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Product life cycle: machining processes monitoring and vibroacoustic signals filtering

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ABSTRACT

Introduction. In modern manufacturing, the product life cycle comprises various stages, from conception to disposal. Among these stages, machining plays a significant role, as it directly influences the durability and functionality of the finished product. With increasing competition and the need to reduce production costs, optimizing machining processes has become a crucial task. Traditionally, conservative technological approaches have been used to ensure processing quality. However, this often leads to decreased productivity and higher costs. Modern monitoring and diagnostic techniques can significantly improve process control, particularly through tool condition monitoring. **The subject.** This paper discusses the stages of the product life cycle and emphasizes the importance of monitoring machining processes. It explores the potential of using vibroacoustic signals to continuously monitor equipment and product conditions. Special attention is paid to the use of vibroacoustic signals for diagnostics and quality control. Modern approaches to filtering these signals, including the use of the fast *Fourier* transform and various window functions, are analyzed in order to improve the accuracy of the analysis and identify potential defects. **The purpose of this work** is to develop an algorithm for an online monitoring system that will monitor the condition of cutting tools based on the creation of a digital shadow using a vibroacoustic complex. The main tasks to be solved are to establish the ranges of applicability of frequency response of acoustic signals and optimal window functions, as well as to establish the relationship between the degree of wear on the cutting tool and the results of vibration diagnostics and surface roughness. **The methods and technologies** for filtering vibroacoustic signals and their application in real–world production settings are discussed. Special attention is given to the role of digital twins in integrating monitoring and filtering data, allowing for the creation of a virtual model of a product to predict its behavior and optimize processes throughout the life cycle. A comparison of various monitoring methods and technologies is conducted, as well as an analysis of practical examples of digital twin implementation in production processes and its impact on improved control. **Results and discussion** are presented, identifying current research and practical advancements, while also proposing existing challenges and promising areas for future research in the fields of monitoring, signal filtering, and the use of digital twins in mechanical manufacturing.

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Introduction

The transformation of industry during the implementation of the «*Industry 4.0*» concept opens up prospects for the use of new high-performance approaches to management at all life cycle stages [1], incl. through the use of digital twins (*DT*) [2, 3]. *DT* technology is the main component of a cyber physical system (*CPS*) [4], which allows collecting and managing large amounts of data (*Big Data*) [5], determining the behavior and reflecting the state of the production system in real time [6], and analyzing, modeling, predicting and optimizing various production processes [7–9].

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Currently, the initiative shown by enterprises is aimed at the synthesis of science, technology, innovation using digitalization and automation of design and production processes [10, 11], etc. At the same time, the emphasis of this initiative is on improving the functioning Continuous Acquisition and Life cycle Support (*CALS*), in particular, on improving Electronic Technical Documentation (*ETD*), digital twin technology [12, 13] and Quality Management Systems (*QMS*) [14, 15]. Product Lifecycle Management (*PLM*) systems are used to manage *ETD*, provide Integrated Logistics Support (*ILS*) [16] data and provide access to it at any stage (Fig. 1).

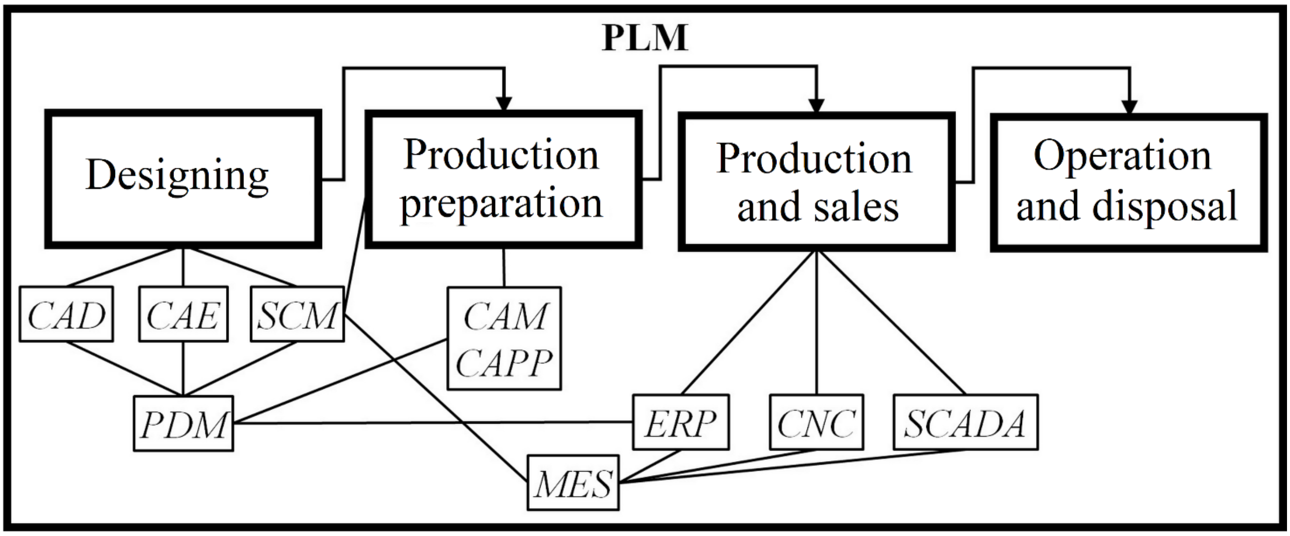


Fig. 1. Information support for the *PLC* stages

At the design stage, Computer-Aided Design (*CAD*) systems and Component Supplier Management (*SCM*) systems are used. Product Data Management systems (*PDM*) are used to solve the problems of joint functioning of *CAD*/*CAE* components (*CAE* – Computer Aided Engineering) [17].

In digital production systems, technological preparation of production (*TPP*) is carried out in the *CAD* system of *TPP*, including automated *TPP-CAPP* (Computer Aided Process Planning) and the development of control programs for Technological Equipment (*TE*) with *CNC-CAM* (Computer Aided Manufacturing).

Program control is performed through a *CNC* system based on specialized computers integrated into the maintenance facility. Information obtained during production can be sent to the Enterprise Resource Planning system (*ERP*). To perform the functions of collecting and processing data on the state of maintenance and Technological Processes (*TP*), a system of software and hardware complex for Supervisory Control and Data Acquisition (*SCADA*) is introduced into the Automated Control System (*ACS*) [18], interacting with the Manufacturing Execution System (*MES*).

According to *GOST 57700.37–202*, a *DT* is a system consisting of a digital model of a product and two-way communication with the product and (or) its components.

The work of the authors *Lu et al.* [7] describes a conceptual model of *DT* consisting of three elements: physical space, digital space and two-way dynamic communication between it; an information model that collects and integrates selected information from existing databases; a methodology describing decision support within the life cycle.

To ensure the stability of *TP* and other production elements that directly affect the quality of the product [19–21], when introducing *DT* into the life cycle stages, it is necessary to pay attention to improving the complex processing and transmission of accumulated streaming data received from a real product and describing its behavior – the Digital Shadow (*DS*) [22, 23]. *DS* helps to concentrate data sets from different subsystems for the purpose of processing and filtering it for use in *DT*. For example, during machining by cutting, an excessively large array of different data on process parameters enters the digital space from the product, some of which are not directly related to *DT*.

Redundant data arises mainly due to the lack of ranges of measured product parameters. At the same time, in repetitive or slightly different processes at the production stage, the actual task when using *DS* is to generate meaningful (effective) data.

Riesener M., *Schuh G.*, *et al.* proposed a *DS* framework that allows the collection and integration of information based on heterogeneous data sources [24, 25]. In the work of the authors *Fedonin O. N. et al.* a structure of automated systems is proposed that ensures the collection and analysis of data from *CNC* metal-cutting machines within the framework of the *MES* [26]. Integration of a *DS* simulation model with *MES* was proposed by *Negri S. et al.* [27] by creating a *DT* used for decision making including an intelligent system that contains rules and knowledge for choosing between alternatives.

Thus, we can conclude that at the moment, various scientific groups are studying *DT* of various levels (hierarchies), starting from *DT* of the cutting tool [5] and ending with *DT* of the operating process. This fact tells us that *PLM* systems can be integrated with *DT* to provide more efficient management of the entire life cycle [7, 22, 28] and be used for modeling and analysis of various processes [29]. For example, through Online Monitoring (*OM*) [30, 31], it is possible to clarify the idea of the technical condition of a vehicle, carry out its diagnostics, predict the remaining service life, etc. [32–34].

Since one of the main elements of the technological system is a metal-cutting tool, then from the point of view of creating *DT* and *DS*, it deserves the greatest attention, both in terms of ensuring the stability of the machining process and in terms of the quality of the resulting surfaces. However, taking into account the multifactorial nature of the machining process, in order to generate *DT* and *DS*, it is necessary to constantly obtain data about the machining process in real time. The authors' works [35–39] describe monitoring systems for Tool Condition Control (*TCC*) in real time at maintenance. An analysis of scientific works [40–42] made it possible to formulate the purpose of monitoring the *ICS*: assessing the state of the *IR*, detecting chips and breakage of the instrument. Considering the difficulty of predicting tool condition, multiple sensors are used [43–45]. However, the presence of a large number of sensors leads to repetitive (redundant) data, which ultimately reduces the efficiency of using *TCC* systems. Thus, the selection of suitable sensors and, accordingly, monitoring methods is important [46–49].

Studies by many authors describe the use of monitoring based on signals of force [40], acoustic emission (*AE*) [42, 50], power, current [51, 52], temperature, etc. [33, 45]. Dynamometers and *AE* devices are expensive equipment, and for measuring signals, incl. cutting force values require highly qualified specialists. The *AE* system is also quite complex and includes: a set of preamplifiers, cable lines, units for preprocessing and converting *AE* signals, a computer with the necessary software [53], information display tools, and system calibration units [54]. The results obtained using temperature sensors are often unreliable because infrared rays do not measure the actual temperature in the cutting zone [33]. Similarly, the use of thermocouple [53] has its disadvantages for milling operations due to the complexity of the process.

At the same time, an analysis of scientific works in recent years shows that the topic of *TCC* using Vibroacoustic (*VA*) signals is studied in fragments. Research mainly focuses on two areas: online vibration-based cutting tool wear analysis [55] and surface roughness analysis using sound signal during machining [51, 56].

Despite the fact that these areas have its own characteristics and methods, the integration of its results can lead to the creation of a more comprehensive and effective *OM TCC* system. Such a system, with proper methodological description, configuration, recording and filtering of *VA* signals, will make it possible to obtain an easily reconfigurable, reliable monitoring complex with low cost, and will also ensure the required product quality, increase productivity and reduce costs due to more accurate measurement data and the processing process.

To implement the concept of monitoring machining on Technological Equipment with *CNC*, it is proposed to form a *DS* using a *VA* complex, which transmits a signal to the software. At the same time, the applied software should have an intuitive, friendly user interface, the data should be structurally ordered, and the software implementation of application functions should be carried out using a client-server design [57–62].

The business objective of using the proposed *DS* is to reduce the number of defects during program development and increase the economic efficiency of the machining process. Machining information is represented by various input data: name of the control program, tool identification number [63, 64], feed rate [65], spindle speed, etc. [66–68]. The monitoring method based on measurements of the *VA* signal, although it does not require accurate information about the absolute interaction of the cutting tool and the part, but in order to generate effective output data it is necessary to set restrictions.

An *FFT* (Fast *Fourier* Transform) filter was used to isolate a narrow band of the sound wave [69–71]. This filter uses the F*F*T method, which allows to effectively analyze the frequency content of the signal. The *FFT* block size determines the frequency resolution of the analysis. The larger the block, the higher the frequency resolution [72]. For example, for a block size of 65,536 points and a sampling rate of 44.1 kHz, the frequency resolution is approximately 0.67 Hz. This allows to accurately determine the presence of certain frequencies in the signal. However, with a large block size, the temporal resolution deteriorates. To improve time resolution, a smaller *FFT* block can be used to better track rapid frequency changes, but frequency resolution will be significantly degraded. With an *FFT* size of 1,024, the frequency grid step will be approximately 43 Hz. This means that frequencies are 43, 86, 129 Hz, etc. will be determined with high accuracy, but intermediate frequencies, such as 50 Hz, may not be visible.

Filtering is used to isolate useful frequency components of a signal and remove noise [73]. In machining applications, this can help isolate vibration frequencies of interest and eliminate unnecessary noise. The following types of filters are used: low-pass filters pass low-frequency components and suppress high-frequency ones; high-pass filters pass high-frequency components and suppress low-frequency ones; bandpass filters pass frequencies in a certain range and suppress frequencies outside this range.

The use of window functions in *FFT* analysis is necessary to minimize side effects associated with window discontinuities in the time signal. When a signal is trimmed for analysis, abrupt changes may occur at the ends of the block, resulting in distortion in the spectrum (spectral leakage).

The *Hann* window function has low sidelobes compared to the rectangular function, and low spectral leakage. Among the disadvantages, one can highlight the low frequency resolution.

The *Hamming* window function has low side lobes compared to the *Hann* function, and low spectral leakage. Among the disadvantages, one can highlight the low frequency resolution in comparison with the *Hann* window function.

The *Blackman* window function has a very low level of side lobes, which allows the level of spectral leakage to be minimized, but the frequency resolution is significantly reduced.

Thus, the goal of this work is to develop an algorithm for the operation of an online monitoring system for monitoring the condition of a cutting tool, based on the creation of a digital shadow, using a vibroacoustic complex. To achieve this goal, it is planned to solve the following tasks:

1) to determine the frequency ranges of the frequency response of the acoustic signal obtained during machining used to analyze the level of wear of the cutting tool;

2) to determine the optimal window function when filtering the acoustic machining signal to isolate the useful signal;

3) to establish experimental relationships between the degree of tool wear, surface microrelief parameters and the frequency response of the vibroacoustic signal.

Research methodology

OM TCC in machining plays a key role in improving production efficiency [74]. It allows for a quick response to wear and other changes in the active contact zone of the tool [35, 75] and the workpiece, thereby ensuring optimal use of the equipment and preventing the need for premature or delayed tool replacement, which in turn can lead to unnecessary downtime, such as planned, and unscheduled. In the case under consideration, optimization of the milling process was based on minimizing the target cost function:

$$F(\vec{x}) = \sum_{i=1}^{n} C(\vec{x})_i \to \min,$$

where ΣC consists of C_1 is equipment operating costs; C_2 is costs for changing tools; C_3 is cost of standard hour; C_4 is cost of the tool.

Then the performance limitation system will have the following form:

$$Q = \{V, n, fz, a_p, t\} \rightarrow \max.$$

where V is a cutting speed, m/min; n is a rotation speed, min^{-1}; fz is a feed per tooth, mm/tooth; a_p is a cutting depth, mm; t is an allowance, mm.

In this work, *DS* was considered from the side of information transfer from the Physical World (*PW*) to *DT*. The proposed Online Monitoring system, consisting of maintenance, *SCADA* and *VA* sensors (*Sensors* are piezoelectric accelerometers "*BC 110*"), due to the diagnostic function, allows to timely detect tool wear and make a decision on replacing the cutting tool, correction or changing the control program (Fig. 2).

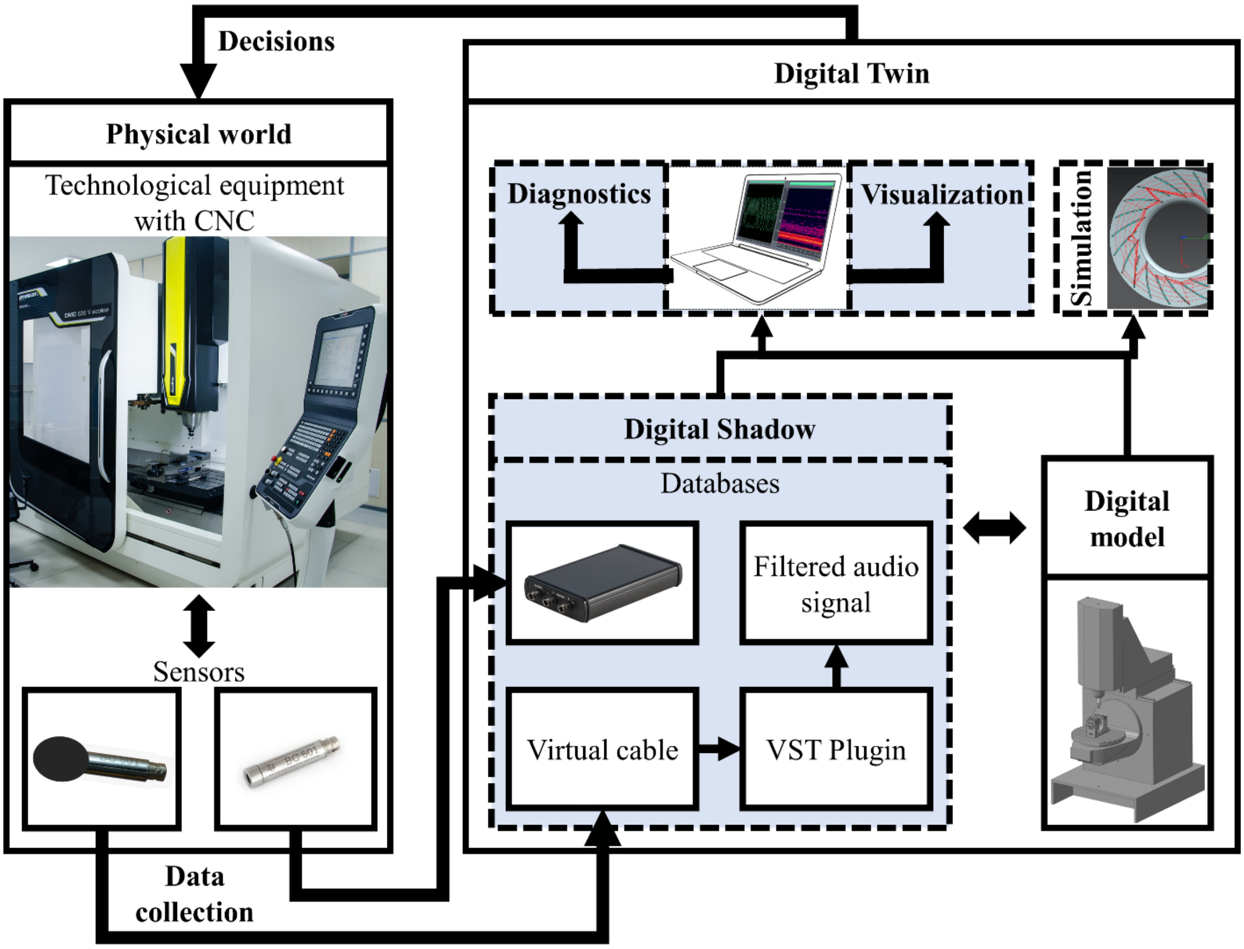


Fig. 2. The scheme of monitoring and the digital twin

The Online Monitoring system analyzes various parameters such as vibration, acoustic signals and surface finish. This allows to not only determine when a tool has reached a critical level of wear and requires replacement [76], but also to monitor less obvious changes that may signal possible problems.

Digital signal processing techniques including *FFT*, window functions, and filtering were used to analyze the resulting *VA* signals. The data received in the form of an acoustic signal is transferred to the software, where noise removal (*De-Noising*) and filtering [35] are carried out in the *VST* plugin using the *Fourier* transform. One of the key elements of the system for transmitting a signal in real time is a virtual cable, which allows displaying information on the operator's graphical interface (Fig 3).

In experimental studies, machining was carried out in the same direction using a cutting fluid, on workpieces having the properties of *AISI 321*, with cylindrical end mills with a diameter of $\boldsymbol{D}$ = 8 mm, $\boldsymbol{z}$ = 2.

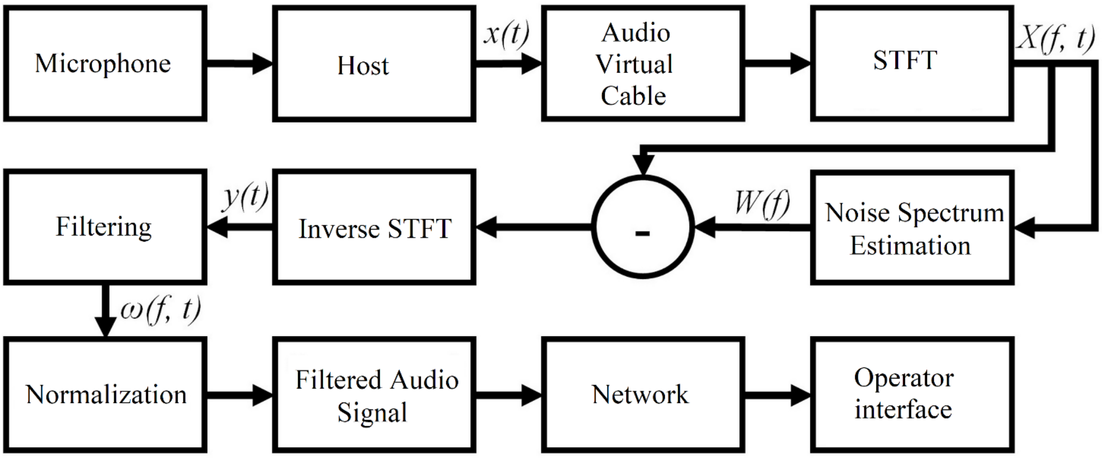


Fig. 3. The process of software processing of an acoustic signal

The tool material used is *CVD* coated carbide *BC20HT*, application range according to ISO is *K10–K20*. The tool overhang ratio was assumed to be ***l/D*** = 4. The feed per tooth was ***fz*** = 0.2 mm/tooth, $\boldsymbol{a_p}$ = 10 mm, ***t*** = 0.4 mm. The spindle speed (***n***) was 1,500 min^{-1}. During milling cutting tools were measured along its length and radius using a *Heidenhain TT140* contact sensor to monitor the degree of tool wear.

Vibroacoustic diagnostics were carried out using the Spectrum Analyzer *ZetLab 017–U2* device based on a *DMG DMU* (Germany) *50 Ecoline* machining center. The amplitude of the acoustic signal ***A*** (dB), changing over time ***t*** (s), vibration acceleration ***a*** (m/s^2), signal frequency ***ω*** (Hz) and the microrelief parameter – roughness – ***Rz*** (μm) were used as output indicators of the efficiency of machining.

The range of perceived frequencies of the microphone was 20 Hz÷20 kHz, resolution was 16 bits and sampling frequency was 44.1/48 kHz. For the optimal balance between time and frequency resolution, the *FFT* size was chosen to be 16,384, which ensures sufficient detail and accuracy of the analysis. Roughness measurements after surface milling were carried out using a *TIME TR 200* profilometer; for this device, the error according to the standard is 3 %. The primary profile filtering process was performed using a 50 % *Gaussian* filter.

Results and discussion

When machining by cutting, vibrations and noises that occur during operation play an important role. Digital signal processing techniques including *FFT* [77], window functions and filtering were used to analyze these signals.

Fig. 4 clearly shows that the microphone records several sound sources, including sounds around the technological equipment, the drive system of the technological equipment, the spindle, the tool, and the cutting process. Therefore, for a more accurate analysis, an acoustic signal within the frequency range characteristic of the cutting process was considered. This allows to better identify specific characteristics and features that may not be obvious in the wider frequency spectrum.

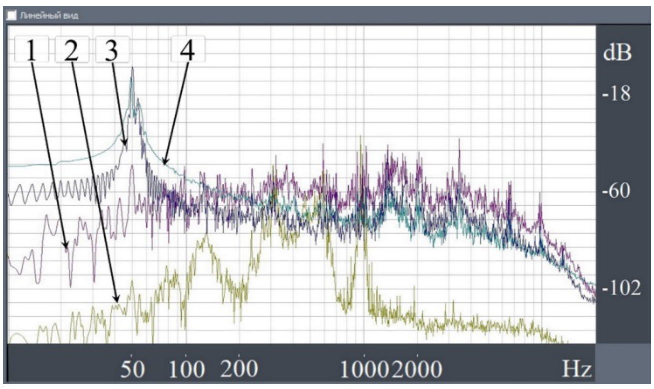


Fig. 4. Frequency response of the acoustic signal:
1 – Initial; ***2*** – After noise removal; ***3*** – Filtered; ***4*** – Filtered and normalized

From Fig. 4 it can be seen that background noise can be identified in the range of 0÷2 kHz, this specified part of the signal can be easily filtered without losing the main signal. Spectrum analysis reveals dominant frequencies and amplitudes that may indicate resonances, defects and tool wear. After spectral subtraction of noise and filtering of the acoustic signal, the frequency response of oscillations is characterized by three main frequencies (Fig. 4) in the range of 20÷200 Hz: ω_0 = 25 Hz – harmonic, a multiple of the frequency of passage of the cutting edges; ω_1 = 50 Hz, which corresponds to the cutting frequency modulated by the revolutions of a two–tooth cutter; resonant frequency ω_2 = 100 Hz, which should be interpreted as the tool outrun.

Thus, the results of acoustic signal processing made it possible to establish a pronounced low-frequency region of 20÷200 Hz, the use of which contributes to a more accurate identification and analysis of acoustic characteristics associated with the cutting process. This is especially important for *VA* diagnostics, where the accuracy and detail of the analysis can make a significant difference in identifying and diagnosing potential problems.

Also in this study, different windows for filtering audio signals are considered. The use of various window functions during filtering allows optimizing the process of extracting a useful signal from the total mass of data. The results of the window functions that were used in this study are presented in Fig. 5.

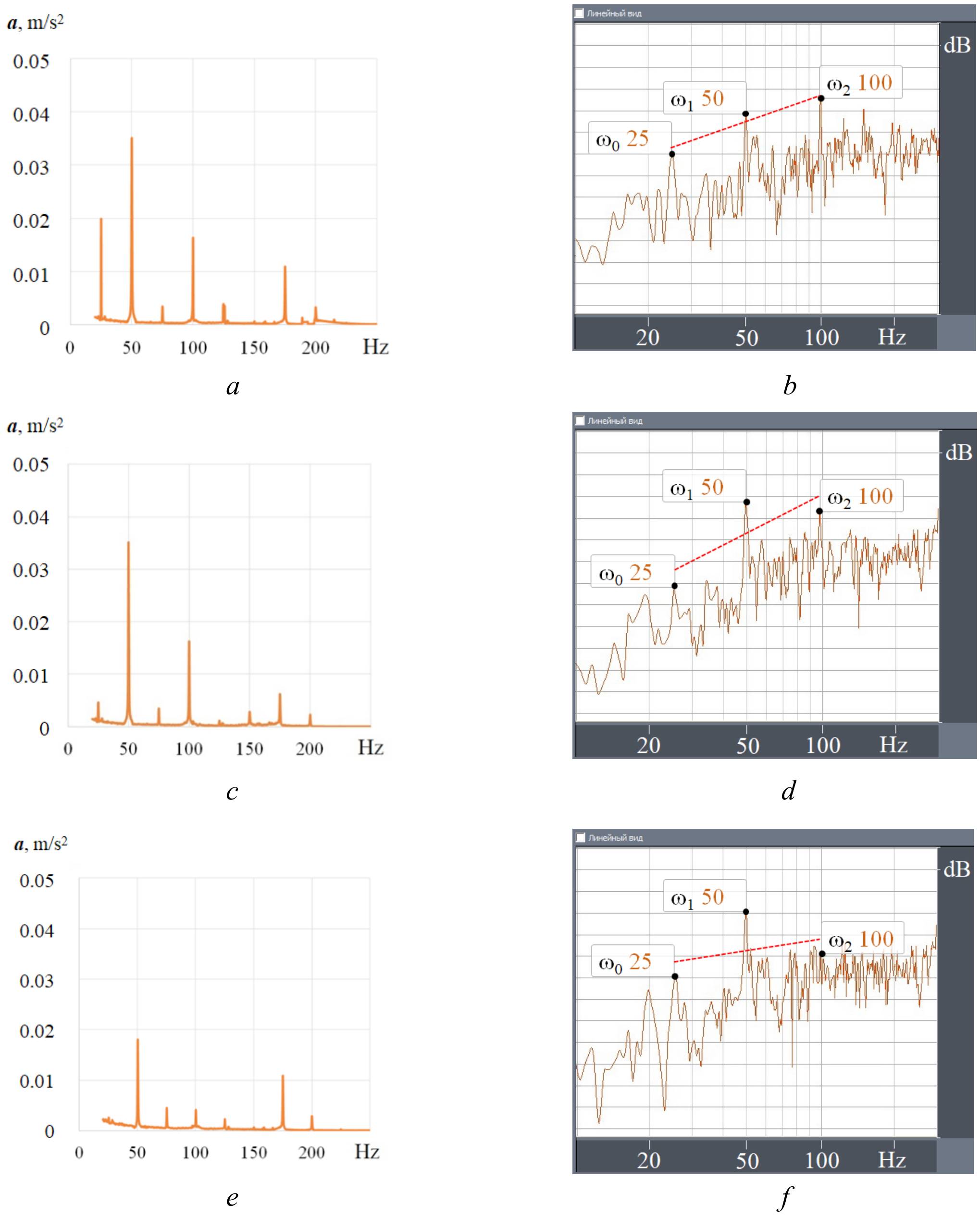


Fig. 5. The spectrum of signals of the passage of the milling cutter cutting edges through the processing zone after the application of window functions, recorded in the form of: *a*, *c*, *e* – vibration acceleration; *b*, *d*, *f* – acoustic signal; *a*, *b* – *Hanning* window; *c*, *d* – *Hamming* window; *e*, *f* – *Blackman* window

The rectangular window due to the high level of side lobes, which can lead to significant spectral leaks, and the *Kaiser* window due to the complexity of tuning the parameters to achieve the optimal result were not used in this work.

As can be seen from Fig. 5, the *Hamming* window function effectively reduces the spectral leakage that occurs when applying the *Fourier* transform. At the same time, the *Hamming* window function provides a good compromise between the width of the main lobe and the level of side lobes in the spectral representation, is easy to implement and does not require significant computational resources. This makes it the preferred choice for many digital signals processing applications, providing the high quality and accuracy of analysis needed to implement an online monitoring system.

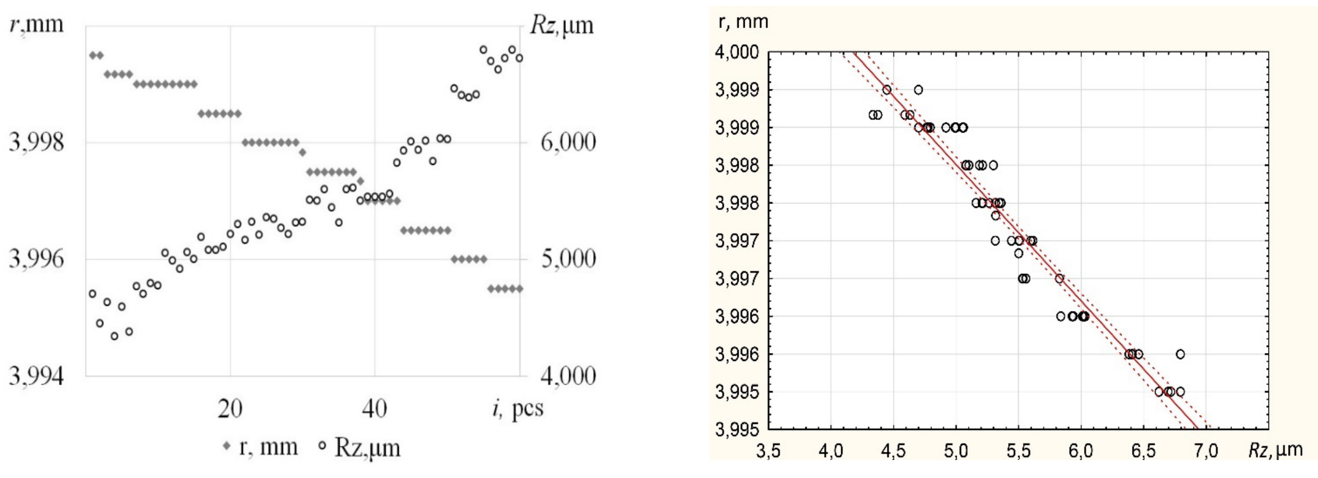
To determine the influence of the degree of tool wear on the parameters of the microrelief and the frequency response of the acoustic signal, experiments were carried out, the results of which are shown in Fig. 6 and Fig. 7.

As can be seen from *Fig. 6*, the surface roughness of the processed material directly depends on the degree of tool wear, and the following correlation dependence has been established: $\boldsymbol{r} = -0.9678$ (strong, negative).

The deviation between the tool diameter with increasing number of machined surfaces is different, at the beginning there is a small dimensional wear of 2–4 μm, which increases ***Rz*** by 20 %. Further, within 6 μm, the roughness increases by 50 % of the minimum values obtained. At the same time, the deflection of the tool increases (Fig. 7), as evidenced by the increase in the resonant frequency $\boldsymbol{\omega_2}$ = 100 Hz. It is important to regularly monitor the condition of the tool and replace it in a timely manner.

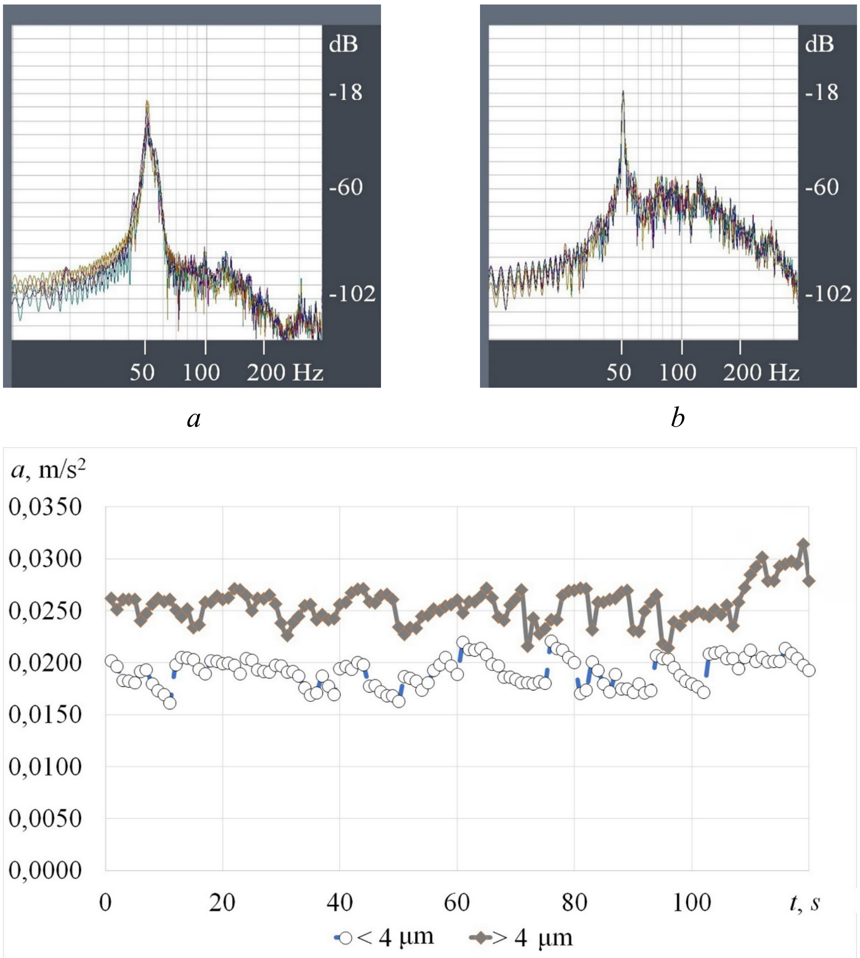
As can be seen from Fig. 7, the sound spectrograms of a worn tool contain higher values than the sound of a new tool, with identical cutting process parameters. This fact is also confirmed by the graph of vibration acceleration at various degrees of tool wear. It is worth noting the difference in density around 50 Hz, but as previously stated, further work is still needed to understand the discrepancies for each specific case.

Thus, based on the conducted research, we can conclude that with the use of a *VA* complex based on the formation of *DS*, Online Monitoring is possible. However, special attention should be paid to the obtained frequency response data of the acoustic signal from the standpoint of its processing and filtering. A significant amount of data obtained should be optimally processed in order to analyze and correlate it with the condition of the cutting tool. To do this, the study determined the frequency ranges of the acoustic signal, within which it is possible to draw conclusions about the current state of the instrument. The next step was to select a specific window function. It depended on signal filtering requirements, such as the acceptable level of spectral leakage and the required frequency resolution. The study analyzed the results of applying these window functions to audio signals to determine the optimal acoustic signal from the point



a *b*

Fig. 6. Dependence of the roughness parameter ***Rz*** on tool wear:
a – distribution; *b* – correlation



c

Fig. 7. The results of *VA* diagnostics:
a – frequency response with wear less than 4 μm; *б* – frequency response with wear more than 4 μm; *в* – vibration acceleration

of view of computational resources and accuracy, as a result, the *Hamming* window function is determined as the most suitable for analyzing the machining process.

The dependences of the frequency response of the acoustic signal and surface roughness on the degree of tool wear are established, on the basis of which conclusions can be drawn about the condition of the cutting tool at stages close to critical in terms of the quality of the resulting surfaces. Although the study was aimed at determining the relationships between tool wear level, tool vibroacoustic signal and surface finish quality, the results of this study can be used to develop new techniques for monitoring tool wear, increasing the efficiency of the material processing process and improving the quality of finished products.

Also, the study made it possible to formulate a sequence of actions for *VA* analysis, which contributes to a more accurate identification and analysis of acoustic characteristics associated with the cutting process:

1) install sensors (accelerometers, microphones) near the working area of technological equipment to record *VA* signals;

2) collect time data of *VA* signals;

3) convert an analog signal to a digital one using an analog-to-digital converter;

4) apply a window function to the collected data to minimize spectral leakage before performing FFT;

5) perform FFT to convert time signal to frequency domain;

6) analyze the spectrum to identify dominant frequency components associated with instrument condition;

7) apply filters to isolate frequency components of interest (apply a low-pass filter to remove high-frequency noise; apply a band-pass filter to highlight frequencies associated with normal tool operation and anomalies; apply a high-pass filter to remove low-frequency noise and vibration.)

8) perform additional analysis of the filtered signal (Compare filtered signals with reference signals to assess the condition of the tool. Identify changes in the sound and vibration spectrum, indicating wear or damage to the tool).

Conclusions

Based on the current state of research described in this paper, as well as an evaluation of the results of the experiments, the following conclusions can be drawn.

1. An algorithm is developed for the operation of an Online Monitoring system for monitoring the condition of a cutting tool during milling, filtering interference and noise in real time based on the formation of *DS* obtained during vibroacoustic analysis. This conclusion stimulates the formulation of new tasks for research in this area.

2. Analysis of the frequency response in the range of 20÷200 Hz made it possible to establish the difference in the spectral density of the acoustic signal over time, an increase in which makes it possible to record the degree of tool wear.

3. The *Hamming* window function is determined to be optimal in terms of computational resources and accuracy of the acoustic signal from the standpoint of its use in the analysis of the machining process.

4. The presence of an acoustic signal correlation is confirmed by measurements of wear on the cutter radius, roughness and the results of vibration diagnostics. At the same time, the Online Monitoring system makes it possible to determine earlier signs of changes in the condition of the tool's cutting edge than measurements recorded by a cycle in the *CNC* control program or measurements of roughness parameters.

References

1. GOST R 56136–2014. *Upravlenie zhiznennym tsiklom produktsii. Terminy i opredeleniya* [State Standard R 56136–2014. Life cycle management for military products. Terms and definitions]. Moscow, Standartinform Publ., 2016. 24 p.

2. Grieves M. *Digital twin: manufacturing excellence through virtual factory replication: whitepaper*. Melbourne, FL, LLC, 2014, pp. 1–7.

3. GOST R 57700.37–2021. *Komp'yuternye modeli i modelirovanie. Tsifrovye dvoiniki izdelii. Obshchie polozheniya* [State Standard R 57700.37–2021. Computer models and simulation. Digital twins of products. General provisions]. Moscow, Russian Institute of Standardization Publ., 2021. 15 p.

4. Ingemansson A.R. Sovremennaya nauchnaya problema povysheniya effektivnosti mekhanoobrabatyvayushchego proizvodstva putem vnedreniya kiberfizicheskikh sistem v ramkakh kontseptsii «Industriya 4.0» [Current scientific problem of efficiency increase in mechanical operation by cyber-physical systems introduction within "Industry 4.0" concept]. *Naukoemkie tekhnologii v mashinostroenii = Science Intensive Technologies in Mechanical Engineering*, 2016, no. 12, pp. 40–44. DOI: 10.12737/23487.

5. Kabaldin Y.G., Shatagin D.A., Kuzmishina A.M. Razrabotka tsifrovogo dvoinika rezhushchego instrumenta dlya mekhanoobrabatyvayushchego proizvodstva [The development of a digital twin of a cutting tool for mechanical production]. *Izvestiya vysshikh uchebnykh zavedenii. Mashinostroenie = Proceedings of Higher Educational Institutions. Machine Building*, 2019, no. 4 (709), pp. 11–17. DOI: 10.18698/0536-1044-2019-4-11-17.

6. Uhlemann T.H.J., Lehmann C., Steinhilper R. The digital twin: realizing the cyber-physical production system for Industry 4.0. *Procedia CIRP*, 2017, vol. 61, pp. 335–340. DOI: 10.1016/j.procir.2016.11.152.

7. Lu Y., Liu C., Wang K.I.-K., Huang H., Xu X. Digital Twin–driven smart manufacturing: Connotation, reference model, applications and research issues. *Robotics and Computer-Integrated Manufacturing*, 2020, vol. 61, p. 101837. DOI: 10.1016/j.rcim.2019.101837.

8. Schleich B., Anwer N., Mathieu L., Wartzack S. Shaping the digital twin for design and production engineering. *CIRP Annals*, 2017, vol. 66, pp. 141–144. DOI: 10.1016/j.cirp.2017.04.040.

9. Padovano A., Longo F., Nicoletti L., Mirabelli G. A Digital Twin based service oriented application for a 4.0 knowledge navigation in the smart factory. *IFAC-PapersOnLine*, 2018, vol. 51 (11), pp. 631–636. DOI: 10.1016/j.ifacol.2018.08.389.

10. Tao F., Anwer N., Liu A., Wang L., Nee A.Y.C., Li L., Zhang M. Digital twin towards smart manufacturing and industry 4.0. *Journal of Manufacturing Systems*, 2021, vol. 58 (B), pp. 1–2. DOI: 10.1016/j.jmsy.2020.12.005.

11. Gimadeev M.R., Davydov V.M., Li A.A. Influence of shaping trajectory on the surface roughness in milling: vibroacoustic monitoring. *Russian Engineering Research*, 2023, vol. 43 (7), pp. 796–801. DOI: 10.3103/S1068798X23070109.

12. Shevchenko D.V. Metodologiya postroeniya tsifrovykh dvoinikov na zheleznodorozhnom transporte [Methodology for constructing digital twins in railway transport]. *Vestnik Nauchno-issledovatel'skogo instituta zheleznodorozhnogo transporta = Russian Railway Science Journal*, 2021, vol. 80, no. 2, pp. 91–99. DOI: 10.21780/2223-9731-2021-80-2-91-99.

13. Altintas Y. *Manufacturing automation: metal cutting mechanics, machine tool vibrations, and CNC design*. UK, Cambridge University Press, 2012. 366 p. DOI: 10.1017/CBO9780511843723.

14. GOST R ISO 9000-2015. *Sistema menedzhmenta kachestva. Osnovnye polozheniya i slovar'* [State Standard R ISO 9000-2015. Quality management systems. Fundamentals and vocabulary]. Moscow, Standartinform Publ., 2015. 42 p.

15. GOST R ISO 9001-2015. *Sistemy menedzhmenta kachestva. Trebovaniya* [State Standard R ISO 9001-2015. Quality management systems. Requirements]. Moscow, Standartinform Publ., 2015. 57 p.

16. Kuznetsova V.B., Kondusov D.V., Serdyuk A.I., Sergeev A.I. Monitoring system for high-tech equipment. *Russian Engineering Research*, 2017, vol. 37 (10), pp. 892–896. DOI: 10.3103/S1068798X17100136.

17. Guarin A., Gomez J., Hincapie M., Guerra D., Molina A. Product development integration using PLM tools: An industrial lathe case study. *IFAC Proceedings Volumes*, 2007, vol. 40 (19), pp. 135–140. DOI: 10.3182/20071002-MX-4-3906.00023.

18. Ingemansson A.R., Tchigirinsky Ju.L. Razrabotka sostava tsifrovykh proizvodstvennykh sistem dlya mekhanicheskoi obrabotki [The designing of composition of digital production systems for metalworking]. *Izvestiya Volgogradskogo gosudarstvennogo tekhnicheskogo universiteta = Izvestia of Volgograd State Technical University*, 2019, no. 8 (231), pp. 21–23. (In Russian).

19. GOST R 50995.3.1–96. *Tekhnologicheskoe obespechenie sozdaniya produktsii. Tekhnologicheskaya podgotovka proizvodstva* [State Standard R 50995.3.1–96. Technological support for products development and production. Technological preparation of production]. Moscow, Gosstandart of Russia Publ., 1997. 20 p.

20. GOST 27.002–2015. *Nadezhnost' v tekhnike. Terminy i opredeleniya* [State Standard 27.002–2015. Dependability in technics. Terms and definitions]. Moscow, Standartinform Publ., 2016. 28 p.

21. GOST 27.003–2016. *Nadezhnost' v tekhnike. Sostav i obshchie pravila zadaniya trebovanii po nadezhnosti* [State Standard 27.003–2016. Industrial product dependability. Dependability requirements: contents and general rules for specifying]. Moscow, Standartinform Publ., 2017. 19 p.

22. Tao F., Qi Q., Liu A., Kusiak A. Data-driven smart manufacturing. *Journal of Manufacturing Systems*, 2018, vol. 48 (C), pp. 157–169. DOI: 10.1016/j.jmsy.2018.01.006.

23. Ladj A., Wang Z., Meski O., Belkadi F., Ritou M., Da Cunha C. A knowledge-based digital shadow for machining industry in a digital twin perspective. *Journal of Manufacturing Systems*, 2021, vol. 58 (B), pp. 168–179. DOI: 10.1016/j.jmsy.2020.07.018.

24. Riesener M., Schuh G., Dolle C., Tonnes C. The digital shadow as enabler for data analytics in product life cycle management. *Procedia CIRP*, 2019, vol. 80, pp. 729–734. DOI: 10.1016/j.procir.2019.01.083.

25. Schuh G., Jussen P., Harland T. The digital shadow of services: a reference model for comprehensive data collection in MRO services of machine manufacturers. *Procedia CIRP*, 2018, vol. 73, pp. 271–277. DOI: 10.1016/j.procir.2018.03.318.

26. Fedonin O.N., Petreshin D.I., Karpushkin V.A. Razrabotka algoritma funktsionirovaniya avtomatizirovannoi sistemy sbora i analiza dannykh s metallorezhushchikh stankov s ChPU [Development of algorithms of the automated data collection and analysis system with a machine tool CNC]. *Vestnik Bryanskogo gosudarstvennogo tekhnicheskogo universiteta = Bulletin of Bryansk State Technical University*, 2014, no. 1 (41), pp. 58–62.

27. Negri E., Berardi S., Fumagalli L., Macchi M. MES-integrated digital twin frameworks. *Journal of Manufacturing Systems*, 2020, vol. 56, pp. 58–71. DOI: 10.1016/j.jmsy.2020.05.007.

28. Jones D., Snider C., Nassehi A., Yon J., Hicks B. Characterising the Digital Twin: a systematic literature review. *CIRP Journal of Manufacturing Science and Technology*, 2020, vol. 29 (A), pp. 36–52. DOI: 10.1016/j.cirpj.2020.02.002.

29. Ritto T.G., Rochinha F.A. Digital twin, physics-based model, and machine learning applied to damage detection in structures. *Mechanical Systems and Signal Processing*, 2021, vol. 155, p. 107614. DOI: 10.1016/j.ymssp.2021.107614.

30. Liu C., Vengayil H., Zhong R.Y., Xu X. A systematic development method for cyber–physical machine tools. *Journal of Manufacturing Systems*, 2018, vol. 48 (C), pp. 13–24. DOI: 10.1016/j.jmsy.2018.02.001.

31. Cai Y., Starly B., Cohen P., Lee Y.-S. Sensor data and information fusion to construct Digital-twins virtual machine tools for cyber-physical manufacturing. *Procedia Manufacturing*, 2017, vol. 10, pp. 1031–1042. DOI: 10.1016/j.promfg.2017.07.094.

32. Wang J., Ye L., Gao R.X., Li C., Zhang L. Digital Twin for rotating machinery fault diagnosis in smart manufacturing. *International Journal of Production Research*, 2019, vol. 57 (12), pp. 3920–3934. DOI: 10.1080/00207543.2018.1552032.

33. Pimenov D.Yu., Kumar Gupta M., da Silva L.R.R., Kiran M., Khanna N., Krolczyk G.M. Application of measurement systems in tool condition monitoring of milling: a review of measurement science approach. *Measurement*, 2022, vol. 199, p. 111503. DOI: 10.1016/j.measurement.2022.111503.

34. Kozochkin M.P., Sabirov F.S., Bogan A.N., Myslivcev K.V. Monitoring sostoyaniya tekhnologicheskogo oborudovaniya na promyshlennykh predpriyatiyakh [Monitoring of process equipment for industrial enterprises]. *Vestnik UGATU = Scientific Journal of Ufa State Aviation Technical University*, 2013, vol. 17, no. 8 (61), pp. 56–62.

35. Gimadeev M.R., Li A.A. Analiz sistem avtomatizirovannogo obespecheniya parametrov sherokhovatosti poverkhnosti na osnove dinamicheskogo monitoringa [Analysis of automated surface roughness parameter support systems based on dynamic monitoring]. *Advanced Engineering Research (Rostov-on-Don)*, 2022, vol. 22, no. 2, pp. 116–129. DOI: 10.23947/2687-1653-2022-22-2-116-129.

36. Qiao Q., Wang J., Ye L., Gao R.X. Digital twin for machining tool condition prediction. *Procedia CIRP*, 2019, vol. 81, pp. 1388–1393. DOI: 10.1016/j.procir.2019.04.049.

37. Qi Q., Tao F. Digital twin and big data towards smart manufacturing and Industry 4.0: 360 Degree comparison. *IEEE Access*, 2018, vol. 6, pp. 3585–3593. DOI: 10.1109/ACCESS.2018.2793265.

38. Cooper C., Wang P., Zhang J., Gao R.X., Roney T., Ragai I., Shaffer D. Convolutional neural network-based tool condition monitoring in vertical milling operations using acoustic signals. *Procedia Manufacturing*, 2020, vol. 49, pp. 105–111. DOI: 10.1016/j.promfg.2020.07.004.

39. Averchenkov V.I., Filippova L.B., Pugach L.I. Programmnyi kompleks opredeleniya velichiny korrektsii na instrument dlya obrabatyvayushchikh tsentrov s datchikami aktivnogo kontrolya [Determination of software tool compensation values in the preparation of automated production of the use of active control sensor tool]. *Izvestiya Tul'skogo gosudarstvennogo universiteta. Tekhnicheskie nauki = News of the Tula state university. Technical sciences*, 2013, iss. 7 (1), pp. 70–78.

40. Zhou C., Guo K., Sun J., Yang B., Liu J., Song G., Sun C., Jiang Z. Tool condition monitoring in milling using a force singularity analysis approach. *The International Journal of Advanced Manufacturing Technology*, 2020, vol. 107, pp. 1785–1792. DOI: 10.1007/s00170-019-04664-4.

41. Cuka B., Kim D.W. Fuzzy logic based tool condition monitoring for end-milling. *Robotics and Computer-Integrated Manufacturing*, 2017, vol. 47, pp. 22–36. DOI: 10.1016/j.rcim.2016.12.009.

42. Barreiro J., Fernandez-Abia A.I., Gonzalez-Laguna A., Pereira O. TCM system in contour milling of very thick-very large steel plates based on vibration and AE signals. *Journal of Materials Processing Technology*, 2017, vol. 246, pp. 144–157. DOI: 10.1016/j.jmatprotec.2017.03.016.

43. Lukyanov A.V., Aleynikov D.P. Issledovanie kolebanii sil vzai-modeistviya frezy s zagotovkoi pri povyshenii skorosti vrashcheni-ya shpindelya [Analysis of oscillations of cutting forces beftveen a mill and a work-piece when increasing the spindle rotation speed]. *Sovremennye tekhnologii. Sistemnyi analiz. Modelirovanie = Modern Technologies. System Analysis. Modeling*, 2017, vol. 56, no. 4, pp. 70–82. DOI: 10.26731/1813-9108.2017.4(56).70-82. (In Russian).

44. Volosova M.A. Avtomatizirovannaya sistema monitoringa i diagnostiki obrabotki otvetstvennykh detalei v mashinostroenii keramicheskim rezhushchim instrumentom [Automated monitoring and diagnostic system for the processing of critical parts in mechanical engineering ceramic cutting tool]. *Innovatsii = Innovations*, 2016, no. 8 (214), pp. 84–87. (In Russian).

45. Rizal M., Ghani J.A., Nuawi M.Z., Haron C.H.C. Cutting tool wear classification and detection using multi-sensor signals and Mahalanobis-Taguchi System. *Wear*, 2017, vol. 376–377 (B), pp. 1759–1765. DOI: 10.1016/j.wear.2017.02.017.

46. Hu M., Ming W., An Q., Chen M. Tool wear monitoring in milling of titanium alloy Ti-6Al-4 V under MQL conditions based on a new tool wear categorization method. *The International Journal of Advanced Manufacturing Technology*, 2019, vol. 104, pp. 4117–4128. DOI: 10.1007/s00170-019-04125-y.

47. Nouri M., Fussell B.K., Ziniti B.L., Linder E. Real-time tool wear monitoring in milling using a cutting condition independent method. *International Journal of Machine Tools and Manufacture*, 2015, vol. 89, pp. 1–13. DOI: 10.1016/j.ijmachtools.2014.10.011.

48. Shaffer D., Ragai I., Danesh-Yazdi A., Loker D. Investigation of the feasibility of using microphone arrays in monitoring machining. *Manufacturing Letters*, 2018, vol. 15 (B), pp. 132–134. DOI: 10.1016/j.mfglet.2017.12.008.

49. Mohamed A., Hassan M., Msaoubi R., Attia H. Tool condition monitoring for high-performance machining systems – a review. *Sensors*, 2022, vol. 22, p. 2206. DOI: 10.3390/s22062206.

50. Vetrichelvan G., Sundaram S., Kumaran S., Velmurugan P. An investigation of tool wear using acoustic emission and genetic algorithm. *Journal of Vibration Control*, 2014, vol. 21 (15), pp. 3061–3066. DOI: 10.1177/1077546314520835.

51. Sahinoglu A., Rafighi M. Investigation of vibration, sound intensity, machine current and surface roughness values of AISI 4140 during machining on the lathe. *Arabian Journal for Science and Engineering*, 2020, vol. 45, pp. 765–778. DOI: 10.1007/s13369-019-04124-x.

52. Hu S., Liu F., He Y., Hu T. An on-line approach for energy efficiency monitoring of machine tools. *Journal of Cleaner Production*, 2012, vol. 27, pp. 133–140. DOI: 10.1016/j.jclepro.2012.01.013.

53. Suslov A.G., Fedorov V.P., Nagorkin M.N., Pyrikov I.L. Kompleksnyi podkhod k eksperimental'nym issledovaniyam tekhnologicheskikh sistem metalloobrabotki po obespecheniyu parametrov kachestva i ekspluatatsionnykh svoistv poverkhnostei detalei mashin [Complex approach to experimental investigations of metal-working technological systems to ensure parameters of quality and operation properties of machinery surfaces]. *Naukoemkie tekhnologii v mashinostroenii = Science Intensive Technologies in Mechanical Engineering*, 2018, no. 10, pp. 3–13. DOI: 10.30987/article_5bb4b1f9abbc54.46761484.

54. Alzugaray-Franz R., Diez-Cifuentes E., Leal-Munoz E., Villaverde San Jose M., Vizán A. Determination of tool wear in peripheral milling operations based on acoustic emission signals. *IACME 2022: Proceedings of the XV Ibero-American Congress of Mechanical Engineering*, 2023, pp. 300–305. DOI: 10.1007/978-3-031-38563-6_44.

55. Moricz L., Viharos Z.J., Nemeth A., Szepligeti A., Buki M. Off-line geometrical and microscopic & on-line vibration based cutting tool wear analysis for micro-milling of ceramics. *Measurement*, 2020, vol. 163, p. 108025. DOI: 10.1016/j.measurement.2020.108025.

56. Patwari A.U., Zamee A.A., Bhuiyan M.H., Sakib S.M. The surface roughness analysis using sound signal in turning of mild steel. *IOP Conference Series: Materials Science and Engineering*, 2019, vol. 703, p. 012011. DOI: 10.1088/1757-899X/703/1/012011.

57. GOST R 51904–2002. *Programmnoe obespechenie vstroennykh sistem. Obshchie trebovaniya k razrabotke i dokumentirovaniyu* [State Standard R 51904–2002. Embedded system software. General requirements for development and documentation]. Moscow, Standartinform Publ., 2012. 36 p.

58. GOST R ISO/MEK 15910–2002. *Informatsionnaya tekhnologiya. Protsess sozdaniya programmnogo sredstva pol'zovatelya* [State Standard R ISO/MEK 15910–2002. Information technology. Software user documentation process]. Moscow, Standartinform Publ., 2012. 98 p.

59. GOST 34.201–89. *Informatsionnaya tekhnologiya. Kompleks standartov na avtomatizirovannye sistemy. Vidy, komplektnost' i oboznachenie dokumentov pri sozdanii avtomatizirovannykh system* [State Standard 34.201–89. Information technology. Set of standards for automated systems. Types, sets and indication of documents for automated systems making]. Moscow, Goskomstandart Publ., 2002. 36 p.

60. GOST 34.601–90. *Informatsionnaya tekhnologiya. Kompleks standartov na avtomatizirovannye sistemy. Avtomatizirovannye sistemy stadii sozdaniya* [State Standard 34.601–90. Information technology. Set of standards for automated systems. Automated systems. Stages of development]. Moscow, Goskomstandart Publ., 2002. 84 p.

61. GOST R ISO/MEK 12207–2010. *Informatsionnaya tekhnologiya. Sistemnaya i programmnaya inzheneriya. Protsessy zhiznennogo tsikla programmnykh sredstv* [State Standard R ISO/MEK 12207–2010. Information technology. System and software engineering. Software life cycle processes]. Moscow, Standartinform Publ., 2011. 105 p.

62. GOST R 15.301–2016. *Sistema razrabotki i postanovki produktsii na proizvodstvo. Produktsiya proizvodstvenno-tekhnicheskogo naznacheniya. Poryadok razrabotki i postanovki produktsii na proizvodstvo* [State Standard R 15.301–2016. System of product development and launching into manufacture. Products of industrial and technical designation. Procedure of product development and launching into manufacture]. Moscow, Standartinform Publ., 2018. 15 p.

63. GOST ISO/IEC 15420–2010. *Avtomaticheskaya identifikatsiya. Kodirovanie shtrikhovoe. Spetsifikatsiya simvoliki shtrikhovogo koda EAN/UPC* [State Standard ISO/IEC 15420–2010. Automatic identification. Bar coding. EAN/UPC bar code symbology specification]. Moscow, Standartinform Publ., 2011. 45 p.

64. Ingemansson A.R. Tekhnologicheskaya podgotovka i adaptivnoe upravlenie v tsifrovykh proizvodstvennykh sistemakh [Technological preparation and adaptive control in digital production systems]. *Vestnik Kuzbasskogo gosudarstvennogo tekhnicheskogo universiteta = Bulletin of the Kuzbass State Technical University*, 2021, no. 4, pp. 5–13. DOI: 10.26730/1999-4125-2021-4-5-13.

65. Suslov A.G., Medvedev D.M., Petreshin D.I., Fedonin O.N. Sistema avtomatizirovannogo tekhnologicheskogo upravleniya iznosostoikost'yu detalei mashin pri obrabotke rezaniem [System for automated wear–resistance

technological control of machinery at cutting]. *Naukoemkie tekhnologii v mashinostroenii = Science Intensive Technologies in Mechanical Engineering*, 2018, no. 5 (83), pp. 40–44. DOI: 10.30987/article_5ad8d291cddcd8.06334386.

66. Tugengold A.K., Izyumov A.I. Printsipy kontseptual'nogo podkhoda k sozdaniyu podsistemy Instrument v smart-pasporte mnogooperatsionnogo stanka [Principles of conceptual approach to creating tool subsystem for multioperation machine smart-passport]. *Vestnik Donskogo gosudarstvennogo tekhnicheskogo universiteta = Vestnik of Don State Technical University*, 2014, vol. 14 (2), pp. 74–83. DOI: 10.23947/1992-5980-2014-2-74-83.

67. Xiurong Z., Yeu W. Process analysis and parameter optimization of five axis NC machine for machining complex curved surface impellers. *2019 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)*, Changsha, China, 2019, pp. 122–124. DOI: 10.1109/ICITBS.2019.00036.

68. Zakovorotny V.L., Gvindjiliya V.E. Sinergeticheskii podkhod k povysheniyu effektivnosti upravleniya protsessami obrabotki na metallorezhushchikh stankakh [Synergetic approach to improve the efficiency of machining process control on metalcutting machines]. *Obrabotka metallov (tekhnologiya, oborudovanie, instrumenty) = Metal Working and Material Science*, 2021, vol. 23, no. 3, pp. 84–99. DOI: 10.17212/1994-6309-2021-23.3-84-99.

69. *Kouguchi J., Yoshioka H*. Monitoring method of cutting forces and vibrations by using frequency separation of acceleration sensor signals during milling process with small ball end mills. *Precision Engineering*, 2024, vol. 85, pp. 337–356. DOI: 10.1016/j.precisioneng.2023.10.013.

70. Lu Z., Wang M., Dai W., Sun J. In-process complex machining condition monitoring based on deep forest and process information fusion. *The International Journal of Advanced Manufacturing Technology*, 2019, vol. 104, pp. 1953–1966. DOI: 10.1007/s00170-019-03919-4.

71. Yao Z., Shen J., Wu M., Zhang D., Luo M. Position-dependent milling process monitoring and surface roughness prediction for complex thin-walled blade component. *Mechanical Systems and Signal Processing*, 2023, vol. 198, p. 110439. DOI: 10.1016/j.ymssp.2023.110439.

72. Accattatis A., Saggio G., Giannini F. A real time FFT-based impedance meter with bias compensation. *Measurement*, 2011, vol. 44 (4), pp. 702–707. DOI: 10.1016/j.measurement.2011.01.00.

73. Guo Y., Shi D., Shen X., Ji J., Gan W.-S. A survey on adaptive active noise control algorithms overcoming the output saturation effect. *Signal Processing*, 2024, vol. 222, p. 109525. DOI: 10.1016/j.sigpro.2024.109525.

74. Chehrehzad M., Kecibas G., Besirova C., Uresin U., Irican M., Lazoglu I. Tool wear prediction through AI-assisted digital shadow using industrial edge device. *Journal of Manufacturing Processes*, 2024, vol. 113, pp. 117–130. DOI: 10.1016/j.jmapro.2024.01.052.

75. Ponomarev B.B., Nguyen S.H. Vliyanie orientatsii instrumenta na sily rezaniya pri kontsevom frezerovanii [The influence of tool orientation on cutting forces during end milling]. *Izvestiya vysshikh uchebnykh zavedenii. Mashinostroenie = Proceedings of Higher Educational Institutions. Machine Building*, 2019, no. 3, pp. 11–20. DOI: 10.18698/0536-1044-2019-3-11-20.

76. Gimadeev M.R., Li A.A. Tool condition monitoring techniques for milling. *Proceedings of the 9th International Conference on Industrial Engineering. ICIE 2023*. Cham, Springer, 2023, pp. 698–707. DOI: 10.1007/978-3-031-38126-3_69.

77. Gowid S., Dixon R., Ghani S. A novel robust automated FFT-based segmentation and features selection algorithm for acoustic emission condition based monitoring systems. *Applied Acoustics*, 2015, vol. 88, pp. 66–74. DOI: 10.1016/j.apacoust.2014.08.007.

Conflicts of Interest

The authors declare no conflict of interest.

Claimed contribution of co-authors:

Gimadeev M.R. – formulation of the basic concept of the study, conducting experiments, preparing the text of the paper and drawing conclusions, presenting the research results in graphs, searching for analytical materials in domestic and foreign sources, preparing a literature review;

Stelmakov V.A. – planning the experiment, conducting experiments, conducting analysis and preparing initial conclusions;

Shelenok E.A. – conducting a critical analysis of materials and drawing conclusions, participating in the discussion of the paper materials, analyzing and supplementing the text of the paper.