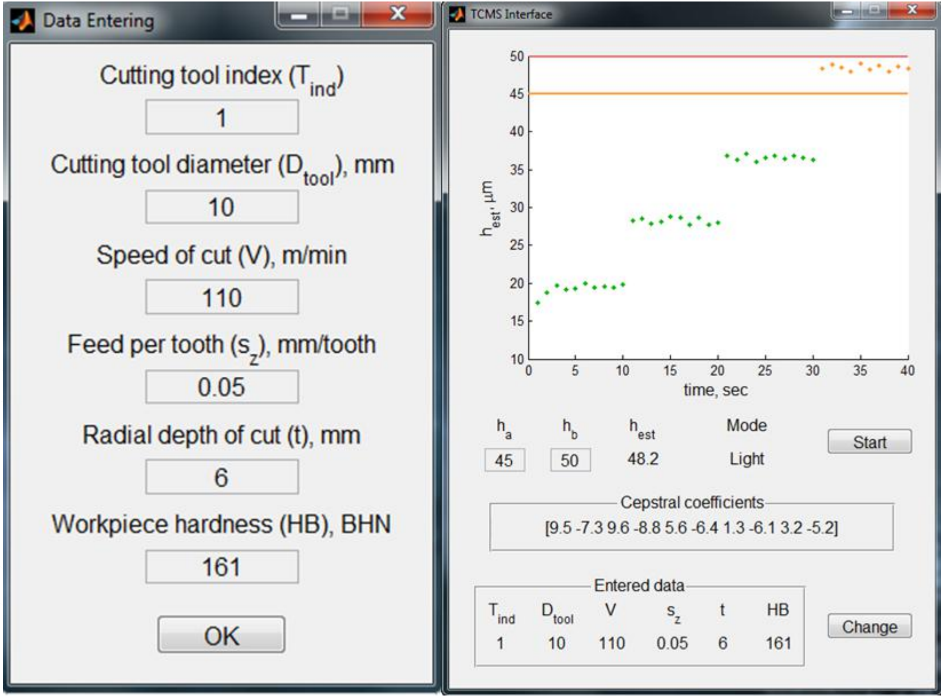
Input: [8.176;-5.117;6.35;-7.391;3.258;-5.027;0.3155;-4.614;1.185;-4.088]

Plot points: 101

Opened system cep2hr, 4 rules

Figure 10. Structure of the fuzzy logic inference system

Entering the parameters of the processing mode done in the data entry window of the interface of the tool state monitoring system (**Figure 11**).



Cutting tool index (T_{ind}): 1

Cutting tool diameter (D_{tool}), mm: 10

Speed of cut (V), m/min: 110

Feed per tooth (s_z), mm/tooth: 0.05

Radial depth of cut (t), mm: 6

Workpiece hardness (HB), BHN: 161

OK

h_a	h_b	h_{est}	Mode
45	50	48.2	Light

Cepstral coefficients

[9.5 -7.3 9.6 -8.8 5.6 -6.4 1.3 -6.1 3.2 -5.2]

Entered data

T_{ind}	D_{tool}	V	s_z	t	HB
1	10	110	0.05	6	161

Figure 11. Tool state monitoring system interface

After input, the data enters the main interface window of the tool state monitoring system implemented with the MatLab software package. The entered data is displayed in the main interface window. The active "Change" button brings up the data entry window, allowing to change the entered parameters. The remaining fields remain empty until the Start / Stop button is activated. When the button is pressed, the microphone is turned on. Streaming and frame-by-frame processing of a signal with a sampling frequency of 20 kHz and a frame size of 20 kHz is performed. At the signal of each frame, the cepstral coefficients are calculated and the radial wear is estimated, which are then displayed in the fields "cepstral coefficients" and "h_{est}", respectively. During the operation of the system, it is possible to set the values of the initial (h_a) and final (h_b) points of the boundary strip, within which the probability of intense wear and subsequent tool breakage increases. To avoid tool breakage during the technological transition, the system recommends changing the cutting mode to an easier one when the starting point of the border strip is reached and stopping the machine when the end is reached. The recommendations are displayed in the "Mode" field. Recommendations for cutting modes based on the following algorithm:

When working up to the border:

$(h_{est} < h_a)$ – according to the program of the CNC Unit (unchanged);

When operating within a border:

$(h_a \leq h_{est} < h_b)$ – light;

When working after a border:

$(h_b \leq h_{est})$ – stop.

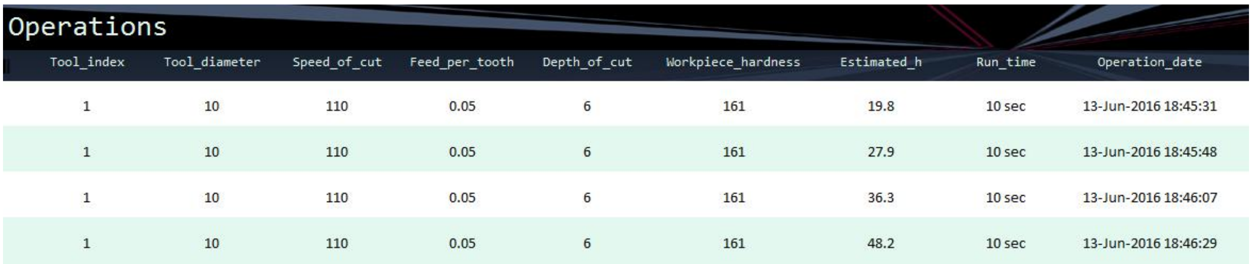
Repeated pressing of the switch-button stops the system operation and sends the entered data, the radial wear estimate, the tool running time and the end date of the transition to the database.

Each sound signal corresponding to time points of 10, 25, 40 and 55 minutes was recognized within 10 seconds. The results shown in Table 3.

Time, min.	10	25	40	55
Evaluation of radial wear values h_r, micron	17,5	28,2	36,9	48,2
	18,8	28,5	36,4	48,8
	19,7	27,8	37,2	48,4
	19,2	28,1	36,1	47,8
	19,3	28,8	36,6	48,9
	20	28,6	36,9	48,1
	19,5	27,7	36,5	48,6
	19,6	28,6	36,9	47,8
	19,5	27,7	36,6	48,5
	19,9	28	36,4	48,2
The predicted value of radial wear h_r, micron	19,6	27,87	36,33	49,27
Accuracy of measurements, %	98,47	98,82	99,12	98,09

Table 3. Statistical sampling of experimental research results

The tool state monitoring system after the shutdown sends data to the database (**Figure 12**) implemented in the Microsoft Office Access 2007 database management system via the JDBC-ODBC (Java Database Connectivity).



Operations

Tool_index	Tool_diameter	Speed_of_cut	Feed_per_tooth	Depth_of_cut	Workpiece_hardness	Estimated_h	Run_time	Operation_date
1	10	110	0.05	6	161	19.8	10 sec	13-Jun-2016 18:45:31
1	10	110	0.05	6	161	27.9	10 sec	13-Jun-2016 18:45:48
1	10	110	0.05	6	161	36.3	10 sec	13-Jun-2016 18:46:07
1	10	110	0.05	6	161	48.2	10 sec	13-Jun-2016 18:46:29

Figure 12. Database of the tool state monitoring system

The developed database stores information about tools that allows you to clearly determine when, what, how much time and under what cutting conditions the tool worked. Also, the database contains information on estimating the radial wear of the cutting tool, which the system provides before shutting down.

6. Conclusion.

In the course of the experimental investigation, the following results of indications of vibro-acoustic emission during the processing were obtained (**Figure 13**).

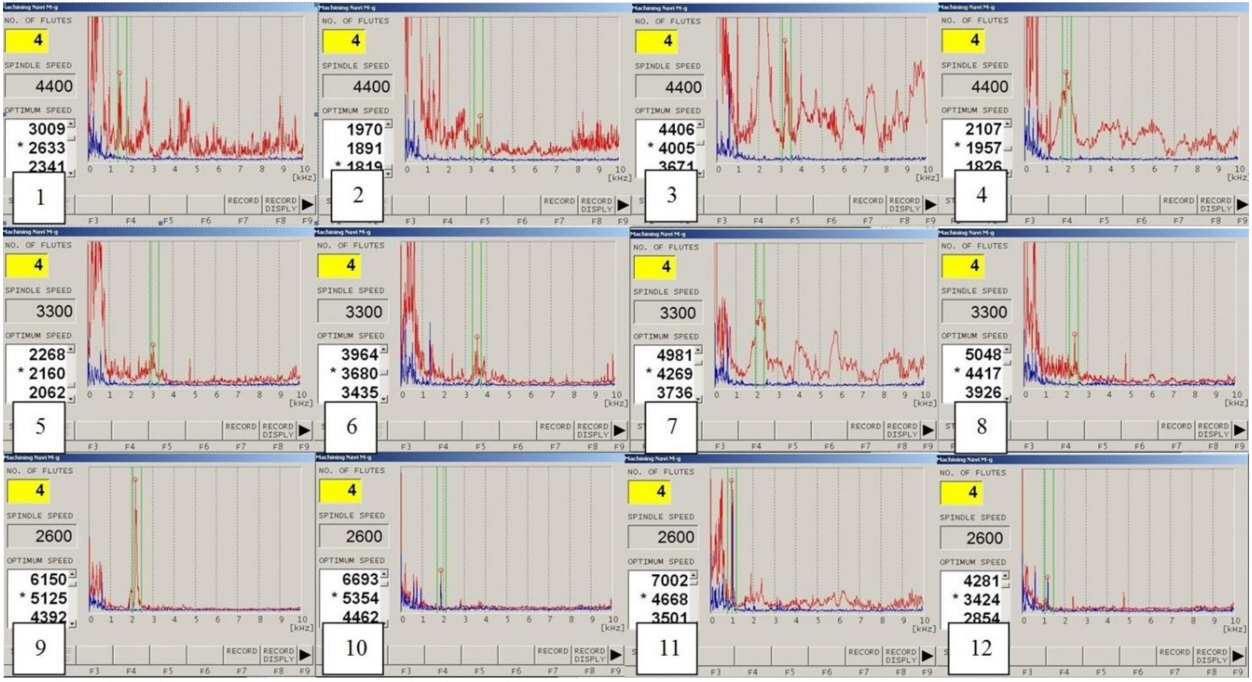


Figure 13. Results of indications of vibro-acoustic emission during processing

The results of scanning the surface after machining each of the cutters with the passing and counter milling are presented, both without correction of the control program, and with application of correction, including the scanning data of the initial surface and the deviation of the values of the resulting surface from the given one. **Figure 14** shows a graph representing the heredity of the allowance when counter-cutting and passing milling with Ø 6mm, 8mm and 10mm cutters, respectively, before and after application of the control program correction.

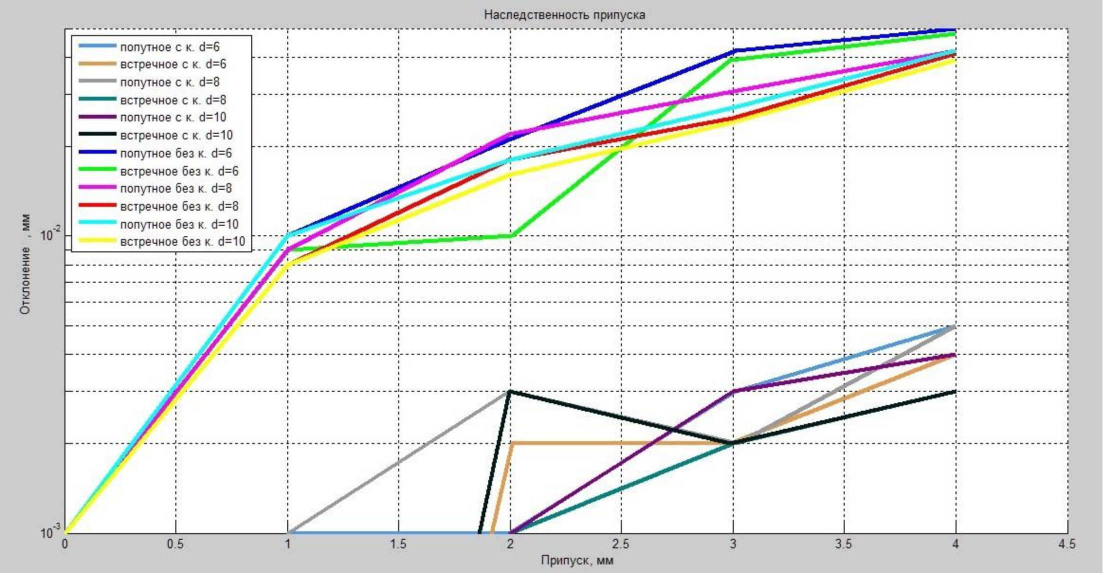


Figure 14. Heredity of the allowance for passing and counter milling before (without c.) and after (with. c) application of the correction

The use of corrective coefficients derived by the knowledge system makes it possible to increase the accuracy of processing and reduce the influence of the heredity of the allowance from ± 0.050mm to ± 0.005mm.

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