International Journal of Progressive Sciences and Technologies (IJPSAT)
ISSN: 2509-0119.

http://ijpsat.ijsht-journals.org
Vol. 29 No. 1 October 2021, pp.659-667

Strategy of Management of Functional Stability of the Information System of the Industrial Enterprise

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Abstract— Using algorithms of nonlinear dynamics, it is possible to form and implement a strategy for managing the functional stability of the information system of the production center. The model of the dynamic system of the control program is built according to the time realization of the input parameters of the system. The output parameters of the system are signals that come from both outside and inside the system and reflect the dynamics of the process. Integrated use of technologies of adaptive self-diagnosis of information systems of production centers in combination with realization of functionally stable production processes with integration of neural network models of dynamic systems of control programs on time realization of input parameters guarantees necessary conditions of property of functional stability of information system of industrial enterprises. Therefore, it allows to maintain the functional stability of the information system of each production center, to optimize technological processes, to increase the efficiency of the enterprise as a whole. The strategy of management of functional stability of the information system of the industrial enterprise with use of a neural network which application combines high productivity and high accuracy of processing of products from plastic is considered in work.

Keywords— dynamic system, functional stability, information system, neural network, technologies of adaptive self-diagnosis.

I. INTRODUCTION

A promising area of research is to ensure the functional stability of ergatic (human-machine) systems. In these systems, the control element is the human operator, and the task of ensuring the functional stability of ergatic systems is to formalize, describe the actions of the operator in a closed control loop, the distribution of functions between the operator and hardware and software. The technology of ensuring functional stability is to organize control of the system; detection of the factor of violations, failures of the subsystem or system; identification of failure and disabling of the identified factor; redistribution of system resources to keep the system running.

In traditional systems of automatic control of autonomous objects, divided into separate channels consisting of sensors, computers and actuators, resources (energy, computing, information), which are allocated to control, are rigidly fixed between the respective channels. The impossibility of redistribution of resources between channels limits the possibility of forming a functionally stable control. The technological basis for ensuring functional stability was the creation of onboard information and control systems, which allowed to complete the resources of the system and to redistribute them. Only the integration of all channels of automatic control systems into a single information-control complex, where the information-control subsystem will include all information sources, transcoding and communication devices, computer system - all computers, and energy subsystem - all actuators and energy sources, will provide it functional stability. It should be borne in mind that the possibility of integrated use of resources and ensuring the functional stability of systems is limited by the conditions of stability of the dynamic system, its controllability and observability according to Kalman. To date, a fairly complete study of the conditions for ensuring functional stability has been conducted for linear non-stochastic stationary models [1].

Generally speaking, ensuring functional stability, reliability and effective management in information systems is a complex complex scientific task, which tried to solve in a large number of works for different information systems [2], [3], [4], [5]. In the case when each production center provides the property of functional stability of technological processes as intended, the conditions for ensuring the property of functional stability of each structural unit of the enterprise in particular and the production enterprise as a whole are achieved. The method of building a functionally stable production system of the enterprise is studied in detail in [6]. Structural conditions for ensuring functionally stable production processes of industrial enterprises were studied in [7], [8], in particular, taking into account the peculiarities of adaptive self-diagnosis of systems in the implementation of production tasks. In [9] the peculiarities of counteracting unauthorized large-scale cyberattacks of information systems were studied, which in turn ensures the functional stability of information systems of industrial enterprises in general and their individual elements in particular.

In this paper, we propose to consider a strategy for managing the functional stability of an information system using a neural network. The approach to this issue is not new and was considered earlier in [10], [11], [12], [13]. But in this paper, attention is focused on the application of algorithms for nonlinear dynamics in the development of a strategy, the application of which combines high productivity and high accuracy in the build-up and milling of plastic products.

II. Materials and Methods

The article considers the application of nonlinear dynamics algorithms [14] and neural networks [15].

III. Results

The main reason for the loss of functional stability of the plastic build-up process during milling is the occurrence of resonant phenomena at one of its frequencies of the dynamic system [13]. If the oscillations of the cutter coincide in phase with the undulation of the surface, then there is a resonance and the dynamic system loses its functional stability. It is obvious that at high speeds, which are inherent in high-speed milling, the process of loss of functional stability leads not only to a deterioration in the quality of the treated surface, but also to the failure of the device. To solve this problem, it is necessary to find the optimal range of speeds for which there will be no resonance. Therefore, during milling, restrictions are imposed, which depend on the technical characteristics of the tool and the device, as well as restrictions imposed by the dynamic system.

Establishing a management strategy for functional stability not only provides processing, build-up and trouble-free operation, but also provides maximum performance, optimization and guaranteed functional stability.

Consider a technique based on the use of nonlinear dynamics algorithms. The output parameters of the system are signals that are recorded by various sensors mounted in close proximity to the area of milling and extension, and reflect the dynamics of the machining process.

Thus, based on the vibroacoustic emission signal obtained during the build-up process, it is possible to construct an attractor, the basic properties of which will be similar to the properties of the whole system. The analysis of the attractor allows to determine the type of dynamics of the build-up process under current modes, the degree of functional stability of the dynamic information system and the magnitude of the influences that can bring the system out of steady state with the transition to chaos or resonance.

The information basis of the functional stability of the system consists of the results of the study of attractors reconstructed by the signals of sensors that characterize the degree of functional stability of the dynamic system for different processing modes.

We use a multilayer neural network (Fig. 1), which will learn by analyzing the dynamics of building and milling in the process of normal staffing and performing approximation of the missing information for those processing modes for which studies of the stability of the dynamic system of the device strategies for managing the functional stability of the information system. That is, the construction of a strategy for managing the functional stability of the information system will be automated, without human intervention, by learning the neural network or, more broadly, by self-learning closed system “dynamic process system + sensors + neural network + functional stability management strategy”.

The same procedure is performed when building plastic, but the analysis of signals during milling, such as classical Fourier analysis and analysis based on Wavelet decomposition, is seriously complicated by the characteristics of the elastic system of the apparatus, which is expressed in significant nonlinearity amplitude-phase-frequency characteristics of system elements.

The greatest nonlinearity in the amplitude-phase-frequency characteristics of a dynamic system is made by its least rigid components: a tool and a part for building plastic. For example, the deviation from the equilibrium position for a constant oscillation process is determined by the fractional-trigonometric function:

$$z(t) = \frac{P_0\left(\sinh \alpha l_u \cos \alpha l_u - \cosh \alpha l_u \sin \alpha l_u\right)}{\alpha^3 E_u J\left(\cosh \alpha l_u \cos \alpha l_u + 1\right)},$$

$$\alpha = \sqrt[4]{\omega^2 \frac{\rho_u S}{g E_u J}},$$

where ρ_u is the density of the material; $S = BH$ is the cross-sectional area; g is the acceleration of gravity; $J = \frac{BH^3}{12}$ is the moment of inertia of the cross section.

The peculiarity of this function is that the trigonometric members of the function, depending on the frequency of oscillations, are in both the numerator and the denominator of the fraction. As a result, at certain values of the frequency of oscillations of the force P_0 the denominator or numerator of the fraction is zero, which leads to the occurrence in the oscillating system, respectively, the phenomena of resonance or antiresonance (Fig. 2).

The oscillations of the system do not fully correspond to the processes occurring in the area of milling due to the nonlinearity of the amplitude-frequency characteristics of the elastic system. Therefore, the receivers located on the elastic elements of the technological system register a distorted picture of acoustic oscillations.

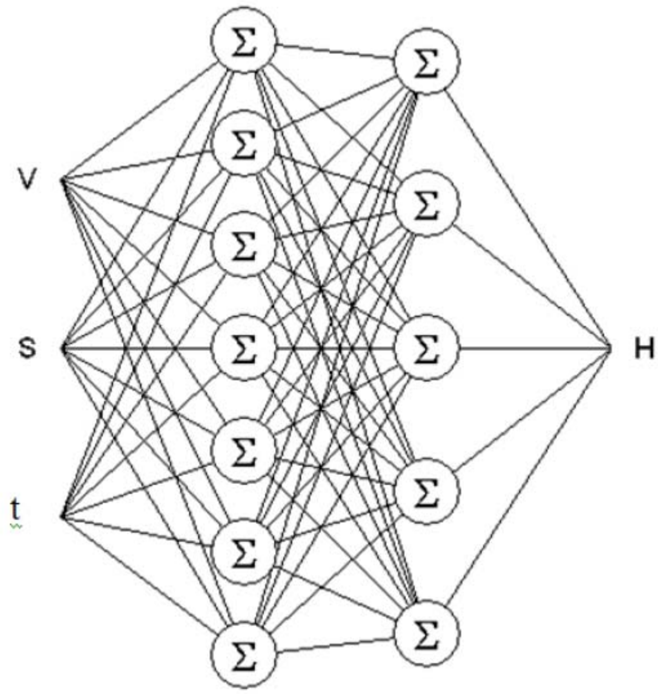

Fig. 1. The use of a two-layer neural network to form a strategy for the functional stability of the information system. Input network parameters: *V* - milling speed; *S* - feed; *t* - depth. Network output: *H* - information entropy of the attractor (used as a criterion of functional stability).

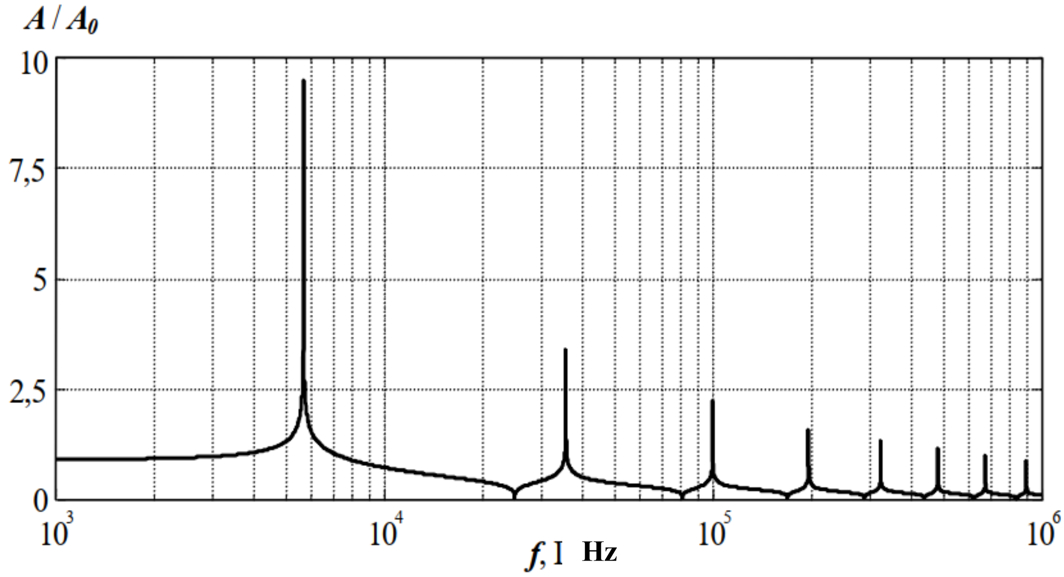

Fig.2. Graph of the dependence of the relative amplitude of the forced oscillations on the frequency of perturbing vibrations with the amplitude A_0 during milling.

Therefore, the total signal is a superposition of the useful component of the signal, which reflects the nature of the processes of plastic deformation occurring in the area of milling, and stationary interference caused by oscillations of the elastic system at natural frequencies (Fig. 3).

Information modeling based on artificial neural networks is the most promising method of extracting information from highly noisy data. Internal regulatory properties are an important feature of neural networks (approximation of a system function based on a finite set of observations), which allow to obtain small generalization errors. The usefulness of these properties of neural networks is manifested in situations where experimental data on the system contain internal redundancy. Redundancy allows you to represent a set of model data that contains fewer parameters than data. Thus, the neural network model compresses experimental information, eliminating noise components and emphasizing continuous, smooth dependencies.

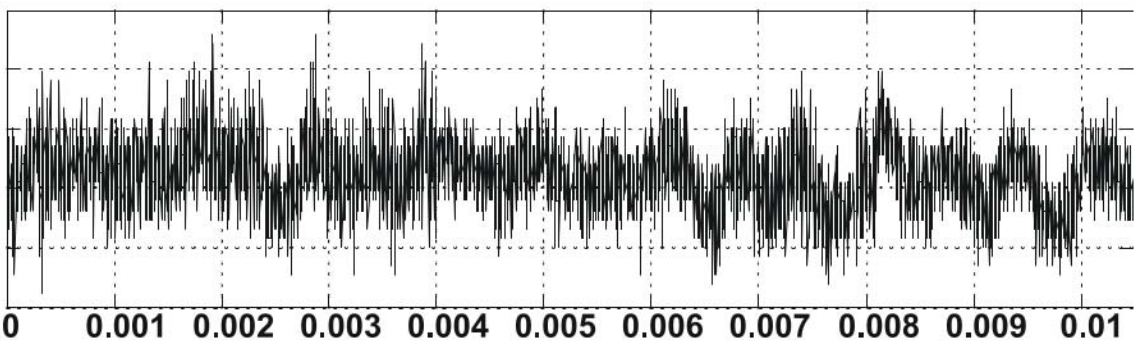

Fig.3. Vibroacoustic emission signal recorded during milling of plastic

To diagnose the dynamics of plastic build-up and milling by the frequency of formation of chip elements f_c, an information model of high-speed machining was built, based on a two-layer counter-spread network. Signals recorded by sensors are used as input data. In the process of processing, chip samples were taken and they determined the frequency f_c of chip formation, which corresponds to this signal recorded by the sensors.

The fast Fourier transform method is used to calculate the energy spectrum of the signal power for each oscillogram. Then the frequency scale of the spectra of all oscillograms is reduced to a single logarithmic form, where each subsequent count is obtained by increasing the previous one by 101/16 times. Thus, the increase in frequency by an order of magnitude is displayed using 16 samples of the scale, and the whole scale for the studied range of 1 kHz - 100 kHz is 32 samples. The transition to the logarithmic scale is carried out by pre-numerical differentiation of the signal spectrum on the old frequency scale, and then numerical integration for new values of the scale using the method of nonlinear interpolation.

Each transformed power spectrum is treated as a vector in a 32-dimensional orthogonal space, where ω_j is the power of the signal emitted in the j-th frequency range. The direction of this vector is determined by the ratio of the values of $\omega_1, \omega_2, \ldots, \omega_{32}$ and the nature of the processes occurring in the area of growth and processing of plastic. The length of the vector is determined by the sensitivity of the sensor and the amplifying characteristics of the measuring instruments. In order to eliminate these dependencies and be able to compare readings from different sensors, all vectors are normalized. Thus, the projections of each vector $\omega_1, \omega_2, \ldots, \omega_{32}$ are normalized to the unit variance and the zero mean.

Preliminary analysis of the initial data using the principal components method showed that, despite the partial overlap of the clusters, there is a visual correlation between the spectral characteristics of the signal and the frequency f_c of chip formation, which is the inverse of t_p^M -relaxation time of plastic shifts in this zone.

The process was simulated by layer-by-layer training of two identical neural networks (one for each of the sensors). The first layers of networks are a self-organizing Kohonen map, size 32x32 neurons with 32 inputs $\omega_1, \omega_2, \ldots, \omega_{32}$). A single-layer perceptron consisting of 6 neurons is used as the second layer.

Intermediate results of network training show that the dimension of the input vectors and the capacitance of the first layer are chosen correctly, as as a result of self-organization of the Kohonen map quite closely repeat the location of signals in the source space shown on the graphs of principal components. However, attempts to build information models based on the signals of each of the sensors gave completely different results.

Based on the signals recorded by the sensor located on the cutter, a full-fledged neural network diagnostic model was obtained, capable of real-time diagnosing 6 discrete values of chip frequency based on acoustic emission signals emitted during build-up and milling. Learning another network that analyzes the signals received from the sensor located on the caliper invariably comes to a standstill.

Consider more opportunities to optimize and maintain the functional stability of the information system of the production center.

Due to the fact that in high-speed processing plastic deformations of the material do not play such a role in energy distribution as in traditional processing, it can be considered with great approximation as a pure process of dynamic mass and heat transfer. Therefore, the natural basis for finding the optimal strategy will be the methods used to solve boundary value problems of field theory. For example, considering the milling zone as a field and solving the problem of thermal conductivity for Dirichlet boundary conditions, then making a gradient descent, you can get a fairly smooth spiral trajectory without fractures and sharp changes in the thickness of the cut layer. The resulting trajectory differs significantly from the standard application in CAM-systems by the absence of tool overloads and the absence of excessive non-working movements.

The structure of the cellular neural network is adequate for many problems with natural parallelism, it is easy to establish a correspondence between the difference pattern and the network topology makes it attractive to use CNN to solve boundary value problems of the field [16], [17].

Thus, the software module independently determines the geometry of the part and forms for each element several trajectories of the tool. Then from the received trajectories the best from positions of high-speed processing that allows to reveal most fully advantages of high-speed milling for the given form of a detail is chosen. Along with the function of generating different processing trajectories, the software module performs the procedure of comparative analysis of the obtained trajectories. After formation of any trajectory the procedure of emulation of milling and calculation of force of milling or building is started. The emulation process is visualized in the form of 2D-animation, which allows you to identify malfunctions or irrational movements (to speed up calculations, 2D-animation mode can be disabled). Graphs of changes in cutting force allow us to judge the presence of tool overloads and the degree of stationary processing.

During material processing, the cutting tool experiences a variable load. And the load on the tool can change many times. Accordingly, there is intense wear of both the cutting tool and the machine. The procedure of emulation of the cutting process in the program "NeuroModule UG" is implemented in such a way that in the process of processing the area of contact of the cutting tool and the processed material is constantly analyzed. Based on the analysis of the volume of material removed and the cutting speed is adjusted at a specific processing point. The purpose of this adjustment is to exclude cases of exceeding the cutting force F_r of the maximum allowable value F_i for this type of tool (tool overload) and cases of exceeding the cutting power P_r of the maximum allowable value P_i for this type of drive of the production center.

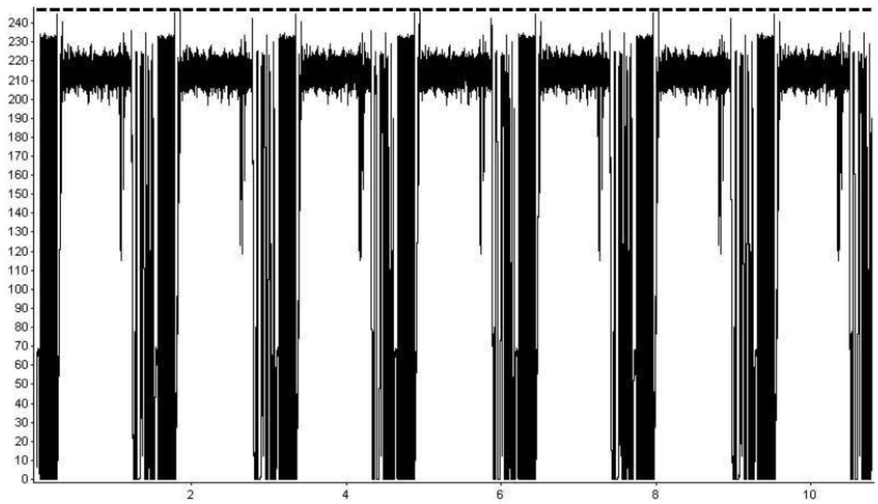

Fig.4. An example of the calculation of cutting forces for different trajectories, taking into account the adjustment of the supply at the risk of overload and the emergence of chaotic modes.

It should be noted that adjusting the feed rate in the event of an overload threat is a compulsory measure that allows for a continuous machining process without tool breakage and jamming in the event of an incorrectly calculated trajectory, and is not a good solution. The fact is that the cutting force F_r nonlinearly depends on the feed rate *V*.

Also during the emulation procedure very much attention is paid to the dynamics of the process. It is known that incorrectly chosen processing conditions can cause the emergence and avalanche of chaos in the dynamic system of processing, building, cutting and elastic system of the apparatus. That is, the process goes from functionally stable to unstable: the controllability of the processing is violated; deteriorating its initial parameters, namely, the roughness of the treated surface and the accuracy of shaping; the probability of breakage of the tool, the equipment sharply increases.

To avoid chaos in the machining process, at the stage of its emulation, one of the cutting conditions is adjusted to the feed rate *V*. The degree of chaos in the machining process is determined by the methods of nonlinear dynamics. The initial data are the dynamics of changes in time of the cutting force F_r and the coordinate velocities V_x, V_y, V_z movement. The initial data are converted into time series with a discrete step along the time axis and on the basis of these series two attractors are built: the attractor of the dynamic processing system and the attractor of the dynamic system of the production center as a whole. Next, by calculating the characteristics of the obtained attractors, namely the fractal dimension D_F, the higher Lyapunov index λ_1 and the self-similarity error Δ_s [16], [17], the degree of chaotic processing for these conditions is estimated. When there is a threat of chaos, the feed rate is adjusted to equalize the transition process, which is a potential initiator of the emergence of chaotic phenomena.

In addition to calculating the forces of milling, building, cutting, the software module analyzes the dynamic loads on the tool and calculates the deflection of the tool [18]. After performing all the calculations, a summary diagram is constructed for all trajectories. The upper half of the diagram shows a comparative graph of productivity trajectories, and the lower half shows a comparative histogram of processing accuracy. The accuracy criterion is the decimal logarithm of the maximum value of the deflection of the tool for a given trajectory, taken with a minus sign.

Next, according to the diagram, the best of the positions is selected from the obtained trajectories, which allows you to most fully reveal the benefits of high-speed milling for this part. The application of this strategy combines high productivity and high processing accuracy. In the case when each production center provides the property of functional stability of technological processes as intended, the conditions for ensuring the property of functional stability of each structural unit of the enterprise in particular and the production enterprise as a whole are achieved.

IV. Conclusion

The use of neural networks and methods of nonlinear dynamics is a more promising method of calculating processing trajectories than the classical ones, which are traditionally used in modern CAM-systems. In particular, common spline interpolation is able to achieve only one of the conditions of high-speed milling - obtaining a smooth trajectory without fractures. At the same time spline interpolation does not save from overloads and premature failure of the expensive cutting tool. Another method - trochoidal processing avoids tool overload, but is not a rational method in terms of performance.

The proposed method of generating smooth spiral trajectories of the tool using cellular neural networks and methods of nonlinear dynamics allows to obtain effective processing trajectories that do not have the above-described disadvantages. Integrated use of technologies of adaptive self-diagnosis of information systems of production centers in combination with realization of functionally stable production processes with integration of neural network models of dynamic systems of control programs on time realization of input parameters guarantees necessary conditions of property of functional stability of information system of industrial enterprises. Therefore, it allows to maintain the functional stability of the information system of each production center, to optimize technological processes, to increase the efficiency of the enterprise as a whole.

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