Digital equipment twin as the basis for the consumer in digital production

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Abstract. A number of neural network models is presented when developing an aggregated digital twin of equipment as a cyber-physical system. Considered in detail are the twins of machining accuracy, chip formation and tool wear, on the basis of which systems for stabilizing the chip forming process during cutting and diagnostics of cutting tool wear are proposed.

1. Introduction
The monograph [1] proposed a single basic control platform, on the basis of which it is necessary to develop both a new generation of process control systems and improve existing CNC systems for digital productions. Such a platform can be open CNC systems of machine tools with large computational resources and high processing speed of a large database, embedded modules of neural processors and communication modules with the industrial Internet. That is, the use of equipment with the ability to use cloud technologies for processing large amounts of data on enterprise servers (local networks), as well as on providers' servers. All this will create the basis of intelligent control for a wide range of process equipment equipped with CNC systems.

In this regard, since the nineties [2], the authors have developed hardware and software for intelligent control of technological equipment. In particular, a number of neural network models for managing technological systems were developed. Criteria for evaluating the dynamic stability of the cutting process based on the approaches of nonlinear dynamics and fractal analysis of vibroacoustic emission signals, as well as the control system and diagnostics of the cutting process are proposed.

The developed unified intellectual platform for expanding the functional capabilities of technological equipment with CNC systems is implemented by embedding high-performance computing modules in them and in-depth learning of artificial neural networks using cloud technologies. For this purpose, a number of applications, algorithms and models have been created [1, 2].

It has been proposed to consider cyber-physical systems as technological equipment with CNC systems, equipped with sensors, with the involvement of cloud technologies for collecting information and its subsequent processing [2].

In order for the developed platform to become the basis of digital transformation at all levels of the machining enterprise, it must analyze data not only from equipment, systems, devices, but also use this data to reduce the time to market new products, increase production flexibility, product quality and production efficiency. processes.
The digital twin (digital twin) is a new word in the modeling of equipment, technological processes and production planning [3]. This is a set of mathematical models that reliably describe processes and interconnections, both on a separate object and within the whole production enterprise using Big Data analysis and machine learning.

Usually, a digital twin is understood as a virtual prototype of a real physical object, product group, or process in which digital information about an object is collected and reused. The digital twin is not limited to collecting data at the stage of its development or implementation, but develops during the entire life cycle of the object, collecting and processing the data coming from it and keeping all their previous history.

The leader in the use of the digital twin is now the company Siemens. [3] According to her definition, the “digital twin” is an ensemble of mathematical models that characterize various states of equipment, technological and business processes in time, in accordance with the current production conditions. Among the mathematical models, a special place is occupied by neural network models. Therefore, the neural network model of the process, or product, is the “digital twin”. In this regard, the Russian priority of the intellectual approach to the management of technological equipment is obvious [2].

2. CNC machines as a cyber-physical system
The cyber-physical system is the main technological unit of digital production [1,2]. It is characterized by high adaptive and intellectual capabilities due to associative perception of information and continuous learning, assessment of the current state and forecasting the future. Able to independently solve optimization problems and make the right decisions based on the analysis of multidimensional data, taking into account various, often hidden factors of real production.

Therefore, according to the concept of intelligent control of technological equipment, the main task in organizing and creating a digital twin is the cyber-physical system. The digital twin is not only an ensemble of mathematical models that characterize various states of equipment, technological processes in time, in accordance with the current production conditions. The digital twin is also a detailed 3D assembly model of objects, reflecting the connections and interactions between nodes. In this regard, the digital twin can be considered as an electronic passport of the cyber-physical system, its digital identity, which records all the data about the processed materials, technological operations, tests and test studies.

Using the digital twin transforms around itself the relevant business processes, reaching the level of "management based on large amounts of data." In this sense, the digital twin forms a model for the representation of all processes and interrelations of the enterprise using it.

The three-level classification of twins is widespread: digital twins are prototypes (Digital Twin Prototype, DTP), digital twins are instances (Digital Twin Instance, DTI) and aggregated twins (Digital Twin Aggregate, DTA). The duplicate prototype (DTP) is needed to describe and create a physical object, contains a basic 3D model, answers the questions “how to create”, “from what”, “what is the functionality”, etc. The superstructure over the DTI set is the aggregated twin (DTA), which is a digital platform that collects data from all counterparts — instances on demand and for constructing certain predictions.

Currently, digital twins are mainly developed for business, there are also examples of successful twins in the oil and gas industry [3]. Literary data on the twins of the equipment of machining industries based on the cyber-physical system are absent in the literature.

Obtaining a digital twin based on a cyber-physical system is possible using traditional analytical approaches based on a mathematical description of physical processes. Another way is to use modern statistical methods, including machine learning.
3. Machine learning methods

There are many methods of machine learning used to build statistical models. They can be attributed to three main groups: regression analysis models, classification models, and anomaly detection models [4-6].

The choice of a particular machine learning method depends on the size, quality and nature of the data, as well as on the type of tasks being solved. Existing machine learning methods require different computational powers and have varying degrees of accuracy. As a rule, it comes down to the possibility of the most accurate approximation of data and the identification of boundaries in the data space. The most versatile and accurate method that can work with a large amount of data and build non-linear dependencies are artificial neural networks (ANN). Neural networks use a large number of settings, which allows you to create highly accurate models of processes operating in regression analysis, classification, and anomaly detection modes.

As the main method used to analyze the quality of the resulting models, use cross-validation (CrossValidation) [7]. Cross-validation allows to evaluate the statistical quality of the source data, by constructing and comparing several models obtained at different training and verification samples. When constructing models of complex objects and systems, it is necessary to reduce the dimensionality of the data and eliminate the effect of multicollinearity of variables. The solution of these problems is possible through the use of the principal component method, which often allows representing multidimensional data in the form of a limited number of components - the component. Such a generalized approach can be applied to eliminate overtraining models.

To improve the quality of the model, Bagging and Boosting algorithms [8,9] are used, the essence of which is to build not a single model, but a whole ensemble of models. This ensemble is working on the same task, and the result of their work is a kind of integral assessment of the probability of an event. This assessment can be presented as a synergistic effect of the work of a group of models, each of which separately works unsatisfactory. Thus, a digital twin can be a complex of statistical models using different combinations of machine learning methods and having passed various stages of verification and improvement.

As mentioned above, in the general case the digital twin based on the cyber-physical system is a multifactorial model of equipment [1], including an ensemble of neural network models, some of which are decisive. These are the neural network of the chip formation process, cutting tool wear, machining accuracy, dynamic stability of the cutting process, the neural network of cutting forces and the neural network of the surface roughness of the machined surface [1].

To solve this problem, a complex of statistical models using machine learning methods was developed. The resulting models are the basis for the digital twin of the CNC lathe. They allow solving regression analysis problems to predict the type of chips, tool wear, machining accuracy, cutting process dynamics, machined surface roughness, cutting forces, as well as classification tasks for assessing the current state of the machine. The process of creating a digital twin is shown in Figure 1.

![Figure 1. Creating a digital twin CNC machine](image-url)
4. Digital equipment twins

The paper discusses in detail the neural network model of the dynamics of the cutting process [1]. The training sample was obtained on the basis of the collection of telemetry data, in the process of mechanical processing using the distributed sensor signal system of vibroacoustic emission, dynamometer and technology of the industrial Internet of things (IIoT). The number of sensors used, their type and spatial orientation was determined in accordance with the layout of the equipment. The presence in the system of a large number of sensors with different spatial orientation is explained by the heterogeneity of materials and structures in different directions, features of signal propagation, as well as the possibility of restructuring the oscillatory system during operation. Thus, the use of a heterogeneous sensor system allowed us to obtain the most complete dynamic picture of the processes in the n-dimensional state-time space. The standard TCP / IP protocol as well as the text format of the JSON (Java Script Object Notation) data exchange was used as a data transfer and acceptance protocol within the industrial Internet of things network.

Analog and digital bandpass filters and wavelet filters were used for preprocessing. The use of Wavelet filters made it possible to eliminate the influence of the noise component in the signals of the AED and to decompose into a periodic and chaotic component based on entropy indicators. Preprocessing of data was carried out on the "edge" device (Edge), which calculated the values of the parameters of the AAA signal and formed data packets for sending to the virtual cloud storage. When constructing mathematical models based on machine learning methods, data structuring and marking is necessary. However, taking into account the peculiarities of the IIoT technology, the construction of relational databases is not always possible, so the approach based on NoSQL technologies was applied. For this, data storage and processing was implemented on a virtual server that simulates the operation of a computing cluster. A special distributed, scalable file system was deployed on this virtual server.

Of particular interest is the development of digital twins processing accuracy (Figure 2), the process of chip formation and wear of the cutting tool.

A statistical linear dependence of the machining error ($\delta$) on compliance ($\omega$) is obtained. The turning of the shaft fixed in the centers was considered. The magnitude of its deformation ($y$) in the middle of the shaft was taken to be $\delta/2$. As is known, compliance is the inverse stiffness value. The statistical dependence of the processing error on compliance with different processing modes and material properties shows that the greater the system compliance, the greater the processing error.

![Figure 2. Neural network model of processing accuracy – a; dependence of machining error on compliance when machining steel 45 ($S = 0.2 \text{ mm/rev}; t = 2\text{mm}$) – b.](image)

The established dependence allows us to simulate the processing error at various values of the compliance of the main components of the process equipment when it is selected. This is necessary when developing a new process technology.
The analysis of the research of the chip formation process showed that the formation of the chip element, and, consequently, the type of chips, is determined by the atomic mechanism of plastic deformation during cutting. That is, the type of crystal lattice affects the appearance of chips: the greater the number of slip systems \(n\), the greater the frequency of formation of a chip element \(f_c\). On this basis, a neural network model of the chip formation process has been developed, shown in Fig. 3. It takes into account both the processing modes and the mechanical characteristics of the metal being processed and the number of slip planes in the chip formation zone.

In the course of further research, an assessment was made of the accuracy of the neural network model, which showed the adequacy of the developed model. In fig. 4 shows the statistical dependence of the frequency of the chip element on the number of slip planes in the chip formation zone, which determines the type of chip.

In Figure 4 it can be seen that the greater the number of slip planes, the higher is \(f_c\). An assessment of the adequacy of the developed model showed that the effect of the strength of the material being processed on \(f_c\) is less than the number of slip planes.

The relationship of the frequency of formation of a chip element with output parameters, in particular, with tool wear \(h\), the curling radius of the chip \(R_c\) and the surface roughness of the treated surface \(R_a\) was studied [1]. The dependence of tool wear indicates that the value of \(f_c\) as tool wear decreases. The increase in cutting speed causes a decrease in the radius of curling of chips, and \(f_{bst}\) increases. Consequently, \(f_c\) can act as a diagnostic parameter for stabilizing the cutting process,
since \( f_c \) correlates with output indicators when machining parts. On this basis, an intelligent system of chip formation stabilization was developed (Fig. 5).

**Figure 5.** Block diagram of an intelligent chip control system: ANN - artificial neural network, \( \varepsilon \) - error, \( F_i \) - frequency of the current (Hz), \( n \) - frequency of the spindle speed (min\(^{-1}\))

As mentioned above, the input parameters of the neural network of the chip formation process are the processing modes, the ultimate strength of the material being processed, etc. On the basis of the input data, a previously trained neural network calculates the frequency of formation of the chip element \( f_c(t) \). The regulation error \( \varepsilon = f_c(t) - f_c(f) \) is determined, where \( f_c(f) \), which is received from the sensor of registration of the signal of the VAE installed in the cutting zone, which also passes through the ADC. Next, you can carry out adjustment of cutting conditions to maintain a constant value \( f_c(f) \) in the cutting zone with the help of additional hardware and software. At the heart of the intellectual system of stabilization of the process of chip formation is the digital twin of the process of chip formation.

The hardware of the developed stabilization system is implemented on the basis of the programmable logic integrated circuit (FPGA) sbRIO 9642xt, the main advantage of which is speed. Thus, the calculation of \( f_c(t) \) occurs with a minimum time delay, which allows you to control the process of chip formation in real time.

Studies have shown that the frictional properties of cutting tools (hard alloys) and nanostructured coatings significantly affect the chip formation process. They help to reduce the values of deformation and energy parameters of cutting. In this regard, based on the atomic approach to the cutting process, an atomic wear mechanism for carbide tools has been developed. A neural network model (digital twin) of the choice of nanostructured coating was also developed to increase its durability.

The atomic tool wear mechanism is based on the following provisions. The cutting process causes the formation of juvenile-clean contact surfaces. The atoms on the surface have unsaturated bonds compared to atoms that are at some distance from the surface. According to the theory of V.K. Grigorovich [11], the interstitial interaction promotes multiple overlapping of valence orbitals and their collectivization. The result is strong metallic bonds. It can be assumed that the periodic formation of such bonds during friction and their rupture causes wear of the refractory phases that make up the tool material.

Figure 6 presents the dependence of the melting point and heat of formation of refractory compounds on the number of valence electrons according to reference data [14, 15]. From fig. 6 it follows that tungsten carbide WC has the largest number of valent electrons. From pure metals, respectively: Fe-8, Co-9, Ti-4.

Therefore, the specified carbide tool wear mechanism is based on the predominant initial wear of the cobalt binder. This leads to the outcrop of carbide grains, and the periodic formation and rupture of metal bonds during friction leads to wear and tear of the carbide grains, as well as their buildup.
The work of friction forces during cutting contributes to the formation of heat and the storage of thermal energy. Considering the above, with the established process of tool wear, we will assume that all thermal energy is absorbed by grains of the carbide phase. They will accumulate thermal energy equal to the ultimate energy of destruction. For the limiting energy of destruction, in the first approximation, let us take $\Delta H$ - the heat of formation of the refractory compound. In this regard, the intensity of wear of the carbide phase grains on the contact surfaces of the tool can be represented as:

$$J = \frac{q_n}{\Delta H} = q_F \cdot \frac{V}{\Delta H} = 0.28 \cdot \frac{S_k}{\Delta H}$$

(1)

$q_n$ is the heat flow power; $q_F$ is the specific force of friction on the back surface of the tool, $\Delta H$ is the heat of fusion of the refractory compound, $V$ is the cutting speed, $S_k$ is the true value of the tensile strength of the metal.

According to (Eq. 1), the wear rate of hard alloys is determined by the strength of the interatomic bonds, which is characterized by their $\Delta H$. The $\Delta H$ value present in the denominator of expression (1) is a constant determined by the nature of the refractory compound. The general dependence of the wear rate $J$ of a carbide tool on the processing speed is non-monotonic [1]. This is explained, first of all, by the nonlinear dependence of the magnitude of the friction force $q_F$ on the cutting mode [1], which determines the power of the heat flow (Eq. 1).

The use of neural network simulation of contact processes during cutting allows the formation of a “virtual” sensor for diagnosing the output cutting parameters, including for dynamic measurement of the wear rate $J$ of the cutting tool. This method refers to indirect measurement methods. The accuracy of such measurements depends on how accurate the friction process model was used or on the accuracy class of the instrument used to capture the data for the training set. To find $J$, we use a two-layer (having two layers of active nonlinear elements) neural network of back propagation.

The search for the optimal network structure was carried out by means of simulation using the Matlab 6 software package. As a result of the simulation, several structures of neural networks with various transforming functions of neurons were considered. Their training was conducted on a training set, obtained by conducting a series of single-factor experiments on turning 45 steel and carbide inserts on various cutting conditions. For the optimal adopted network structure, giving the smallest maximum error for a certain period of time training.

Their training was conducted on a training set, obtained by conducting a series of single-factor experiments on turning 45 steel and carbide inserts on various cutting conditions. For the optimal adopted network structure, giving the smallest maximum error for a certain period of time training.
The structure of the optimal neural network (digital twin) tool wear is shown in Fig.8. The first layer of the network contains 6 neurons, the second, the output layer consists of one neuron. The exponential sigmoid is used as the activation function of the neurons of both layers.

**Figure 7.** The structure of the neural network of wear of the cutting tool

In the conditions of digital production, it is important to both predict wear and control the wear process of the cutting tool. In this regard, on the basis of the neural network model of tool wear, a system has been developed that makes it possible to diagnose its wear in real time.

5. Conclusions

The use of a digital twin of equipment based on a cyberphysical system in the development of technological processes makes it possible to identify improved product quality and reduce the risk of tool breakage and abnormal equipment operation. The digital twin allows you to optimize the processing modes, taking into account the technical and dynamic state of each production unit. This provides a highly accurate assessment of the production capacity of the enterprise in the preparation of the production program. It is also possible to detect equipment malfunctions in real time, based on the data mining of the distributed sensor system.

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