UDC 517.9

Oleksandr A. Fomin[1]**,** Candidate of Technical Sciences, Associate Professor, Department of Computerized Control Systems, E-mail: fomin@opu.ua, ORCID: 0000-0001-5199-8913
Vitaliy D. Pavlenko[1]**,** Doctor of Technical Sciences, Professor, Professor Department of Computerized Control Systems, E-mail: pavlenko.vitalij@mail.ru, ORCID: 0000-0002-5655-4171
Oleksandr G. Derevyanchenko[1]**,** Doctor of Technical Sciences, Professor, Department of Material Science, E-mail: algdrv@opu.ua, ORCID: 0000-0002-4679-3339
Vladimir A. Vodichev[1]**,** Doctor of Technical Sciences, Professor, Head of Electromechanical Systems with Computer Control Department, E-mail: vva@eei.opu.ua, ORCID: 0000-0002-7204-1149
Oleksandr D. Ruban[1]**,** Leading Engineer, Innovative Information Technologies Department,
E-mail: westsoldierru–ban@gmail.com, ORCID: 0000–0001–5199–8913
[1]Odessa National Polytechnic University, Shevchenko Avenue, 1, Odessa, 65044, Ukraine

AN APPROACH TO THE CONSTRUCTION OF A NONLINEAR DYNAMIC MODEL PROCESS CUTTING FOR DIAGNOSIS CONDITION OF TOOLS

Annotation. *The features of the use of the theory of integral series in applied problems of identification of nonlinear dynamic systems in the field of diagnosing the state of cutting tools are considered. The prospects for developing a method for estimating the states of cutting tools based on indirect measurements using integral non-parametric dynamic models based on experimental input-output data using test pulse effects on the cutting system are substantiated. This approach allows increasing the efficiency of diagnosis by reducing the amount of calculations, as well as, the reliability of the diagnosis by simultaneously taking into account the nonlinear and inertial properties of the system in integrated non-parametric dynamic models. In addition, the models in question are capable of describing faults caused by both changes in the system parameters and its structure, as well as can be used in test and functional diagnostics.*

A method has been developed for building information models of cutting tool states based on indirect measurements using test pulse effects on a cutting system in the form of loads with impacts and recording system responses, on the basis of which information models are built in the form of multidimensional transition functions.

A block diagram of the organization of the experiment "input-output" in the framework of the problem of diagnosing the state of the tool under the conditions of pulse effects on the cutting system to obtain the primary diagnostic information is proposed. The methods of forming test pulse loads of the cutting system by successive insertion of the cutting tool into the work piece with different cutting depths, with variable feed and with variable cutting duration are considered.

The computational experiment demonstrates the advantages of information models in the form of multidimensional transition functions for modeling nonlinear dynamic systems in problems of diagnosing the states of cutting tools. It has been established that multidimensional second-order transition functions can be used as an effective source of primary data in the construction of automated technical diagnostics systems.

Keywords: *nonlinear dynamic systems; multidimensional transition functions; identification; information models; technical diagnostics*

Introduction

Production systems of the CIM (Computer Integrated Manufacturing) level, the corresponding methods and technologies are finding more and more widespread use in modern machine-building [1]. With the increasing complexity of modern means of production and the conditions of their exploitation to the quality of the cutting tool (CT) used in flexible manufacturing modules.

Therefore, there is an obvious need to develop new methods and systems for monitoring and diagnosing CT states [2].

To ensure the high quality of production processes in modern metal-cutting machines, the method of direct monitoring of the condition of the cutting tool wearing using vision systems is used [2-4].

The processing of a sequence of images of wear zones of tools coming from the system of technical vision, requires a very significant expenditure of time and computational resources on preliminary data processing to increase their quality, contours and textures selection of wearing zones. On the basis of the processed images, information models are formed and classifiers are built.

The time factor for constructing models for diagnostic tasks is essentially weighing, since the processing speed on metal-cutting machines is constantly increasing.

At the same time, the intensity of wearing processes is increases.

Therefore, a significant investment of time for data processing and diagnosis can lead to a delay in decision making.

To increase the efficiency of diagnostics, methods are used that develop the approach of direct control of the states of CT, for example, reduction of feature space [5-9]. At the same time, operations of processing visual data remain the slowest link in automated technical diagnostics systems (ASTD) with direct control of the sequence of images of CT. Therefore, methods of indirect control and diagnostics of the state of tools become more promising.

Formulation of the problem

In modern technological processes, machining operations take place, the specificity of which leads to the appearance of periodic "shock" loads on the cutting part of the CT. An example would be the operation of the so-called "shock" turning [10], during which the front surface of the cutting part of the cutter periodically perceives the "shock" load.

The specific conditions of using CT, periodic dynamic loads determine a number of features of the wear of such tools. There is the appearance of defects such as microcracks and microscopes on the cutting edges.

To date, there are no adequate models of the cutting process that take into account nonlinear dynamics. Therefore, there is a need to develop methods for the identification of non-linear cutting systems with dynamic "shock" loads for subsequent use in technical diagnostics systems.

Analysis of recent research and publications

Today, in flexible manufacturing modules, three groups of control methods are used: direct, indirect, and combined [2; 3].

From the literature on technical diagnostics such diagnostic methods as functional, test and combined are known [2; 3].

When implementing direct methods of control and test diagnostics, the object of analysis is directly the cutting part (CP) of the instrument. Measurements, as a rule, are made during the interruption of machining in a special control position of the machine or in an instrumental store of flexible manufacturing modules.

Touch sensors are used that periodically determine the spatial position of top of worn tool or a system of technical vision, providing periodic recording of images of wear zones with an estimate of their change over time [2-4; 11].

Known indirect methods of control and diagnostics of CT [2; 12-20], based on measurements of torque, cutting power, components of cutting forces, acoustic emission, dimensions and roughness of the machined surface of the part and etc.

Applied to the CT, functional diagnostics is carried out in the process of machining, when the tool experiences only working influences in the cutting system. The corresponding signals are recorded by indirect control methods. Test diagnostics of CT states provides for the formation of test effects on the instrument.

Combined diagnosis of CT is concluded in the application of both working and test influences on the instrument. Its advantage is the use of heterogeneous signs, which provides a comprehensive assessment of the state of the CT.

In flexible manufacturing modules, very high cutting speeds are used [13; 14; 18], which leads to an increase in the wear of the CT and a reduction in their working life. Accordingly, there is a need to reduce the time spent on the processes of monitoring and diagnosing CT, otherwise the corresponding control actions on the technological system will be carried out with a delay. For example, with all the advantages and high accuracy of recording the size and shape of CT wear zones using technical vision systems [2-4], registration, processing and recognition of corresponding digital images is associated with significant time costs.

The research conducted by the authors showed that a very promising method of indirect control (respectively, functional and test diagnostics) of tools under roughing and semi-finishing machining is the method of estimating the response of the cutting system to periodic "shock" loads of CT [2].

The aim of the work is to build a non-linear dynamic model of the cutting process, obtained on the basis of input-output experiment data using test impulses on the cutting system.

To achieve the goal identified the following tasks.

1. Analysis of the problem of constructing nonlinear continuous dynamic models of CT in the systems of technical diagnostics and the substantiation of information models for the primary description of objects of various natures based on multidimensional transition functions (MTF).

2. Development of a method for identifying CT states on the basis of indirect measurements by using test pulse effects on the cutting system in the form of loads with "shocks" and recording system responses, on the basis of which information models are built in the MTF as a diagnostic source information. Such a method, in contrast to the existing ones, makes it possible to simultaneously take into account the nonlinear and inertial properties of the CT, to increase the efficiency of building information models

and the accuracy of diagnosis using the obtained models.

The object of research is the process of identifying continuous dynamic systems.

The subject of research is the methods of identification of nonlinear dynamic cutting systems under pulsed loads.

Research methods

Theoretical studies are based on the theory of nonparametric identification, modeling of nonlinear dynamic systems, and functional analysis for building information models based on the MTF.

To filter out the noise of the measured signal, elements of the theory of wavelet transforms are used.

To solve applied problems of modeling, elements of the theory of computational experiments are used.

Experimental studies were carried out on a universal milling machine tool mod. 675P. Samples were processed (specify dimensions) of gray cast iron with end mill tools. To simulate the step loading of the cutting system, i.e. the formation of pulsed impacts on it was carried out short-time incisions of the CT into the work piece and the registration of responses of the cutting system to these impacts.

Development of a mathematical model based on integrate series

Conversion of input vector $\mathbf{X}=(x_1, x_2, ..., x_v)$ into the output vector $\mathbf{Y}=(y_1, y_2, ..., y_\mu)$ at any time t i.e. A mathematical model of a nonlinear dynamic object can be represented in general form using the operator $A_\tau(t)$

$$\mathbf{Y}(t)=A_\tau(t)[\mathbf{X}(\tau)], \quad (1)$$

where:

$$t\in\Omega_t,\ \tau\in\Omega_\tau;\ \Omega_\tau=[t_0,t]\subset\Omega_t=[t_0, T],$$

t_0, T – respectively, the initial and final moments of the interval of observation of the object.

The dynamic object operator can be specified in various forms. Often, the object operator is defined as a system of differential equations expressing in an implicit form the relationship between the input and output variables of the object. Another and, in most cases, the most convenient form of describing the dynamic properties of an object is the representation of the relation between its input and output signals in an explicit form, when the solution of differential equations is not required. This representation, which takes into account the nonlinear and dynamic properties of an object, is a description based on the expansion of the operator $A_\tau(t)$ into an integral series [21-24].

For a wide class of nonlinear dynamical systems, the dependence between the action of $\mathbf{X}(t)$ and the reaction $\mathbf{Y}(t)$ in explicit form can be represented by a functional power (integral) series by Volterra [25-30].

The input – output ratio for continuous nonlinear dynamic systems with an unknown structure (black box type) with one input and one output can be represented as the next Volterra series:

$$\begin{aligned} y(t)=w_0 &+ \int_0^t w_1(\tau)\,x(t-\tau)d\tau + \\ &+\int_0^t\int_0^t w_2(\tau_1,\tau_2)x(t-\tau_1)x(t-\tau_2)d\tau_1 d\tau_2 + \\ &+\int_0^t\int_0^t\int_0^t w_3(\tau_1,\tau_2,\tau_3)x(t-\tau_1)\times \\ &\times x(t-\tau_2)x(t-\tau_3)d\tau_1 d\tau_2 d\tau_3+...= \\ &=w_0(t)+\sum_{n=1}^{\infty} y_n(t). \end{aligned} \quad (2)$$

where:

$x(t)$ and $y(t)$ – respectively, the input and output signals of the system;

$w_n(\tau_1,...,\tau_n)$ – multidimensional weight function of the n-th order (n = 1,2,3, ...), symmetric with respect to real variables $\tau_1,\ldots,\tau_n$ function;

$w_0(t)$ – free member of the series, with zero initial conditions $w_0(t)\equiv 0$;

t – current time.

The series (2) with zero initial conditions can be written in abbreviated form:

$$\begin{aligned} y(t)=\sum_{n=1}^{\infty} y_n[x(t)] = \\ =\sum_{n=1}^{\infty}\int_0^t \dots \int w_n(\tau_1 \dots \tau_n)\prod_{r=1}^{n} x(t-\tau_r)d\tau_r \end{aligned} \quad (3)$$

where:

$y_n[x(t)] = y_n(t)$ – n-th partial component of the response system.

Development of methods for constructing nonlinear dynamic models based on integer series based on input-output measurements

Building a model (identification) of a dynamic object from experimental data – determining the parameters and structure of the mathematical model that provide the best match for the output coordinates of the model and the object for the same input effects.

A practical way to check the degree of efficiency of building a mathematical model is to compare and numerically evaluate the reactions of a real object and a model obtained by feeding their inputs of the same signal.

In solving the problem of identification, identification criteria play an important role. In most cases, the criterion of the minimum root-mean-square error is used.

$$\varepsilon = \sqrt{\frac{1}{k}\sum_{t=1}^{k}(w_t - \hat{w}_t)^2}, \tag{4}$$

where: k – the number of reports on the observation time interval;

w_t – reference values of multidimensional weight function;

$\hat{w}_t$ – evaluation values of the multidimensional weight function obtained as a result of processing experimental data (system responses) at discrete points in time t.

Thus, the main task is to restore the dynamic characteristics of the system based on measurements of the responses of the system to specially selected test signals.

Building a model of a nonlinear dynamic system in the form of a MTF consists in choosing the type of test actions $x(t)$and developing an algorithm that would allow for measured responses $y(t)$ allocate partial components $y_n[x(t)]$ and determine based on their multidimensional weight functions $w_n(\tau_1,\ldots,\tau_n)$, n=1,2,…

Using step test signals

If the test signal $x(t)$ is the single function θ (t) (Heaviside step function), then the solution of (2) is the first-order transition function and the diagonal sections of the n-th order $\hat{h}_n(t,\ldots,t)$ ($n=\overline{2,N}$).

To determine the subdiagonal cross sections of transition functions of the n-th order ($n\geq 2$) of nonlinear dynamic systems, it is tested using n test step signals with given amplitudes and different intervals between signals. With the appropriate processing of the responses, we obtain the subdiagonal cross sections of n – dimensional transition functions $h_n(t - \tau_1,\ldots, t - \tau_n)$, which represent the n – dimensional integrals of the n-th order kernels $w_n(\tau_1,\ldots,\tau_n)$

$$h_n(t-\tau_1,\ldots,t-\tau_n) = \int_0^{\infty}\ldots\int_0^{\infty} w_n(t-\tau_1-\lambda_1,\ldots,t-\tau_n-\lambda_n)d\lambda_1\ldots d\lambda_n. \tag{5}$$

Definition of cross sections of n – dimensional transition functions for nonlinear dynamic systems with one input and one output in the case when test actions are the sum of k (k=1, 2,…, n) step signals (i = 1, 2, …, k), with a time shift t on τ_1, ..., τ_k, for nonlinear dynamic systems with one input and one output, the estimate of the nth order transition characteristic is performed according to expression [31]:

$$\hat{h}_n(t-\tau_1,\ldots,t-\tau_n) = \frac{1}{n!a^n}\sum_{\delta_{\tau_1},\ldots,\delta_{\tau_n}=0}^{1}(-1)^{n-\sum_{i=1}^{n}\delta_{\tau_i}}\hat{y}(t,\delta_{\tau_1},\ldots,\delta_{\tau_n}), \tag{6}$$

where:

$\hat{y}_n(t,\delta_{\tau_1},\ldots,\delta_{\tau_n})$ – estimation of the n-th partial component of the response the diagnostic object at the time t, obtained as a result of processing the experimental data, under the action of a multi-step signal at its input with amplitude a; and if $\delta_{\tau_i}=1$ (i =1,2, …, n), then the test action contains a stepped signal with a shift by τ_i, otherwise, with $\delta_{\tau_i}=0$ – it does not contain it.

Development of a method for constructing a nonlinear dynamic model of the cutting process using stepped test signals

The method of constructing models of states of radiation sources on the basis of indirect measurements by using multi-stage test signals on the cutting system is implemented in the following sequence:

Step 1. Formation of periodic stucco effects on the cutting system $x_k = k\alpha\theta(t)$, where k = 1, 2,..., n is the number of stages with an amplitude multiple of α. The need for multiple step load on the cutting system due to its non-linearity. The formation of stepped exposures x_k is realized in the form of a series of CT inserts into the workpiece (within the allowance to be removed at this technological transition).

Step 2. Registration of the response of the cutting system $y_k(t)$ to stepwise impacts x_k.

Step 3. Building the information model $h(t)$ in the form of MTF by expression (6) based on the received responses $y_k(t)$.

A block diagram of the organization of the "input-output" experiment with step loads (steps 1 and 2) for obtaining primary diagnostic information is presented in Fig. 1.

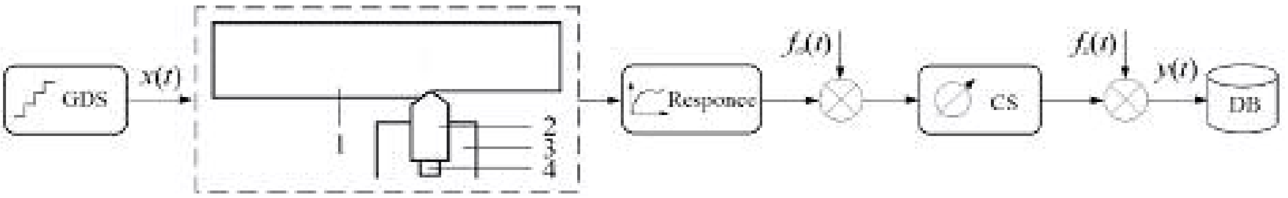

Fig. 1. Block diagram of the organization of the "input-output" experiment within the framework of the task of diagnosing the cutting process with periodic shock loads:
1 – blank; 2 – CT (cutter); 3 – cutter holder; 4 – indirect control sensor

Fig. 2. View of the processing zone of the work piece with a stepped control signal

Experimental implementation of the method of indirect control of the states of the CT by means of stepwise influences on the cutting system was carried out on a universal milling machine mod. 675P. A control signal with different amplitudes of the cutting depth $s = k\alpha\theta\ (t)$, specified by the diagnostic signal generator, is used as an input step signal. As a result of the action of the stepped control signal in the work piece 1, the cutter 2 is cut out in the work piece 1, and the tool grooves are machined. View of the processing zone of the work piece is shown in Fig. 2.

The response of the cutting system is recorded by the measuring device (control sensor) SC and stored in the database (DB). Signals $f_o(t)$ and $f_s(t)$ are added to the response of the system - interference from the cutting process and the sensor, respectively.

The formation of the test pulse (GDS) loading of the cutting system can be realized by sequential plunging (loading – unloading CP) of the CT into the workpiece with depths of cutting s_1, s_2 ($s_1 < s_2$, where s is the cutting depth due to allowance, timed on this technological transition). The cutting speed V, feed S, cutting time T are constant. The variable is the active length of the cutting edge of the diagnosed CT.

A series of cuts with a variable feed can be proposed as the second loading scheme of a CT, a series of cuts with a variable duration can be used as the third scheme.

This paper discusses the operation of face milling. With tool wear, the cutting forces and, accordingly, the amplitudes of the system responses change, which can be used to estimate the residual life of the mill.

Indirect control sensor 4, as an element of the automated control system for the electric drive of the milling machine [32; 33] measures the output signal – the active power of the asynchronous main-motion electric motor W.

In Fig. 3 shows the input control signal (depth of cut s, mm) in the form of steps with two amplitudes.

In Fig. 4 shows the output signal: oscillogram of the change in the active power of the asynchronous electric motor of the main motion W, kW, which reflects two jumps corresponding to two step effects on the milling cutter.

In this example, the cutting system response contains high-frequency noise. Recently, approaches based on wavelet transform have been increasingly used to eliminate them. These approaches have advantages in comparison with filters based on the Fourier transform, since they allow to effectively eliminating localized interference, which filtering using the Fourier transform is inefficient due to the use of the basis of infinitely oscillating functions [34].

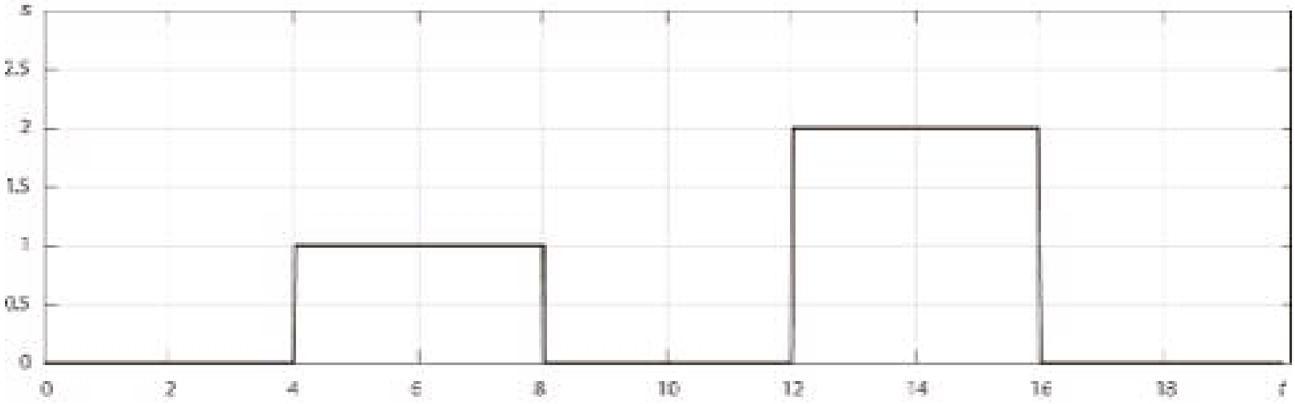

Fig. 3. The input signal corresponding to a stepwise increase in the depth of cut (on the abscissa axis – processing time t, s; on the axis of ordinates – depth s, mm)

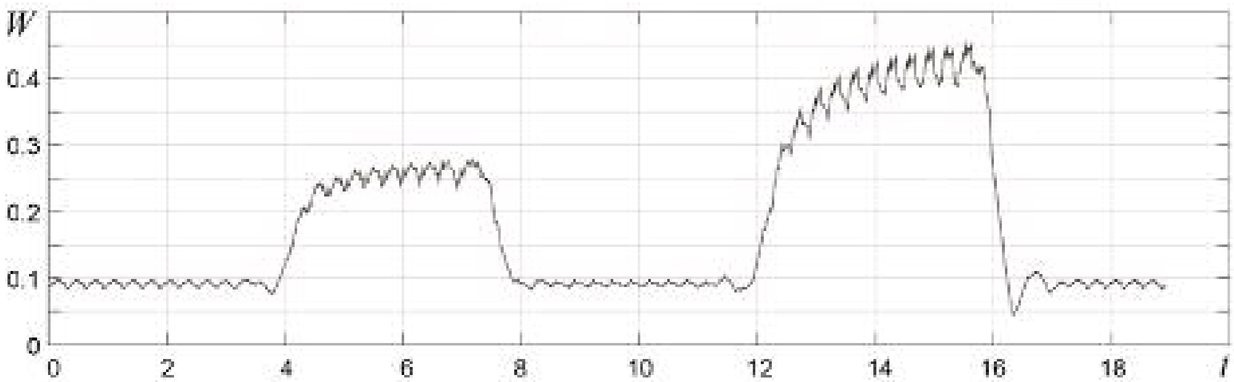

Fig. 4. The response of the cutting system in the form of – changes in the active power of the cutting process W, kW in time t, s

Noise suppression is usually achieved by removing high-frequency components from the signal spectrum, which is an additive mixture of the information component obtained as a result of processing the responses and noise due to the inaccuracy of the measuring apparatus [35]. With respect to wavelet expansions this can be implemented directly removing detailing coefficients of high frequency levels. By setting a certain threshold for their level, and cutting off the detail coefficients by it, it is possible to reduce the noise level.

The wavelet transform of the signal $y(t)$ – leads to the family of functions $C(a,b)$, where a is the scale and b is the position. In turn: where $\Psi\left(\frac{t-b}{a}\right)$ – is the family of wavelet functions, R is the set of real numbers, and $a \in R/\{0\}, b \in R$.

Known classes of discrete orthogonal wavelets, such as Haar, Daubechies, Symlets, Coiflets, BiorSplines, Dmeyer, are effectively used in practice to remove noise in signals. In this paper, in order to increase the computational stability of deterministic identification methods, noise reduction (smoothing) procedures are applied to the resulting responses based on wavelet transform using a Coiflet wavelet of order 4 [34].

In Fig. 5 presents the results of filtering the response of the cutting system based on wavelet transforms. This signal is used further to identify the states of the cutting system.

The construction of the information model $h(t)$ in the form of MTF is carried out using the obtained responses $y(t)$ (time interval $t \in [4; 8]$ on Fig. 5) and based on the expression (6).

The results of identifying a test nonlinear dynamic system using step signals — estimates of the first order transition function $h_1(t)$, and the diagonal cross section of the second order transition function $h_2(t,t)$ are presented as graphs in Fig. 6.

Using a nonlinear dynamic model of the cutting process in the tasks of cutting tool diagnostics

Using the considered method of constructing a nonlinear dynamic model of the cutting process, models were constructed using a cutting tool belonging to different classes of states Ω_1 and Ω_2.

In Fig. 7 presents the estimates of the first-order transition function $h_1^1(t)$ и $h_1^2(t)$ for the cutting process using the CT belonging to different classes of states Ω_1 and Ω_2.

In Fig. 8 presents the estimates of the second-order transition function $h_2^1(t,t)$ и $h_2^2(t,t)$ for the cutting process using CT belonging to different classes of states Ω_1 and Ω_2.

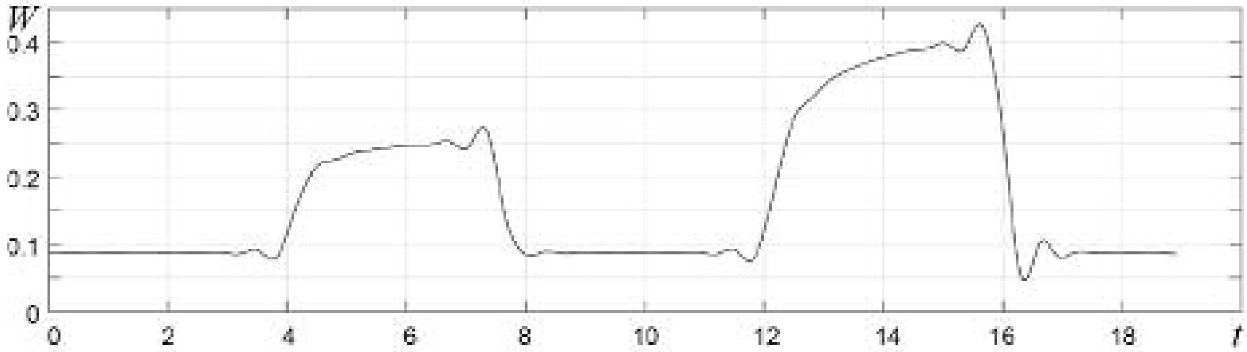

Fig. 5. Filtering the response of the CS: changing the active power of the cutting process W, kW in time t, s

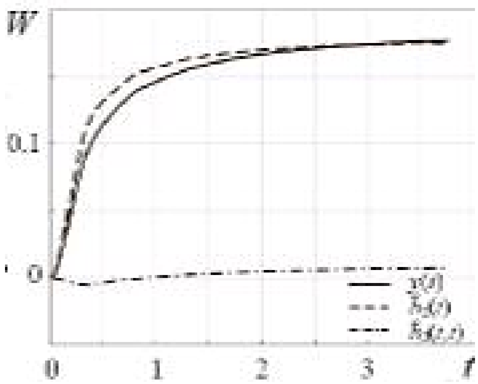

Fig. 6. The results of the identification of the test non-linear dynamic system using step signals (on the abscissa axis – processing time t, s, on the axis of ordinates – active power of the cuttinprocess W, kW)

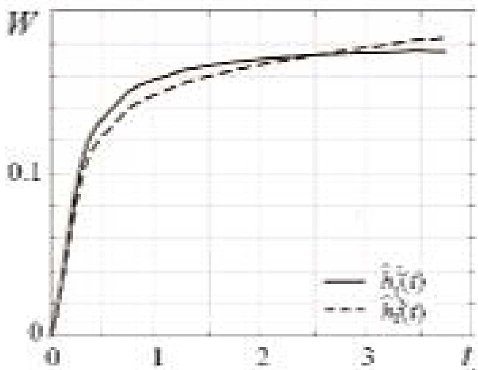

Fig. 7. Estimates for the first order transition functions $h_1^1(t)$ и $h_1^2(t)$ for the CT belonging to the classes of states Ω_1 and Ω_2 (on the abscissa axis – processing time t, s, on the axis of ordinates – active power of the cutting process W, kW)

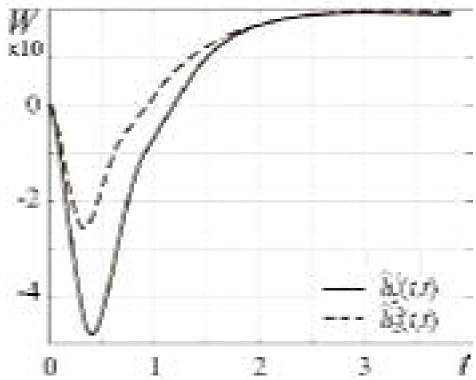

Fig. 8. Estimates for the first order transition functions $h_2^1(t,t)$ и $h_2^2(t,t)$ for the CT beloning to the classes of states Ω_1 and Ω_2 (on the abscissa axis – processing time t, s, on the axis of ordinates – active power of the cutting process W, kW)

The deterministic approach to classifying CT states according to a linear model (Fig. 7), represented by an estimate of the first order transition functions $h_1^1(t)$ и $h_1^2(t)$, is difficult because the functions $h_1^1(t)$ и $h_1^2(t)$ for the Ω_1 and Ω_2 state classes form overlapping regions [36].

At the same time, the transition functions of the second order $h_2^1(t,t)$ и $h_2^2(t,t)$ contain a greater diagnostic value – they carry more information about the state of the CT (belonging to one of the classes of states Ω_1 and Ω_2).

Conclusions and prospects for further research

As a result, the work successfully solved the problem of constructing a nonlinear dynamic model of the cutting process, obtained on the basis of the input – output experiment data using test pulse effects on the cutting system. The resulting model adequately reflects the state of the cutting tool according to the results of indirect measurements and can be used in diagnostics tasks.

In the process of solving the problem of constructing a non-linear dynamic model of the cutting process, the following results were obtained.

1. The choice of an information model for describing nonlinear dynamic systems based on integral non-parametric dynamic models in the form of multidimensional transition functions is substantiated. The main advantages of using integral non-parametric dynamic models in diagnostic tasks are the ability to simultaneously take into account the nonlinear and inertial properties of systems, describe faults caused both by changes in system parameters and its structure, as well as ease of use in test and functional diagnostics .

2. A block diagram of the organization of the "input-output" experiment is proposed within the framework of the task of diagnosing the state of the tool under impulse effects on the cutting system.

3. A method for constructing a nonlinear dynamic model of the cutting process on the basis of indirect measurements using test pulse effects on the cutting system and recording system responses has been developed. After processing the received responses, an information model of the cutting system is constructed in the form of multidimensional transition functions. Unlike diagnostic methods using technical vision systems, this method makes it possible to increase the efficiency of building an information model of the cutting process and the reliability of diagnosing the cutting tool.

4. A computational experiment confirms the advantages of using information models in the form of multidimensional transition functions in problems of diagnosing the states of cutting tools. It has been established that multi-dimensional second-order transition functions have a greater diagnostic value and can be used as a source of primary data in the construction of automated technical diagnostics systems.

Referenes

1. Mamalis, A. G. (2006). "Modern aspects of advanced manufacturing", Suchasni tehnologii u mashinobuduvanni, [Modern technologies in mechanical engineering], Vol, 2, Kharkiv, Ukraine, NTU "KhPI", pp. 58-73.

2. Derevyanchenko, O. G., Pavlenko, V. D., Fomin, O. O, Bovnegra, L.V. & Pavlenko, S. V. (2013). Intellektual'nye sistemy raspoznavanija sostojanij rezhushhih instrumentov, [Intelligent recognition systems for cutting tools], Odesa, Ukraine, *Publ. Astroprint*, 300 p. [in Russian].

3. Derevyanchenko, O. G., Pavlenko, V. D. & Andreev, A. V. (1999). Diagnostirovanie sostojanij rezhushhih in-strumentov pri precizionnoj obrabotke, [Diagnosing the states of cutting tools with precision machining], Odessa, Ukraine, *Publ. Astroprint*, 184 p. [in Russian].

4. Rifai, A. P., Fukuda, R. & Aoyama, H. (2019). "Image based identification of cutting tools in turning-milling machines", *Japan Society for Precision Engineering,* Vol. 85, Issue 2, pp. 159-166. DOI: 10.2493/jjspe.85.159.

5. Pavlenko, V. & Fomin, A. (2008). "Methods for Black–Box Diagnostics Using Volterra Kernels", *Proc. of the 2nd Int. Conf. on Inductive Modeling,* (ICIM'2008), Kiev, Ukraine, pp. 104-107.

6. Lenkov, S., Zhyrov, G., Zaitsev, D., Tolok, I., Lenkov, E. (2017). "Features of modeling failures of recoverable complex technical objects with a hierarchical constructive structure", *Eastern-European Journal of Enterprise Technologies,* Vol 4, No. 4 (88), pp. 34-42. DOI: 10.15587/1729-4061.2017.108395.

7. Povoroznyuk, A. I. & Somova, A. A. (2008). Formirovanie sistemy informativnyh diagnosticheskih priznakov na osnovanii kolichestvennogo vyrazhenija ih znachimosti, [Formation of a system of informative diagnostic features based on a quantitative expression of their significance], Herald of the National Technical University "KhPI", Series of "Informatics and Modeling", No. 24, pp. 137-141 [in Russian].

8. Povoroznyuk, A. I. (2007). Formirovanie diagnosticheskih intervalov chislennyh priznakov pri differencial'noj diagnostike, [Formation of diagnostic intervals of numerical signs in the differential diagnosis], Bulletin of the Khmelnytsky National University, No. 3, Vol. 1, pp. 106-109 [in Russian].

9. Subbotin, S. & Oliinyk, A. (2017). "The Sample and Instance Selection for Data Dimensionality Reduction, Recent Advances in Systems, Control and Information Technology", *Advances in Intelligent Systems and Computing,* Vol. 543, pp. 97-103. DOI: 10.1007/978-3-319-48923-0_13.

10. Prokopyv, N. M., Bondarenko, V. P., Kharchenko, O. V. & Tsap, I. V. (2008). Vlijanie uslovij spekanija splava VK10 OM na kinetiku i mehanizmy iznosa ego v uslovijah chistovogo i udarnogo tochenija, [Influence of sintering conditions of VK10 OM alloy on the kinetics and mechanisms of its wear under conditions of finishing and impact turning], *Cutting and tooling in technological systems,* Kharkiv, Ukraine, Vol. 75, pp. 312-327 [in Russian].

11. Kumar, P., Chauhan, S. R., Pruncu, C. I., Gupta, M. K., Pimenov, D. Y., Mia, M. & Gill, H. S. (January 2019). "Influence of different grades of CBN inserts on cutting force and surface roughness of AISI H13 die tool steel during hard turning operation", Vol. 12, Issue 1. DOI: 10.3390/ma12010177.

12. Lu, Z., Ma, P., Xiao, J., Wang, M. & Tang, X. (February 2019). "On-line Monitoring of Tool Wear Conditions in Machining Processes Based on Machine Tool Data", Zhongguo Jixie Gongcheng, *China Mechanical Engineering,* Vol. 30, Issue 2, pp. 220-225. DOI: 10.3969/j.issn.1004-32X.2019.02.013.

13. Chungchoo, C. & Saini, D. (January 2019). "On-line tool wear estimation in CNC turning operations using fuzzy neural network model", *International Journal of Machine Tools and Manufacture,* Vol. 42, Issue 1, pp. 29-40. DOI: 10.1016/S0890-6955(01)00096-7.

14. Liang, S. Y., Hecker, R. L. & Landers, R. G. (May 2004). "Machining process monitoring and control: The state-of-the-art", *Journal of Manufacturing Science and Engineering*, Transactions of the ASME, Vol. 126, Issue 2, pp. 297-310. DOI: 10.1115/1.1707035.

15. De Oliveira, J. F. G. & Dornfeld, D. A. (2001). "Application of AE contact sensing in reliable grinding monitoring", *CIRP Annals – Manufacturing Technology,* Vol. 50, Issue 1, pp. 217-220. DOI: 10.1016/S0007-8506(07)62108-8.

16. Xie, Z., Li, J. & Lu, Y. (February 2019). "Feature selection and a method to improve the performance of tool condition monitoring", *International Journal of Advanced Manufacturing Technology,* Vol. 100, Issue 9-12, pp. 3197-3206. DOI: 10.1007/s00170-018-2926-5.

17. Zhang, X., Tsang, W.-M., Yamazaki, K. & Mori, M. (February 2013). "A study on automatic on-machine inspection system for 3D modeling and measurement of cutting tools", *Journal of Intelligent Manufacturing,* Vol. 24, Issue 1, pp. 71-86. DOI: 10.1007/s10845-011-0540-6.

18. Saravanan, R., Asokan, P. & Sachithanandam, M. (2001). "Comparative analysis of conventional and non-conventional optimisation techniques for CNC turning process", *International Journal of Advanced Manufacturing Technology,* Vol. 17, Issue 7, pp. 471-476. DOI: 10.1007/s001700170146.

19. Dang, J., Liu, G., Chen, Y., An, Q., Ming, W. & Chen, M. (May 2019). "Experimental investigation on machinability of DMLS Ti6Al4V under dry drilling process", *Materials and Manufacturing Processes,* Vol. 34, Issue 7, pp. 749-758. DOI: 10.1080/10426914.2019.1594254.

20. Sahu, N. K., Andhare, A. B., Andhale, S. & Abraham, R. R. (May 2018). "Prediction of surface roughness in turning of Ti-6Al-4V using cutting parameters, forces and tool vibration", *Materials Science and Engineering,* Vol. 346, Issue 1. DOI: 10.1088/1757-899X/346/1/012037.

21. Sidorov, D. N. (2013). Metody analiza integral'nyh dinamicheskih modelej: teorija i prilozhenija, [Methods of analysis of integral dynamic models: theory and applications], Irkutsk, Russian Federation, *Ed. ISU*, 293 p. [in Russian].

22. Simani, S., Fantuzzi, C. & Patton, R. J. (2003). "Model-Based Fault Diagnosis in Dynamic Systems Using Identification Techniques", *Publ. Springer-Verlag,* New York.

23. Katipamula, S. & Brambley, M. R. (January 2005). "Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems. A Review, Part I", HVAC&R Research, Vol. 11, No. 1.

24. Cheng, C. M., Peng, Z. K., Zhang, W. M. & Meng, G. (November 2016). "Volterra-series-based nonlinear system modeling and its engineering applications: A state-of-the-art review", *Mechanical Systems and Signal Processing,* pp. 1-25. DOI:10.1016/j.ymssp.2016.10.029.

25. Doyle, F. J., Pearson, R. K. & Ogunnaike, B. A. (2002). "Identification and control using Volterra models", Germany, *Springer Publ.*, 314 p.

26. Franz, M. O. & Scholkopf B. (2006). "A unifying view of Wiener and Volterra theory and polynomial kernel regression", *Neural Computation*, Vol. 18(12), pp. 3097-3118.

27. Apartsyn, A. S., Solodusha, S. V. & Spiryaev, V. A. (2013). "Modeling of nonlinear dynamic systems with Volterra polynomials: elements of theory and applications", *International Journal of Energy Optimization and Engineering*, Vol. 2, No. 4, pp. 16-8.

28. Pavlenko, V. D., Pavlenko, S. V. & Speranskyy, V. O. (2014). "Identification of Systems Using Volterra Model in Time and Frequency Domain", Advanced Data Acquisition and Intelligent Data Processing, *River Publishers*, Chapter 10, pp. 233-270. DOI: 10.5772/58354.

29. Pavlenko, V. D., Speranskyy, V. O., Dombrovskyi, M. (2015). "The Engineering Software Tools for Nonlinear Dynamical Systems Identification Based on Volterra Models in Frequency Domain", *Proceedings of the 8th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications,* Warsaw, Poland, Vol. 1, pp. 386-391. DOI: 10.1109/IDAACS.2015.7340763.

30. Fomin, O., Masri, M. & Pavlenko, V. (2016). "Intelligent Technology of Nonlinear Dynamics Diagnostics Using Volterra Kernels Moments", *International Journal of Mathematical Models and Methods in Applied Sciences*, *Publisher NAUN,* Vol. 10, pp. 158-165. ISSN: 1998-0140.

31. Pavlenko, V. D. (August 2006). "Estimation of the Volterra Kernels of a Nonlinear System Using Impulse Response Data", *Proc. the Eighth All–Ukrainian International Conference Signal/Image Processing and Pattern Recognition (UkrOBRAZ'2006),* Kiev, Ukraine, pp. 191-194.

32. Vodichev, V. A. & Aldairi, Ali. (2018). "Investigation of the automated control system for the electric drive of the milling machine", *Electrotechnical and Computer Systems,* No. 29 (105), pp. 169-172.

33. Tonconogy, V. M., Zelinskiy, S. A. & Vodichev V. A. (2017). "Ways of implementation of vibrations suppression methods at parts machining with CNC machine tools", Odessa National Polytechnic University, Pratsi, Vol. 1(51), pp. 34-39.

34. Voskobojnikov, Yu. E., Gohakov, A. V. & Colcker, A. B. (2010). Fil'tracii signalov i izobrazhenij: Fur'e i vejvlet algoritmy (s primerami v Mathcad): monografija, [Filtration of signals and images: Fourier and wavelet algorithms (with examples in Mathcad): monograph], Novosibirsk State University of Architecture And Civil Engineering (Sibstrin), 188 p. [in Russian]

35. Verlan, A. F., Fedorchuk, V. A. & Ivanyuk, V. A. (2010). Komp'juterne modeljuvannja v zadachah dinamiki elektromehanichnih system, [Computer modeling in the problems of dynamics of electromechanical systems], IPME named. G. E. Pukhov, Kamyanets-Podilsky Ivan Ogienko, Kamenets-Podolsky National University, 204 p. [in Russian].

36. Fomin, O. Medvedev, A. & Pavlenko, V. (September 2015). "Technology of Intelligent Diagnostics based on Volterra Kernels Moments", Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, *Proc. of the 8th IEEE International Conference IDAACS–2015,* Warsaw, Poland, pp. 796-801.

Received 05.03.2019

УДК 517.9

[1]**Фомін, Олександр Олексійович,** кандидат технічних наук, доцент кафедри комп'ютеризованих систем управління, E-mail: fomin@opu.ua, ORCID: 0000-0001-5199-8913
[1]**Павленко, Віталій Данилович,** доктор технічних наук, професор, професор кафедри комп'ютеризованих систем управління, E-mail: pavlenko.vitalij@mail.ru, ORCID: 0000-0002-5655-4171
[1]**Дерев'янченко, Олександр Георгійович,** доктор технічних наук, професор кафедри матеріалознавства, E-mail: algdrv@opu.ua, ORCID: 0000-0002-4679-3339
[1]**Водічев, Володимир Анатолійович,** доктор технічних наук, професор, завідувач кафедри електромеханічних систем з комп'ютерним управлінням, E-mail: vva@eei.opu.ua, ORCID: 0000-0002-7204-1149
[1]**Рубан, Олександр Дмитрович,** провідний інженер відділу інноваційних інформаційних технологій, E-mail: westsoldierruban@gmail.com, ORCID: 0000–0001–5199–8913
[1]Одеський національний політехнічний університет, пр. Шевченка, 1, Одеса, Україна, 65044

ПІДХІД ДО ПОБУДОВИ НЕЛІНІЙНОЇ ДИНАМІЧНОЇ МОДЕЛІ ПРОЦЕСУ РІЗАННЯ ДЛЯ ДІАГНОСТУВАННЯ СТАНІВ ІНСТРУМЕНТІВ

Анотація. *Розглядаються особливості використання теорії інтегральних рядів у прикладних задачах ідентифікації нелінійних динамічних систем в задачах діагностування станів ріжучих інструментів. Обгрунтовано перспективи розробки методу оцінки станів різальних інструментів на основі непрямих вимірювань з використанням інтегральних непараметричних динамічних моделей, побудованих на базі експериментальних даних «вхід–вихід» при використанні тестових імпульсних впливів на систему різання. Такий підхід дозволяє підвищити продуктивність діагностування за рахунок зменшення обсягу обчислень, а також, достовірність діагнозу за рахунок одночасового обліку нелінійних та інерційних властивостей системи в інтегральних непараметричних динамічних моделях. Крім того, розглянуті моделі здатні описувати несправності, викликані як зміною параметрів системи, так і її структури, а також, можуть використовуватися при тестовому та функціональному діагностуванні.*

Розроблено метод побудови інформаційних моделей станів різальних інструментів на основі непрямих вимірювань з використанням тестових імпульсних впливів на систему різання у вигляді навантаження з ударами та реєстрації відгуків системи, на основі яких будуються інформаційні моделі у вигляді багатовимірних перехідних функцій.

Запропонована структурна схема організації експерименту «вхід-вихід» в рамках задачі діагностування стану інструменту в умовах імпульсних впливів на систему різання для отримання первинної діагностичної інформації. Розглянуто способи формування тестових імпульсних навантажень системи різання шляхом послідовного врізання ріжучого інструменту в заготовку з різними глибинами різання, зі змінною подачею різання і зі змінною тривалістю різання.

Обчислювальний експеримент демонструє переваги інформаційних моделей у вигляді багатовимірних перехід-них функцій для моделювання нелінійних динамічних систем в задачах діагностування станів ріжучих інструментів. Встановлено, що багатовимірні перехідні функції другого порядку можуть використовуватися в якості ефективного джерела первинних даних при побудові автоматизованих систем технічного діагностування.

Ключові слова: *нелінійні динамічні системи; багатовимірні перехідні функції; ідентифікація; інформаційні моделі; технічна діагностика*

УДК 517.9

[1]**Фомин, Александр Алексеевич,** кандидат технических наук, доцент, доцент кафедры компьютеризированных систем управления, E-mail: fomin@opu.ua, ORCID: 0000-0001-5199-8913
[1]**Павленко Виталий Данилович,** доктор технических наук, профессор кафедры компьютеризированных систем управления, E-mail: pavlenko.vitalij@mail.ru, ORCID: 0000-0002-5655-4171
[1]**Деревянченко, Александр Георгиевич,** доктор технических наук, профессор, профессор кафедры материаловедения, E-mail: algdrv@opu.ua, ORCID: 0000-0002-4679-3339
[1]**Водичев, Владимир Анатольевич,** доктор технических наук, профессор, зав. кафедры электромеханических систем с компьютерным управлением, E-mail vva@eei.opu.ua, ORCID: 0000-0002-7204-1149
[1]**Рубан, Александр Дмитриевич,** ведущий инженер отдела инновационных информационных технологий, E–mail: westsoldierruban@gmail.com, ORCID: 0000–0001–5199–8913
[1]Одесский национальный политехнический университет, пр. Шевченко, 1, Одесса, Украина, 65044

ПОДХОД К ПОСТРОЕНИЮ НЕЛИНЕЙНОЙ ДИНАМИЧЕСКОЙ МОДЕЛИ ПРОЦЕССА РЕЗАНИЯ ДЛЯ ДИАГНОСТИРОВАНИЯ СОСТОЯНИЙ ИНСТРУМЕНТОВ

Аннотация. *Рассматриваются особенности использования теории интегральных рядов в прикладных задачах идентификации нелинейных динамических систем для диагностирования состояний режущих инструментов. Обоснованы перспективы разработки метода оценки состояний режущих инструментов на основе косвенных измерений с использованием интегральных непараметрических динамических моделей, построенных на базе экспериментальных данных «вход–выход» при использовании тестовых импульсных воздействий на систему резания. Такой подход позволяет повысить оперативность диагностирования за счет уменьшения объема вычислений, а также, достоверность диагноза за счет одновременного учета нелинейных и инерционных свойств системы в интегральных непараметрических динамических моделях. Кроме того, рассматриваемые модели способны описывать неисправности, вызванные как изменением параметров системы, так и ее структуры, а также могут использоваться при тестовом и функциональном диагностировании.*

Разработан метод построения информационных моделей состояний режущих инструментов на основе косвенных измерений с использованием тестовых импульсных воздействий на систему резания в виде нагрузок с ударами и регистрации откликов системы, на основе которых строятся информационные модели в виде многомерных переходных функций.

Предложена структурная схема организации эксперимента «вход-выход» в рамках задачи диагностирования состояния инструмента в условиях импульсных воздействий на систему резания для получения первичной диагностической информации. Рассмотрены способы формирования тестовых импульсных нагружений системы резания путем последовательного врезания режущего инструмента в заготовку с различными глубинами резания, с переменной подачей резания и с переменной длительностью резания.

Вычислительный эксперимент демонстрирует преимущества информационных моделей в виде многомерных переходных функций для моделирования нелинейных динамических систем в задачах диагностирования состояний режущих инструментов. Установлено, что многомерные переходные функции второго порядка могут использоваться в качестве эффективного источника первичных данных при построении автоматизированных систем технического диагностирования.

Ключевые слова: *нелинейные динамические системы; многомерные переходные функции; идентификация; информационные модели; техническая диагностика*