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Development of digital twin of CNC unit based on machine learning methods*

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Разработка цифрового двойника станка с ЧПУ на основе методов машинного обучения***

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Introduction. It is shown that the digital twin (electronic passport) of a CNC machine is developed as a cyber-physical system. The work objective is to create neural network models to determine the operation of a CNC machine, its performance and dynamic stability under cutting.

Materials and Methods. The development of mathematical models of machining processes using a sensor system and the Industrial Internet of Things is considered. Machine learning methods valid for the implementation of the above tasks are evaluated. A neural network model of dynamic stability of the cutting process is proposed, which enables to optimize the machining process at the stage of work preparation. On the basis of nonlinear dynamics approaches, the attractors of the dynamic cutting system are reconstructed, and their fractal dimensions are determined. Optimal characteristics of the equipment are selected by input parameters and debugging of the planned process based on digital twins.

Research Results. Using machine learning methods allowed us to create and explore neural network models of technological systems for cutting, and the software for their implementation. The possibility of applying decision trees for the problem of diagnosing and classifying malfunctions of CNC machines is shown.

Discussion and Conclusions. In real production, the technology of digital twins enables to optimize processing conditions considering the technical and dynamic state of CNC machines. This provides a highly accurate assessment of the production capacity of the enterprise under the development of the production program. In addition, equipment failures can be identified in real time on the basis of the intelligent analysis of the distributed sensor system data.

Введение. В статье показано, что цифровой двойник (электронный паспорт) станка с ЧПУ разрабатывается как киберфизическая система.

Цель работы — создание нейросетевых моделей, определяющих функционирование станка с ЧПУ, его производительность и динамическую устойчивость при резании.

Материалы и методы. Рассматриваются вопросы создания математических моделей процессов механической обработки с использованием системы сенсоров и промышленного интернета вещей. Оценены методы машинного обучения, подходящие для реализации названных задач. Предложена нейросетевая модель динамической устойчивости процесса резания, позволяющая оптимизировать процесс механической обработки на этапе технологической подготовки производства. На основе подходов нелинейной динамики реконструированы аттракторы динамической системы резания и определены их фрактальные размерности. Выбраны оптимальные характеристики оборудования по входным параметрам и отладке планируемого технологического процесса на основе цифровых двойников.

Результаты исследований. Использование методов машинного обучения позволило создать и исследовать нейросетевые модели технологических систем обработки резанием и программное обеспечение для их реализации. Показана возможность применения деревьев решений для задачи диагностики и классификации неисправностей станков с ЧПУ.

Обсуждение и заключения. В реальном производстве технология цифровых двойников позволяет оптимизировать режимы обработки с учетом технического и динамического состояния станков с ЧПУ. Это обеспечивает высокоточную оценку производственных мощностей предприятия при составлении производственной программы. Кроме того, на основе интеллектуального анализа данных системы распределенных сенсоров можно выявить неисправности оборудования в режиме реального времени.

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Introduction. The single core control platform proposed in [1] serves as the basis for the development of a new generation of the processing equipment control systems, and it also provides improvement of the numerical control systems (CNC) for digital productions. Open CNC systems of machines with long-lived computational resources and high speed processing of a large database (DB), embedded neural processor modules and communication modules with industrial Internet can be such a platform. In the latter case, we are talking about the applicability of cloud technologies for processing large amounts of data on enterprise servers (local networks) and providers. All this will create the basis of intelligent control for a wide range of the CNC process equipment.

Since the nineties of the 20th century [2], the authors of the presented research have been developing software products for intelligent control of the processing equipment. In particular, the criteria were proposed for evaluating the dynamic stability of the cutting process, based on the methods of nonlinear dynamics and fractal analysis of the vibroacoustic emission (VAE) signals. The authors have created a single platform for enhancing various technological equipment with CNC systems. It is implemented through embedding high-performance computing modules and deep learning of artificial neural networks into the CNC systems using CUDA nVidia technologies. In the framework of this work, the CNC process equipment accomplished with sensors is studied. It applies cloud technologies for collecting and processing information using the developed techniques. Such systems will be considered as cyber-physical ones [3].

It is assumed that the platform developed by the authors will become the basis for digitalization at all levels of the enterprise. To this end, it should not only analyze the data of equipment, systems, and devices, but also use the information obtained in this way to reduce time on market launch of new products, to increase production flexibility, product quality and efficiency of production processes.

Digital twin is a new word in the modeling of equipment, processes and production planning [3]. This is a set of mathematical models that describe reliably the processes and interrelationships on a single object and within an entire production enterprise using big data analysis and machine learning.

The leader in the application of digital twins is Siemens [3]. According to its definition, a digital twin is an ensemble of mathematical models. They characterize various equipment conditions, production and business processes over time, in accordance with current production conditions. Neural network circuits hold a specific place among such mathematical models; i.e. a neural network model of a process or product is its digital twin [2].

The base unit of the digital production is a cyber-physical system (CPS) [1]. Its high adaptive and intellectual capabilities are due to the following features:

- associated perception of information,
- ongoing training
- assessment of the current condition and forecasting of the future one.

CPS is able to analyze multidimensional data considering even hidden factors of the real production. Based on this data, it can autonomously solve optimization problems and make right decisions. Therefore, CPS is the key element in creating a digital twin. In this case, the following is meant by the digital twin:

- a set of mathematical models that characterize various equipment conditions, production processes over time, according to the current production conditions;
- detailed 3D assembly object models, reflecting connections and interactions between nodes.

From this point of view, a digital twin can be considered as a digital identity of the CPS, an electronic passport, which records all the data on the materials being processed, the performed technological operations, and testing.

Currently, digital twins are mainly created for commercial purposes. They operate successfully in the oil and gas industry. At the same time, there is no data on the twins of the equipment of machining industries based on CPS in the literature.

Digital twins based on CPS can be obtained through the following:

- traditional analytical approaches based on the mathematical description of physical processes;
- modern statistical methods including machine learning.

Materials and Methods. Machine learning methods used to build statistical models can be divided into three groups: regression analysis models, classification models, and outlier detection models [4–6] (Table 1).

Table 1

Basic Machine Learning Methods

Regression analysis	Classification	Outlier detection
Linear regression	Logistic regression	Support vector method
Bayesian regression	Decision Trees Forest	Principal component analysis
Decision Trees Forest	Decision Jungles	K-means
Decision Trees	Decision Trees	Neural networks
Quantile Fast Forest Regression	Support vector method	Kohonen self-organizing maps
Neural networks	Bayes point machine	
Poisson regression	One-vs-All	
Ordinal regression	Neural networks	

The selection of the machine learning method depends on the size, quality and nature of the data, as well as on the type of tasks to be solved. The existing methods require different computational performance, and they have varying degrees of accuracy. Mostly, they are evaluated by the possibility to achieve accurate approximation of the data and to identify the boundaries in the data space. The method of artificial neural networks (ANN) is the most universal and accurate one, it enables to operate a large amount of data and to build non-linear dependences. Neural networks use a large number of settings, which opens up possibilities for creating highly accurate models of processes operating in the regression analysis, classification, and outlier detection modes.

The basic method for analyzing model quality is cross-validation. It allows for evaluating the statistical quality of the source data through constructing and comparing several models obtained from different training and verification samples. When building models of complex objects and systems, it is required to reduce the data dimensionality and eliminate the effect of multicollinearity of variables. The solution to such problems is possible due to the application of the principal component method, which represents multidimensional data in the form of a limited number of components. Such a generalized approach can be applied to eliminate retraining of models. The basic methods of machine learning are presented in Table 1.

To improve the quality of the model, bagging and boosting algorithms are used. It is about building not one model, but a set of models solving the same task. The result of this work is a kind of integral assessment of the probability of some event. This assessment can be presented as a synergistic result of a set of models, each of which individually performs poorly. Thus, a digital twin can be a set of statistical models that use various combinations of the machine learning methods and have passed through various stages of verification and improvement.

So, in general, a digital twin based on the CPS is a multifactor model of the equipment [1], which includes an ensemble of electronic (i.e., neural network) models. In this case, the following neural networks will be decisive: those of dynamic stability of the cutting process, of cutting forces, and of the machined surface roughness. Cutting forces cause elastic pressing in the “tool - workpiece” system, which specifies errors in shape and size.

To solve this problem, a complex of statistical models was developed using machine learning methods. The resulting models are the basis for the digital twin of the CNC lathes. They provide solving the regression analysis problems to predict the dynamics of the cutting process under various machining conditions, roughness of the machined surface, and cutting forces. In addition, these models help to solve the classification problems for evaluating the machine current condition. A process diagram of creating a digital twin is shown in Fig. 1.

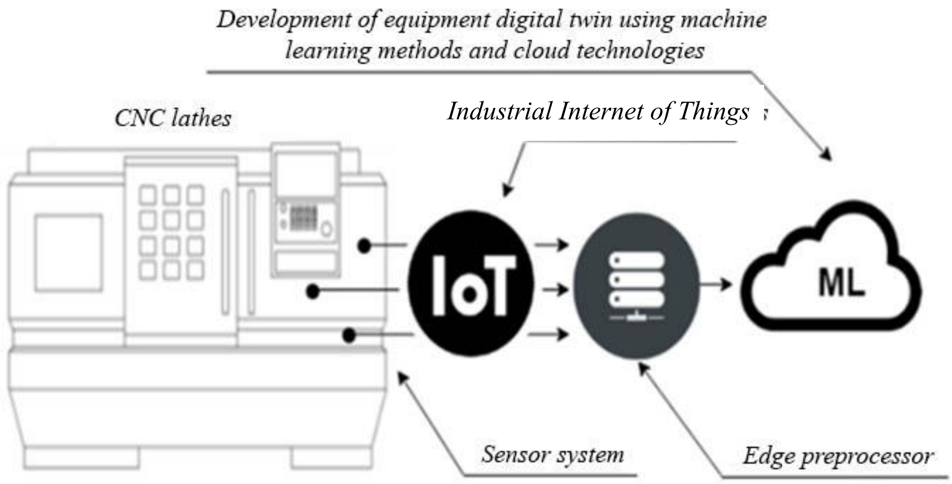


Fig.1. Process diagram of creating a digital twin of CNC machine

Consider in more detail the neural network model of the cutting process dynamics. The training set was obtained on the basis of telemetry data collected under machining through the distributed sensor system of the VAE signal, dynamometer, and Industrial Internet of Things technology (IIoT). The number of sensors, their type and spatial orientation were determined in accordance with the equipment layout. The presence of a large number of sensors with different spatial orientation in the system is explained by the heterogeneity of materials and structures, the signal propagation features, as well as the possibility of restructuring the oscillatory system under operation. Hence, the application of a heterogeneous sensor system could obtain the most complete dynamic picture of the processes in the n-dimensional "state – time" space. The standard TCP/IP protocol and JSON (JavaScript Object Notation) were used as the data transceiving protocol within the IIoT network.

Analog and digital band pass filters, as well as wavelet filters, were used for the signal preprocessing. The application of wavelet filters provided:

- elimination of the noise term impact in the VAE signals;
- identification of periodic and chaotic components based on the entropy factors.

Data pre-processing has been performed on an "edge" device (Edge), which calculates the values of the VAE signal parameters and forms data packets for pushing them to the virtual cloud storage. The development of mathematical models based on the machine learning methods requires structuring and data separation. However, considering the IIoT technology aspects, the construction of relational DB is not always possible; therefore, an approach based on NoSQL technologies was applied. For this, data storage and processing were implemented on a virtual server that simulates the operation of a computing cluster. A special distributed, scalable file system was deployed on this server.

Freeware utilities, libraries and the Hadoop project frameworks (one of the most successful and common big data technologies) were used as a basis. In particular, the Hadoop Common software shell manages the HDFS distributed file system and the HBase database [4]. To perform the distributed computing and processing of large volumes of data, MapReduce was used, which provides automatic parallelization and distribution of tasks on a cluster. nVidia CUDA graphics processors were used to speed up the training of neural network models.

Research Results. A recurrent INS with the sigmoidal neuron activation function was selected to create a statistical model of the cutting dynamics. The data obtained under the industrial equipment operation was used as a training set. During training, the backpropagation algorithm was used. At the end of the learning process, the model obtained was verified on the basis of the mean square derivation values. Fig. 2 shows the monotonous decrease of error. Moreover, its distribution is normal, and it is near zero value, which implies good quality of the model obtained.

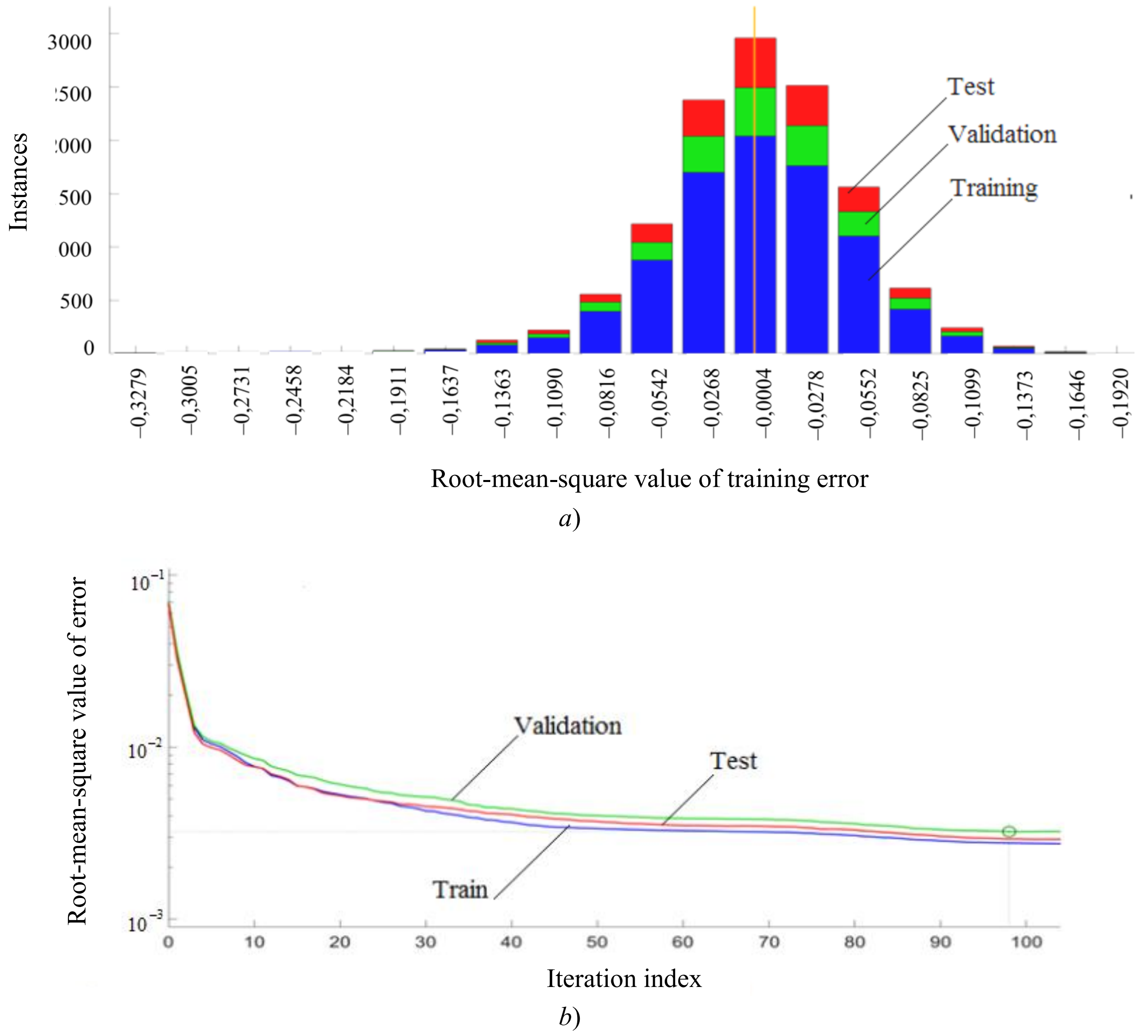


Fig. 2. Assessment of model quality obtained: diagram of training error distribution (*a*); dependence of root-mean-square error on learning iteration (*b*)

The ANN obtained (Fig. 3) consists of 17 input neurons that acquire information on processing conditions and on the previous dynamic condition.

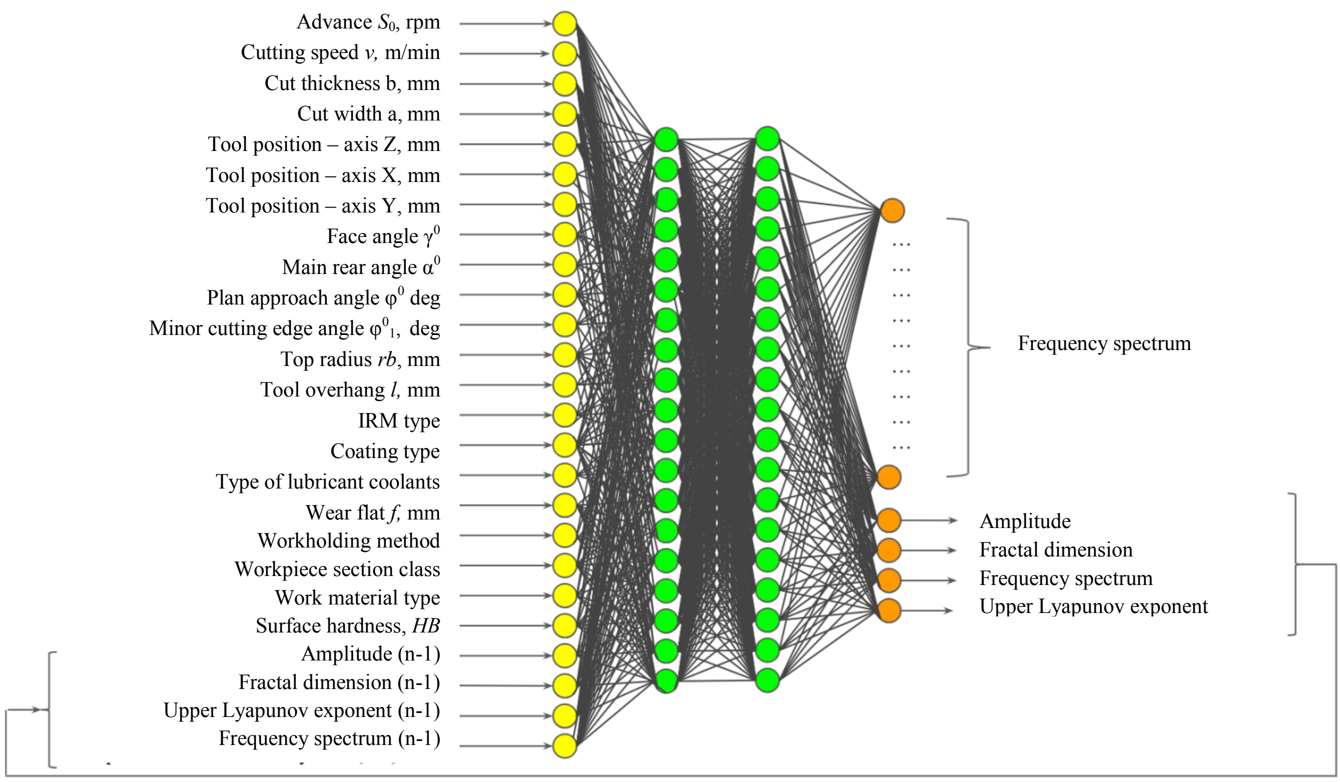
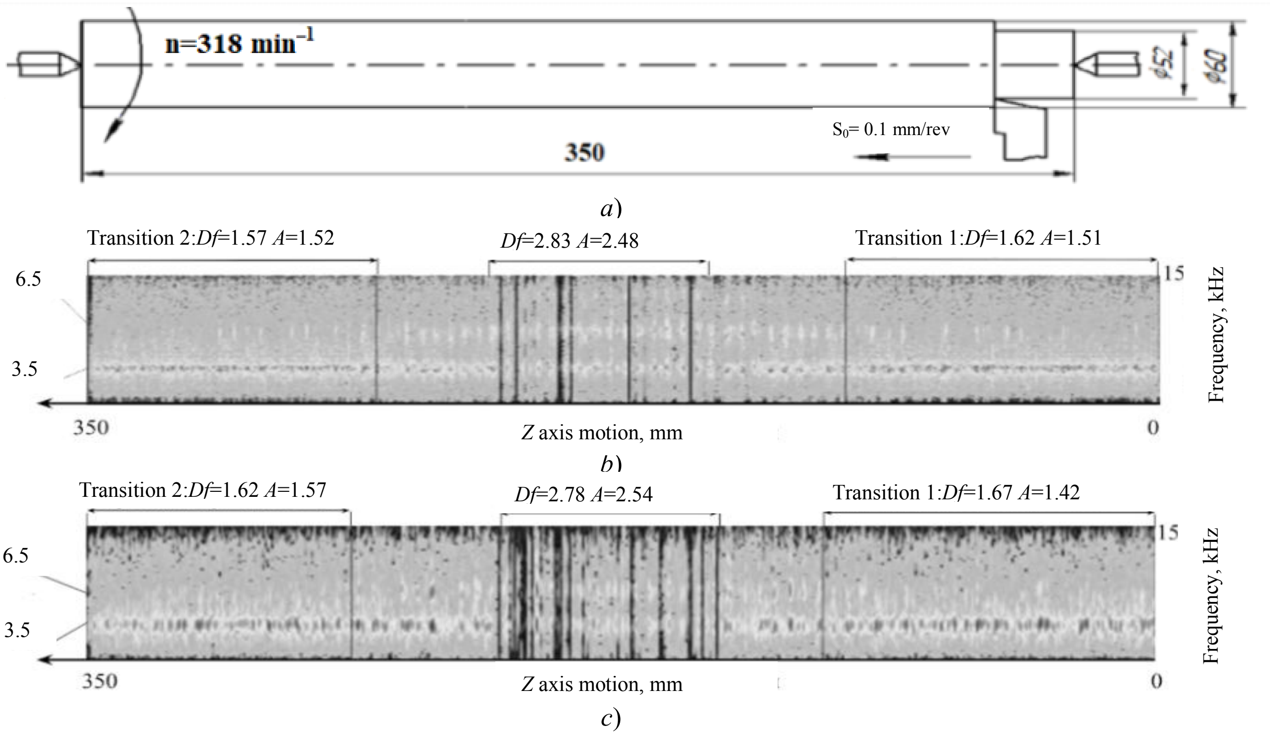
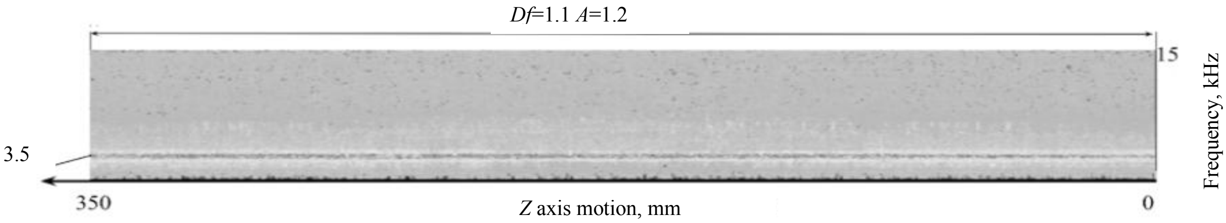


Fig. 3. Neural network model of dynamic stability of cutting process

The output layer of neurons gives information on the dynamic state of the cutting system. The hidden layer is formed by 38 neurons. This ANN is able to simulate the cutting system dynamics for various machining conditions at given instants.

To assess the adequacy of the neural network model, a simulation of the machining process was carried out at a CNC turning center. A shaft of stainless 12X18H10T steel fixed on both sides in the center, as shown in Fig. 4, *a*, was used as the workpiece.





d)

Fig. 4. Neural network simulation results:
treatment scheme (*a*), prototype cutting process (*b*), real-world cutting process (*c*), cutting process after optimization (*d*)

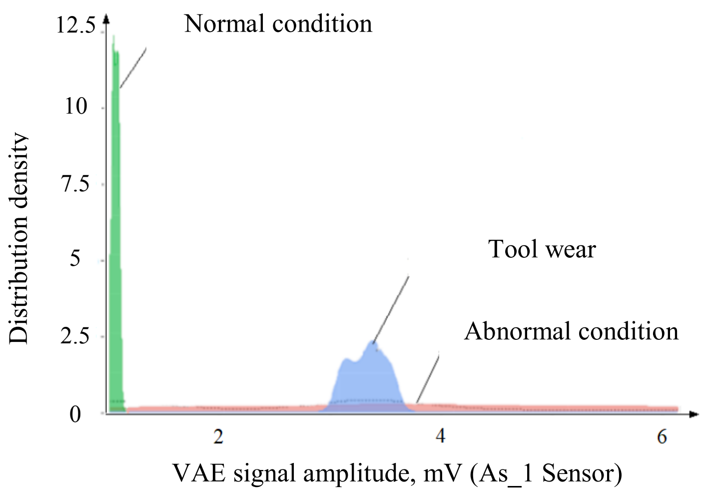
The modes were defined in accordance with the production standards for machining parts of this type on a CNC lathe. The simulation of the tool motion relative to the workpiece was provided by a variable on the ANN input layer responsible for the machine support position along *Z* axis. This variable spacing was 0.01 mm at the distance from 0 to 350 mm. Thus, the dynamic state of the cutting system was obtained for 35 thousand tool positions on *Z* axis. The recorded dynamic states are reflected in the corresponding spectrogram (see Fig. 4, *b*): there are two dominant self-oscillation frequencies (3.5 kHz and 6.5 kHz) and two phase transitions.

To confirm the simulation results, a full-scale experiment was carried out with similar processing conditions and recording of the VAE signal. According to the experimental data obtained, a spectrogram of the machining process was constructed (see Fig. 4, *c*). It also shows two dominant frequencies in the 3.5 kHz and 6.5 kHz areas and two phase transitions. As a result, the simulation error in different machining areas was from 3% to 7%. As can be seen from Fig. 4, the proposed production standards do not allow obtaining a product of a given quality. This may be the cause of defects, and, considering the workpiece runout, – of tool breakage.

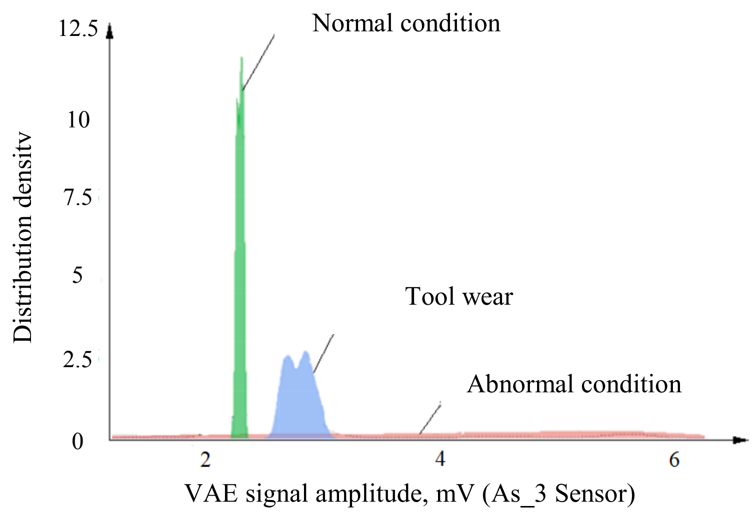
The use of the above-mentioned norms leads to an inadequate assessment of the plant capacity and, accordingly, to a poor-quality formation of the production program. Removal of this disadvantage at the design-engineering stage is fraught with additional time and financial expenditures. Therefore, the modes factored in the norms of production are adjusted. For this, the optimal values of the technological conditions vector are calculated using the ANN and the gradient descent method. Objective optimization functions were the VAE signal amplitudes, fractal dimension and information entropy, which should tend to a minimum. The processing speed and the bevel value on the face surface were selected as optimization parameters. Upon completion of the optimization process, new treatment modes were obtained: $V = 90$ m/min; $S = 0.1$ mm/rev; $f\gamma = 0.2$ mm.

These modes were also evaluated according to the results of a full-scale experiment with recording and processing the VAE signal. As can be seen from Fig. 4, *d*, optimization of the processing conditions made it possible to increase the dynamic stability of the cutting process through reducing the amplitude of self-oscillations by half, and the fractal dimension ($Df = 1.1$). Hence, the dynamic machining quality was improved without loss of productivity.

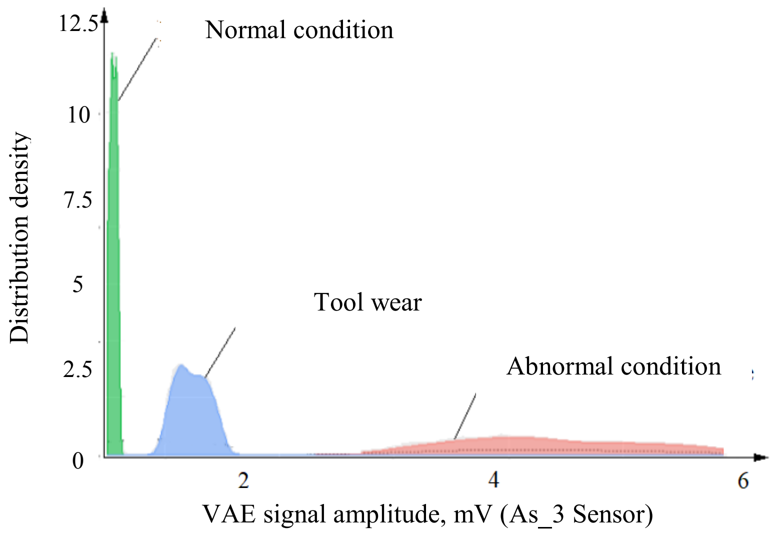
In a similar way, models were obtained for predicting the roughness values of the machined surface and cutting forces. Cutting forces determine the processing accuracy, causing an elastic pressing of the part and tool, and, consequently, the part shape error. These neural network models are multilayered artificial neural feedforward networks (Fig. 5).



a)



b)



c)

Fig. 5. Distribution of amplitude values of sensor signal: As_1 (*a*), As_2 (*b*), As_3 (*c*)

Neural network models as part of the digital twin are applicable not only under real production conditions, but also when choosing and justifying the purchase of equipment. At this stage, it is possible to select the optimal characteristics of the equipment and debug the planned process on digital twins.

To assess the current condition of the equipment, a classification model was developed using decision trees [5]. Values of the VAE signal amplitude at different points of time from three sensors located on the tool (As_1), at the front spindle support (As_3) and at the rear center (As_2) were selected as attributes for decision-making. Three conditions were used as classes: Normal, Tool wear, and Abnormal. Any condition, when the quality of the treated surface and the operation of the equipment were unsatisfactory, was implied as abnormal. The criterion for tool wear was considered bevel on the rear surface (h = 0.15 mm). Upon receiving the learning sample, an exploratory data analysis was performed.

Fig. 5 shows the correspondence of the distribution of the VAE signal amplitude values of the As_1 sensor to the three groups of conditions. The data obtained from this sensor differentiates well the normal condition and tool wear. However, the values corresponding to the abnormal condition have intersections with data from the other groups. Therefore, the information from the As_1 sensor cannot be used with high accuracy to classify conditions.

Fig. 5, *b,* characterizes the distribution of signal amplitude values from the As_2 sensor. The data obtained have low information value due to two shortcomings:

- intersections of the values of the abnormal condition group with other classes;

- weak differentiation of the normal condition and tool wear (this is due to their close location).

Fig. 5, *c,* shows the distribution of signal amplitude values from the As_3 sensor. The information from this sensor identifies well the values of the abnormal condition, while there are no intersections of the values of all classes of conditions. Thus, the exploratory data analysis enables to draw a conclusion on the possibility of obtaining a statistical model for the classification of the CNC machine condition.

The CART algorithm was used to train the model [3]. It divides the data into specific subsets at different levels. The objective minimization function of informational entropy is used as a separation criterion. Hence, each new level has a more specific content of attributes. A set of all levels obtained is represented as a hierarchical tree structure consisting of nodes and branches, and the branching conforms to the standard logical rules.

From the entire set of attributes, a value of the division condition for the root node is chosen, which better minimizes the informational entropy values. Then, branches are built from each node received, and a similar division into new nodes takes place. Such branching may continue until all values of the training sample are classified. In general, such a tree will represent a complex branched structure that ideally classifies the current sample. However, it may show very low accuracy when working with new data. Therefore, it is necessary to optimize the tree size. It can be carried out using a cross-validation, on the basis of which several candidate trees are built, and, in total, the tree that showed the best result is selected. Alongside with this, pruning is performed until this procedure increases dramatically the error.

Fig. 6 shows the model obtained for classifying the equipment condition based on the readings of the VAE sensors using a decision tree.

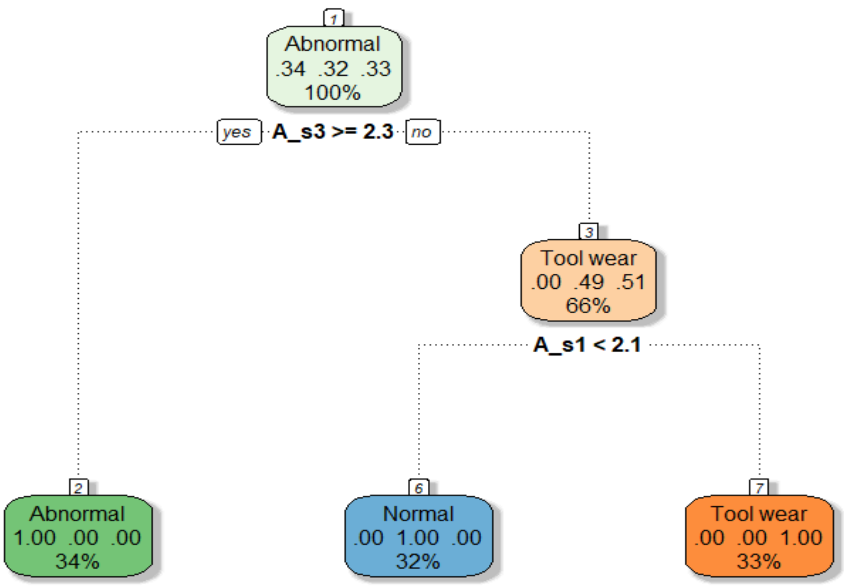


Fig. 6. Decision tree for classifying equipment condition

The first condition chosen is the VAE signal amplitude readings from the As_3 sensor. If the VAE amplitude is greater than or equal to 2.3, then the condition is uniquely abnormal. This judgment is supported by the exploratory data analysis. In the contrary case, the subsequent splitting occurs, and the data from the As_1 sensor determines the classification. If the VAE amplitude of the As_1 sensor is less than 2.1, the condition is considered normal; if it is more, then we are talking about the tool wear.

As can be seen from Fig. 6, the decision-making does not take into account readings of the As_2 sensor. Low information content of the signal from this sensor was also detected under the exploratory analysis.

High accuracy of the determination of the abnormal operation mode based on the analysis of the signal from the As_3 sensor may be related to the place of its installation (front spindle support). Most likely, the dynamic processes in the spindle assembly caused this condition, which also affected the machining quality. On considering the nonlinear processes of oscillations dispersion in the elastic machine system, this information reached other sensors in already heavily distorted form.

At this, the As_1 sensor mounted on the tool specifies its wear with high accuracy. This can be explained by the dominant role of the cutter in the general oscillatory system.

The As_2 sensor mounted on the rear center records information for classifying the condition with the least efficiency. This can be explained by the distance of As_2 from the main dynamic processes.

Hence, the described method can be applied not only to the task of classifying the equipment condition, but to the determination of the optimal number of sensors and their locations. However, it is necessary to consider the possibility of restructuring dynamic processes in the cutting system when changing processing conditions and natural tear wear of machine parts.

Discussion and Conclusions. The use of digital equipment twins under manufacturing planning reveals bottlenecks in the technological operations, improves product quality, and reduces tool breakage and equipment failure risks. Digital twins can optimize the processing modes taking into account the technical and dynamic condition of each production unit. This approach provides a highly accurate assessment of the production facilities under the development of the production program. Besides that, real-time equipment faults are detected through the intelligent data analysis of the distributed sensor system.

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