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AUTOMATED SYSTEM FOR DIAGNOSTICS OF THE PARTS PROCESSING

This work investigates the creation and implementation of an automated system for diagnosing the processing of parts, which is based on the use of methods for analyzing acoustic emission and elastic deformations. Its key task is to identify the degree of wear and predict the residual resource of the tool, which allows you to improve the quality of processing, reduce the number of scrap and optimize production processes. The system is implemented in a production environment, which helps to increase the efficiency of equipment operation and reduce the risk of emergency situations. The proposed algorithms provide the ability to quickly respond to changes in processing parameters and prevent tool failures. The system analyzes the received data in real time, which allows you to adjust processing modes, reducing the load on the equipment and increasing overall productivity. The use of machine learning and big data processing methods increases the accuracy of wear assessment and adaptation of technological parameters to changing operating conditions. Determining critical limit values allows you to avoid emergency situations and ensures stable operation of the equipment. The main advantage of the system is its integration with CNC systems, which makes it possible to automatically change processing modes without operator intervention. It also supports the use of cloud technologies for centralized storage and data analysis, which increases the accuracy and speed of decision-making. Data on the condition of the tool is used for statistical analysis of its efficiency and optimization of processing parameters. Studies have shown that the system helps to increase the tool life, reduce the number of scrap and reduce energy consumption. Reducing waste and improving the quality of finished products improves the economic efficiency of production. Further development may include the introduction of multi-sensor systems, digital twins and neural network algorithms for even more accurate prediction and adaptation of technological processes.

Keywords: *automated system, diagnostics of the processing process, cutting tool, vibroacoustic signal, elastic deformations.*

Formulation of the problem. In modern industrial production, the main priorities remain to increase productivity, reduce costs, and ensure high product quality. The intensive development of automated technologies and digital systems allows to significantly improve the efficiency of processing parts, optimize control processes, and minimize the risks of unexpected equipment failures. Automated processing process control systems are an integral part of modern production, providing continuous monitoring of processing parameters and prompt detection of deviations from normal operating modes [1, p. 3].

One of the most important elements of mechanical processing is the cutting tool, on which the quality and accuracy of manufacturing parts largely depends. During operation, the cutting tool is subjected to significant mechanical stress, which leads to its wear, deformation, and gradual failure. Untimely detection of tool wear can lead to deterioration of processing quality, an increase in the percentage of defective products, and increased production costs. Traditional methods of controlling the performance of cutting tools are often ineffective due to their limited speed and insufficient accuracy.

The introduction of automated control systems for the processing of parts allows for timely determination of its wear, prediction of the residual resource and correction of processing modes. Such systems are based on the analysis of various physical parameters, in particular acoustic emission, elastic deformations, temperature characteristics, etc. Analysis of these parameters in real time makes it possible to detect critical deviations and prevent emergency situations [2, p. 121].

Automated control systems contribute not only to increasing production productivity, but also to reducing the human factor in the decision-making process. For example, when detecting signs of increased tool wear, the system can automatically change cutting modes, reduce feed or rotation speed, which allows extending the tool life and ensuring stable product quality.

Another important aspect of automated control is integration with other production systems, in particular with control systems for CNC machines. Such integration allows for the creation of unified information environments in which data on the condition of the tool and processing parameters are constantly analyzed and used to improve technological processes. This contributes to the creation of the concept of "smart manufacturing" [3, p. 9], which involves the use of artificial intelligence, machine learning and IoT (Internet of Things) for automatic decision-making and adaptation of production processes to changing conditions.

The transition to "smart manufacturing" necessitates a shift from reactive maintenance to proactive, data-driven diagnostics. By leveraging the Industrial Internet of Things (IIoT), sensors can stream high-frequency data to edge computing units that process information locally, reducing latency in critical decision-making. This ecosystem allows for the synchronization of the digital twin with the physical machine, providing a sandbox for testing optimized cutting parameters without risking damage to the actual equipment**.**

The use of artificial intelligence and big data methods in control systems opens up new opportunities for predicting the condition of the tool and optimizing processing. For example, the use of machine learning algorithms allows you to analyze large data sets on processing parameters, identify patterns of tool wear and, based on this, adjust operating modes to minimize negative impacts [4, p. 257]. Such methods can significantly increase the reliability and accuracy of control, reduce losses due to premature tool retirement and ensure more efficient use of resources.

In addition, automated control systems for the processing of parts actively use augmented reality (AR) and digital twins technologies [5, p. 37]. A digital twin is a virtual copy of a physical object (for example, a machine tool or cutting tool), which reflects its state and dynamics of changes in real time. This allows you to simulate the behavior of the system under different conditions, predict potential malfunctions and optimize operating modes without the need for real experiments. It is worth noting that automated control systems are also an important tool for flexible production. They allow you to quickly adapt to changes in the design of parts, introduce new processing technologies and ensure stable product quality even in small-batch and small-batch production [6, p. 409]. In addition, the ability to integrate such systems into cloud platforms allows you to store and process data on remote servers, which improves the speed of analysis and the efficiency of production process management.

Analysis of recent research and publications. In the future, the development of automated control systems for the processing of parts will be aimed at increasing their speed, accuracy and adaptability to changing production conditions. In particular, an important direction is the development of multifunctional sensor systems that can simultaneously control several parameters (vibration, temperature, etc.) and perform a comprehensive analysis of tool wear [7, p. 5]. Additionally, the introduction of self-adaptive algorithms based on neural networks will allow control systems to independently change the analysis parameters depending on the operating conditions of the tool.

Task statement. The purpose of the work is: to develop an automated system for processing parts based on measuring acoustic emission and elastic deformations, which allows for timely detection of tool wear, predicting its residual resource and correcting technological processing modes.

To achieve this, the study focuses on the synergistic relationship between high-frequency acoustic signals and low-frequency mechanical strains. The integration of these two distinct physical phenomena provides a more holistic view of the tool-workpiece interface than single-sensor systems. Specifically, the research aims to validate a mathematical model that translates these raw physical inputs into a singular, actionable "wear index" that can be interpreted directly by CNC controllers.

Thus, the development and implementation of such systems is an important step towards the digitalization of production processes, increasing their flexibility and efficiency. The integration of automated control with modern technologies of artificial intelligence, machine learning and IoT allows to create high-tech systems that are able to work in dynamic conditions of modern production and provide continuous control of product quality. Automated control systems allow to significantly reduce production losses, improve the forecasting of the technical condition of equipment and ensure high reliability of mechanical processing [8, p. 4]. As a result, enterprises are able to reduce costs for maintenance and repair of equipment, which in the long term contributes to increasing the competitiveness and efficiency of the entire production process.

Outline of the main material of the study. The cutting process is accompanied by a set of physico-chemical phenomena, in particular mechanical, electrical, thermal, adhesive and diffusion processes that occur during the interaction of the cutting tool with the workpiece. Each of these factors affects the processing parameters, which contain information about the cutting conditions. Determining the dependence between them and the degree of tool wear makes it possible to assess its condition and predict the residual service life.

The results of experimental studies confirm that the most informative characteristics for controlling the process of processing parts are the parameters of acoustic emission and elastic deformations [9, p. 16].

Therefore, the proposed control system should be based on the analysis of the signals of these processes. At the same time, the key diagnostic indicator is acoustic emission in the cutting zone, since it is formed under the influence of the main physico-mechanical phenomena and is a reliable indicator of the technical condition of the tool. That is why in the developed system, the assessment of its wear and adjustment of the technological process will be carried out on the basis of the received signals.

The automated machining control system contains two levels of diagnostics. The first provides prompt response and emergency stop in case of exceeding the permissible deformation limits. Sudden changes in the behavior of the material may indicate a critical level of wear, the presence of hard inclusions in the workpiece or a sharp increase in the depth of cut during roughing [10, p. 4]. One of the main reasons for an emergency stop may be a sudden tool failure. Analysis of changes in the characteristics of elastic deformations allows for timely identification of such cases and rapid response to them.

The second level performs the function of assessing the condition of the tool and predicting its further wear. This predictive level operates as a continuous monitoring loop that compares real-time data against a historical baseline of tool performance stored in the system's database. By utilizing a correction factor, the system accounts for variations in material hardness and tool geometry, ensuring that the diagnostic output remains accurate even when switching between different production batches. This level is not merely observational; it serves as the "brain" of the adaptive control system, calculating the precise moment when a tool's efficiency drops below the economic threshold. It is based on the analysis of the combination parameter of acoustic emission [11, p. 13], which takes into account…

$$W_M = \frac{A^2 \cdot N_\Sigma}{K_\varepsilon} \tag{1}$$

where $A^2 \cdot N_\Sigma$ – acoustic emission power; A – acoustic emission signal amplitude; N_Σ – acoustic emission signal activity; K_ε – coefficient reflecting the influence of elastic deformations on the cutting process, can be described through the elastic modulus of the material and the conditions of interaction of the tool with the workpiece.

The values of the amplitude and activity of the acoustic emission signal are determined by analyzing the obtained acoustic emission signal data, and the elastic deformation parameter [12, p. 162] is calculated by the following formula:

$$K_\varepsilon = \frac{\sigma \cdot \varepsilon}{E} = \frac{F_c \cdot \Delta L}{A \cdot L \cdot E} \tag{2}$$

where E is the modulus of elasticity (Young's modulus); $\sigma = \frac{F_c}{A}$ is the stress, which is calculated as the cutting force (F_c) per unit area (A); $\varepsilon = \frac{\Delta L}{L}$ is the relative strain, defined as the ratio of the change in length (ΔL) to the initial length (L).

Using the ratio of the combination parameter of acoustic emission W_M and the value of cutting tool wear, the degree of tool wear h_u is analyzed, the intensity of wear is calculated and mathematical models of wear are simulated. Based on these models, tool wear is predicted. After analyzing the degree of wear, intensity and previously predicted values, a conclusion is made about the possibility of making changes to the processing modes to reduce wear.

The mathematical model of cutting tool wear is described as follows:

$$h_u = \frac{\Delta h_u + \left(k_w \cdot j_u \cdot A^2 \cdot N_\Sigma\right)}{\frac{F_c \cdot \Delta L}{A \cdot E \cdot L}} = \frac{A \cdot \left(\Delta h_u + \left(k_w \cdot j_u \cdot A^2 \cdot N_\Sigma\right)\right) \cdot E \cdot L}{F_c \cdot \Delta L} \tag{3}$$

where Δh_u – existing wear, mm; j_u – wear intensity $\left(j_u = \frac{h_u(i)}{h_u(i-1))}\right)$; k_w – correction factor for the ratio of tool wear and the combination parameter of acoustic emission, which is determined experimentally for various combinations of materials "tool – part" and entered into the database.

The calculation of the predicted wear of the cutting tool is carried out using the following formula:

$$h_{pr}\left(i+1\right)=(j_u\cdot\frac{h_u\left(i\right)+h_u\left(i-1\right)}{2} \qquad (4)$$

The general functional block diagram of the automated control system for the processing of parts is shown in Fig. 1, and the algorithm of its operation is presented in Fig. 2.

The control system consists of a sensor that measures the acoustic emission signal (pos. 1, Fig. 1). The received signal passes through an amplifier (pos. 2) and a low-pass filter (pos. 3), after which it is fed to an analog-to-digital converter (ADC, pos. 6). The signal that registers the elastic deformations of the cutting tool (pos. 4) is processed in a similar way: it is first amplified (pos. 5), and then transmitted to the ADC input.

Further analysis of the parameters is performed using a computer (pos. 12), which contains a unit for estimating the intensity and degree of wear (pos. 7). The unit for estimating wear functions by performing a fast Fourier transform (FFT) on the acoustic signals to isolate the frequency bands most associated with adhesive and abrasive wear. Simultaneously, the elastic deformation data is filtered to remove the "noise" of the machine's own structural vibrations, leaving only the pure strain data caused by the cutting force. This cleaned data is then fed into the mathematical models to generate a real-time prediction of the tool's flank wear (h_u). In this module, based on data on the maximum and minimum values of elastic deformations (pos. 8), emergency conditions are monitored. If the permissible limits are exceeded, the system sends an emergency stop signal to the actuators (pos. 15), which include the engine control unit, the feed control system and other modules.

In addition, in block 7, the intensity of wear of the cutting tool is analyzed using the correction factor k_w, which is stored in the database (pos. 9). For a more accurate assessment, the operating modes of the technological and processing system are taken into account, information about which comes from the CNC block (pos. 13) according to the control program (pos. 14).

After determining the level of wear, the data is transmitted to block 10, where the machining process is simulated, the residual tool life is estimated and its further state is predicted based on information from the CNC. In block 11, corrective and control signals are generated that allow changing the machining modes, which are then transmitted to the CNC.

If the correction of technological parameters is impossible, the system initiates a stop of the production process or issues a command to replace the tool. The CNC, receiving the corresponding signals from block 11, makes changes to the control commands that are sent to the actuators (pos. 15).

Conclusions. Automated control systems for the processing of parts are an important element of modern production, as they can significantly increase the accuracy and stability of mechanical processing. The use of methods for analyzing acoustic emission and elastic deformations provides effective monitoring of the technical condition of the tool in real time. This allows for timely detection of signs of wear, prediction of residual life and prevention of emergency situations.

Integration of such systems with CNC, machine learning technologies and the Internet of Things contributes to the automatic correction of processing parameters, minimizing the human factor. By reducing the reliance on operator intuition, the system ensures a standardized level of quality that is independent of the workforce's experience level. The ability to automatically adjust feed rates and spindle speeds in response to tool degradation effectively extends the "sweet spot" of the tool's lifecycle, maximizing the

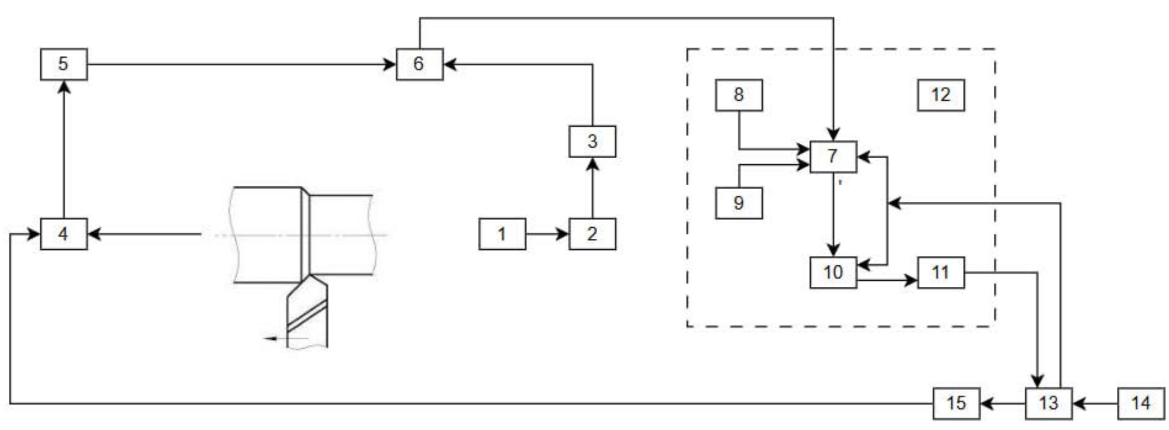

Fig. 1. Block diagram of an automated control system for the processing of parts

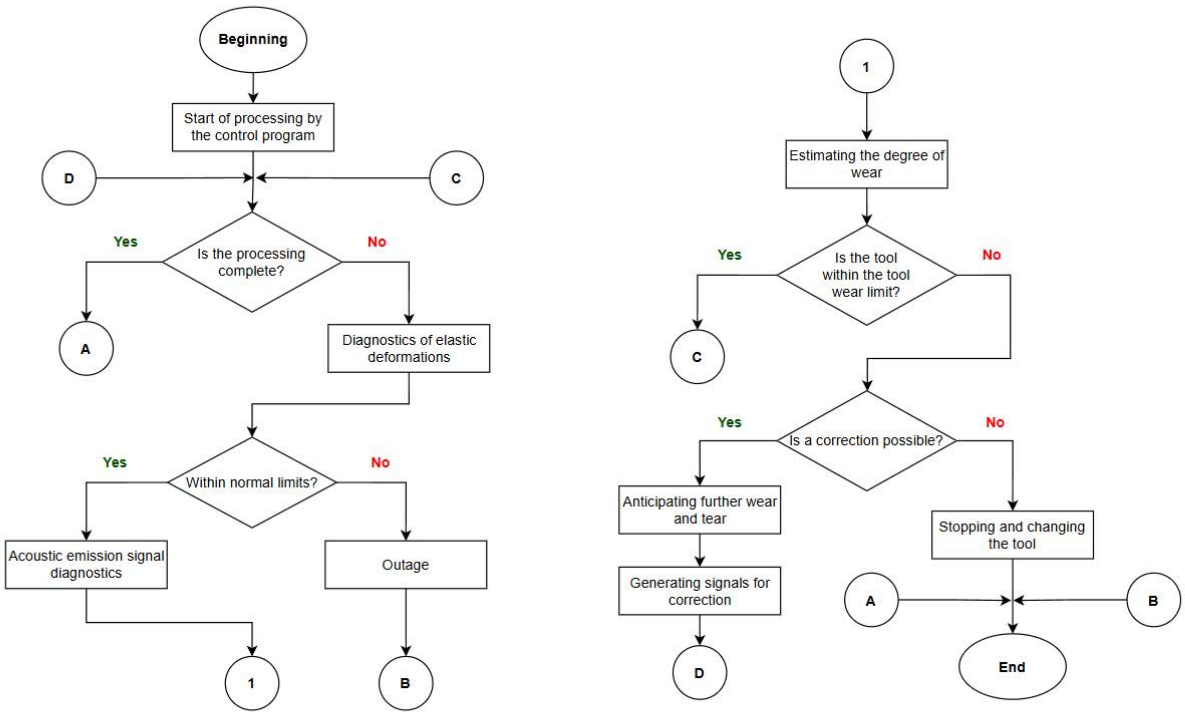

Fig. 2. Algorithm of functioning of the automated control system for the processing of parts

volume of material removed before a replacement is required. This leads to a measurable decrease in the cost-per-part and a significant reduction in the environmental footprint of the manufacturing process due to lower energy and material waste. This, in turn, helps to reduce production costs, optimize tool use and increase the overall efficiency of equipment.

Further development of such systems may include the introduction of self-learning algorithms, digital twins and cloud technologies for centralized data analysis. All this will contribute to increasing the reliability of production processes, reducing the level of defects and creating more flexible and adaptive technological solutions in industry.

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Шевченко В.В., Полушко М.М. АВТОМАТИЗОВАНА СИСТЕМА ДІАГНОСТИКИ ПРОЦЕСУ ОБРОБКИ ДЕТАЛЕЙ

У цій роботі досліджується створення та впровадження автоматизованої системи діагностики процесу обробки деталей, яка базується на використанні методів аналізу акустичної емісії та пружних деформацій. Її ключовим завданням є виявлення ступеня зношування та прогнозування залишкового ресурсу інструменту, що дає змогу підвищити якість обробки, зменшити кількість браку та оптимізувати виробничі процеси. Система впроваджується у виробниче середовище, що сприяє підвищенню ефективності функціонування обладнання та зниженню ризику виникнення аварійних ситуацій. Запропоновані алгоритми забезпечують можливість швидкого реагування на зміну параметрів обробки та запобігання відмовам інструменту. Система виконує аналіз отриманих даних у режимі реального часу, що дозволяє коригувати режими обробки, знижуючи навантаження на обладнання та підвищуючи загальну продуктивність. Застосування методів машинного навчання та обробки великих даних підвищує точність оцінки зношування та адаптацію технологічних параметрів до змінних умов експлуатації. Визначення критичних граничних значень дозволяє уникати аварійних ситуацій та забезпечує стабільну роботу обладнання. Основною перевагою системи є її інтеграція з системами ЧПК, що дає можливість автоматично змінювати режими обробки без втручання оператора. Також вона підтримує використання хмарних технологій для централізованого зберігання й аналізу даних, що підвищує точність і швидкість прийняття рішень. Дані про стан інструменту застосовуються для статистичного аналізу його ефективності та оптимізації параметрів обробки. Проведені дослідження показали, що система сприяє збільшенню ресурсу інструменту, зниженню кількості браку та зменшенню енергоспоживання. Скорочення відходів і підвищення якості готової продукції покращує економічну ефективність виробництва. Подальший розвиток може передбачати впровадження мультисенсорних систем, цифрових двійників та нейромережевих алгоритмів для ще більш точного прогнозування і адаптації технологічних процесів.

Ключові слова: *автоматизована система, діагностика процесу обробки, різальний інструмент, віброакустичний сигнал, пружні деформації.*

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