ADAPTIVE CONTROL OF THE ORE CRUSHING PROCESS IN CONE CRUSHERS BASED ON NONLINEAR PREDICTIVE MODEL

Mykhailenko O.,
Ph.D. (Engineering), Assistant Professor of the Power Supply and Energy Management Department of Kryvyi Rih National University, Kryvyi Rih, Ukraine

Shchokin V.,
Doctor of Technical Sciences (Engineering), Professor, Acting Director of Scientific Research Institute of Occupational Safety and Ecology in the Mining and Metallurgical Industry of the Kryvyi Rih National University, Kryvyi Rih, Ukraine

Shchokina O.,
Senior Instructor of the Power Supply and Energy Management Department of Kryvyi Rih National University, Kryvyi Rih, Ukraine

Abstract

The paper deals with the development adaptive control system of the ore crushing process based on nonlinear block-oriented dynamic models. It is define that the best dynamic approximation quality according to the minimum coefficient of variation of the root-mean-square error and identification time are provided by applying a hybrid structure that combines the Wiener model, the Hammerstein-Wiener model and the Laguerre orthonormal functions. Using the recursive least squares algorithm for parametric identification enables to adapt the disturbances caused by changes in the mining mass characteristics. A nonlinear model predictive control system of the ore crushing process is also developed. A method of control formation is proposed and based on the block-oriented model static nonlinearities inversion. The obtained system demonstrated high dynamics quality and low computational load on the digital controller.

Keywords: ORE CRUSHING PROCESS, ADAPTIVE CONTROL, NONLINEAR MODEL PREDICTIVE CONTROL, BLOCK-ORIENTED MODELS, IDENTIFICATION, SIMULATION.

Introduction. The problem of the effective use of natural and energy resources in the context of constantly rising prices for fuel and electricity is a leading place in the state policy of Ukraine. In the production field, resource and energy capacity is inherent in the technological processes of ore-enrichment plants, which include the ore preparation for enrichment by means of multi-stage crushing with subsequent grinding in the mills. In the structure of the ore processing cost the crushing operation share is the biggest, which is due to high energy costs.

The main factors influencing the energy consumption of a mill include particle-size distribution of the raw materials. Taking into account that grinding is preceded by crushing operations, the increase in the efficiency of ore preparation in general can be achieved by obtaining as much as possible fine and smooth ore at this processing stage. Thus, energy costs are transferred to less energy intensive process. This can be achieved either by the complete re-equipment of technological lines or by optimizing the operating modes of an existing technological installation by developing new and improving existing methods and algorithms for controlling it. From the economic point of view, the advantage is given to the last solution.

Existing methods and systems of automated control of the ore crushing process do not allow to control the particle-size distribution of the finished product effectively enough, therefore the development of adaptive control systems, which will allow to provide high characteristics of particle-size in conditions of fluctuations of ore properties, changes in the characteristic of technological equipment and the presence of obstacles in data transmission channels is an actual scientific task. For qualitative adaptive control formation, an adequate mathematical description of the plant must be known. Taking into account the nonlinearity of the ore crushing process, in predicting its behavior, it is advisable to use block-oriented models (BOM) because of a clear separation of linear and nonlinear parts. This feature allows to use a wide range of linear dynamic models and static nonlinear functions in plant modeling.

Thus, providing a given particle-size distribution of the finished product with crushing ore in cone crushers by applying adaptive control with a predictive block-oriented structure to parametrizate the trajectory of control actions, which will allow with introduction into production to increase profits from the functioning of existing equipment by reducing the cost of the ore preparation product is currently the topical issue.

Analysis of literary data and problem statement. Today, in the theory of identification the following directions related to the synthesis of nonlinear system models are widely searched: models based on Volterra series use, nonlinear input-output models (NARX, NARMAX, NOE, etc.), block-oriented models (Hammerstein, Wiener and Hammerstein-Wiener) and fuzzy-neural network models.

For a nonlinear Volterra system, the relationship between input and output can be represented in the form of an infinite series [1]. The disadvantage of the practical use of this type of model lies in the estimation of a large number of unknown characteristics with truncation of infinite series [2, 3]. Also, parametric identification can be performed using a sufficiently deep sampling [3]. However, due to the lack of feedback on the output Volterra model provides guaranteed stability.

In contrast to Volterra nonlinear system, nonlinear input-output models have an output feedback that allows us to obtain a mathematical description of the dynamic process in a more compact form [3].

Depending on the type of operator, the following models are distinguished: NARX (nonlinear ARX), NARMAX (nonlinear ARMAX), NOE (nonlinear OE). As in the Volterra system, the regressors number of these models increase with rising polynomial orders and sampling depths. This disadvantage is especially critical for the NARMAX model. NARX, NARMAX and NOE models are sensitive to external disturbances and noise in data transmission channels. Also the modeling accuracy of the plant dynamics depends on the sampling period [4].

Block-oriented nonlinear models (BOM) are conventionally divided into nonlinear static and linear dynamic blocks. In the Hammerstein model, a nonlinear static block is located in front of a linear dynamic part. In the Wiener model, on the contrary, the linear block precedes the nonlinear one. In the Hammerstein-Wiener model, the dynamic part of the model is between two nonlinear blocks.

The complexity of the parametric identification of block-oriented models lies in the need to consider the interrelations between structural elements. Many methods and algorithms for evaluating the characteristics of the considered functions and models have been developed and investigated [5]. However, if there is information about the nature of static nonlinearities, the process of developing a model is significantly reduced. In this case, the identification is a subject to an exclusively linear dynamic model. In the tasks of automated precise control, it is expedient to use the block-oriented models (BOM) in conjunction with the systems of Laguerre orthonormal functions (OBF) through a clear separation of linear and nonlinear parts [6].

To determine the structure of a nonlinear model that will allow to provide acceptable prediction of the plant reaction to change the controls, a comparative analysis of the approximation quality should be performed using three typical unified BOMs: Hammerstein, Wiener and Hammerstein-Wiener. In connection with the use of the Laguerre model to represent the linear part of these models, it is necessary to adapt their traditional mathematical description in the space of states by analogy with [7].

The model predictive control (MPC) method has demonstrated high efficiency in technological processes control. The principle of control is to predict the system behavior at a certain interval and ensure that it is best approximated to the output of the plant to the reference signal [8-10] by solving the optimization problem. In this case, the most common form of the objective function is the quadratic criterion.

Taking into account the nonlinearity of the ore crushing process, it is expedient to consider possible ways of solving the predictive control problem, provided that the predictive model is also nonlinear (NMPC). A simpler method is linearization of the nonlinear model around the operating point [11] and the application of linear predictive control (MPC) methods. However, the qualitative characteristics of such controller significantly deteriorate at significant deviations from the nominal operation conditions, which is explained by the inability of the linearized model to describe the global behavior of the nonlinear system.

NMPC control is a form of nonlinear programming problem, so methods of sequential quadratic programming or internal point [12] can be used to find the optimal trajectory of control actions. However, as a result, we see the increase of the computing load on the controller and the system's performance at computing in real time. This is due to the more complex iterative procedure of finding a solution to the problem of nonlinear programming, in comparison with the linear one.

The third method is based on the application of the static nonlinearity inversion method [11], which is convenient to use with block-oriented systems because of the independence of linear and nonlinear block models. At the same time, formulating the task of predictive control, the replacement of the source coordinates, control actions and signals of the task by intermediate reciprocal variables is carried out. Then, to determine the control vector, algorithms of linear or quadratic programming are used, depending on the absence or presence of restrictions on the input-output variables. However, the use of nonlinear compensators can lead to quasi-optimal and often sub-optimal solutions of the modified predictive control task.

The key task in model predictive control is to determine the future control steps, that is, the sequence of amplitudes of control action or its increments. Given the high sampling frequency and the long horizons of prediction, the number of elements of the vector of controls that need to be determined may be sufficiently significant, which reduces the time of finding the optimal solution, due to the large computational load [13].

The research [14] is focused on reducing the time of settlement operations of MPC control by reducing the controls sequence number degrees of freedom within the prediction horizon. In research [15], the computational efficiency of determining the trajectory of control increases due to its approximate representation of wavelet functions. Similarly, in researches [13, 16], the approximation of the control trajectory is carried out by a system of orthonormal basis Laguerre functions. This allows to use a unified descriptor of the controls sequence. As a result, after determining the structure of the model (its order), the number of parameters to be identified is significantly reduced and limited by parameters of a set of orthonormal functions.

The advantage of using MPC in the conditions of the ore mining processes control is determined by the possibility of taking into account the physical and technological constraints of the process by imposing restrictions on the amplitude, increment of control and output coordinates and confirmed by researches [17, 18]. The second, more general advantage is the definition of control effects in real time. In this case, the speed is limited only by the frequency of tacting modern hardware controllers and the speed of optimization algorithms convergence.

The purpose of the work. The purpose of the study is to develop principles and structure of ore crushing process adaptive control system based on the predictive model, which provide the formation and maintenance of the specified homogeneity of the crushed product and the control size class output under the influence of uncontrolled disturbances caused by fluctuations of the ore raw material characteristics, changes in the parameters of technological equipment and errors in data transmission channels.

Results of the development of nonlinear models of the ore crushing process in cone crushers and studying the quality of their structural and parametric identification approximating the process dynamics. The dynamics of the control plant can be described by a model constructed on the basis of orthonormal Laguerre functions, which is represented as follows in the state-space discrete form [6, 16]:

$$\begin{aligned} L[k+1] &= \Phi\, L[k]\mathrm{k} + \Gamma u[k], \\ y[k] &= \mathrm{C}^T L[k], \end{aligned} \tag{1}$$

where p – the order of the model; $L[k] = \begin{bmatrix} l_1[k] & l_2[k] & \cdots & l_p[k] \end{bmatrix}^T$ – state vector consisting of Laguerre functions; Φ – the lower triangular matrix of size $(p \times p)$; Γ – a vector-column of size $(p \times 1)$:

$$\Phi = \begin{bmatrix} \psi & 0 & 0 & \cdots & 0 \\ \vartheta & \psi & 0 & \ddots & 0 \\ -\psi\vartheta & \vartheta & \psi & \ddots & \vdots \\ \vdots & \vdots & & \ddots & 0 \\ (-\psi)^{p-2}\vartheta & (-\psi)^{p-3}\vartheta & \cdots & \vartheta & \psi \end{bmatrix}, \tag{2}$$

$$\Gamma = \sqrt{\vartheta} \begin{bmatrix} 1 \\ -\psi \\ \psi^2 \\ \vdots \\ (-\psi)^{p-1} \end{bmatrix}; \mathrm{C} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_p \end{bmatrix}, \tag{3}$$

where $\vartheta = \left(1-\psi^2\right)$; ψ – a scale factor that must be within $0 \le \psi < 1$ to ensure system stability.

The task of the Laguerre OBF model (1) parametric identification is reduced to the definition of coefficients vector C (3) components and the scale factor ψ.

The modified Hammerstein model containing the static nonlinearity in the part describing the effect of input actions on the state of the state vector can be represented as follows:

$$\begin{aligned} L[k+1] &= \Phi L[k] + \Gamma \Xi\left(u[k]\right), \\ y[k] &= \mathrm{C}^T L[k], \end{aligned} \tag{4}$$

where $\Xi[k] = \left[g_1\left(u[k]\right) \;\; g_1\left(u[k]\right) \;\; \cdots \;\; g_m\left(u[k]\right) \right]^T$ – $g_i : \mathrm{R}^m \to \mathrm{R}$ – static nonlinear functions; $L[k] \in \mathrm{R}^n$ - Laguerre model state vector; $u[k] \in \mathrm{R}^m$ - input vector.

Similarly, the Wiener model is formulated:

$$\begin{aligned} L[k+1] &= \Phi L[k] + \Gamma u[k], \\ y[k] &= \Psi\left(\mathrm{C}^T L[k]\right), \end{aligned} \tag{5}$$

where $\Psi(\cdot) : \mathrm{R}^n \to \mathrm{R}$ - static nonlinear function, which connects the Laguerre model state vector with the block-oriented model output.

By combining the two previous models (4) and (5) we obtain the Hammerstein-Wiener model in the state-space:

$$\begin{aligned} L[k+1] &= \Phi L[k] + \Gamma \Xi(u[k]), \\ y[k] &= \Psi(\mathrm{C}^T L[k]). \end{aligned} \tag{6}$$

To perform the series of computational experiments as an plant an improved [22] analytical model of the ore crushing process [21, 20] was used along the channels "rotation speed – homogeneity of the crushed product" and "rotational speed – control size class output".

The calculations were carried out in the MATLAB software package on a PC with the following configuration: Intel Core i3-3120M 2.5 GHz 4GB RAM Win7 x64.

To assess the accuracy of the approximation of the crushing process characteristics and the model predictive control quality, the coefficient of variation of the root-mean-square error between the test and model data is used:

$$CV\left(RMSE\right)=\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i-\hat{y}_i}}{\sum_{i=1}^{n}\hat{y}_i\Big/n},\qquad(7)$$

where y_i – test value; $\hat{y}_i$ – model value; n – the number of measurements.

The ore crushing process model identification was carried out according to the structural scheme (see Fig. 1). As already mentioned above, the multi-zone model of a cone crusher was adopted as an identification plant, the adequacy of which is confirmed by studies [20-22]. The inputs $u_\omega[k]$ i $u_\theta[k]$ were subjected to test samples corresponding to the laws of changing the rotation speed and closed side setting of the technological unit. Outputs were taken off the original values that characterize the qualitative parameters of the crushing process, namely the control size class output in crushed ore $y_\gamma[k]$ and the general index of its homogeneity $y_{CV}[k]$.

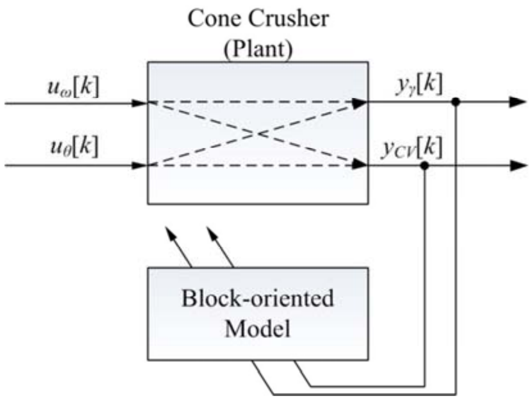

Fig. 1. Block-diagram of the ore crushing process model structural-parametric identification

Carrying out the research, the parametric identification of the Laguerre model was initially carried out using adaptive algorithms: least-mean squares algorithm (LMS), normalized least-mean squares algorithm (NLMS), recursive least squares algorithm (RLS) [12-14]. After obtaining a mathematical description of the linear part, an iterative evaluation of the parameters of static nonlinearities was performed. Stationary nonlinearities of BOM are approximated by piecewise linear functions with iterative estimation of their parameters by nonlinear optimization algorithms (Gauss-Newton, Levenberg-Marquardt and the fastest descent) at each step of the calculations, followed by a choice of values that minimize the accuracy of the modeling CV(RMSE). The results of computational experiments for models of regime parameters of the crushing process are summarized in table 1.

The obtained data demonstrate that the best approximation of the process characteristics by control size class output is achieved using the Wiener model and the recursive algorithm for estimating the Laguerre OBF parameters. The accuracy of this model is 1.9% higher than that of nonlinear systems of the same structure, but with other parametric identification algorithms and 26.5 times higher than the linear model with the RLS algorithm [22].

Table 1

The accuracy of block-oriented models identification with Laguerre OBF and adaptive parameter estimation algorithms

Model	Identification algorithms	CV(RMSE), %	
		Control size class output, %	Coefficient of variations of size density function
Hammerstein with Laguerre OBF	LMS	20,65	11,14
	NLMS	21,03	4,19
	RLS	21,75	3,85
Wiener with Laguerre OBF	LMS	2,029	1,69
	NLMS	2,028	1,85
	RLS	1,99	3,13
Hammerstein-Wiener with Laguerre OBF	LMS	11,67	0,62
	NLMS	19,22	0,52
	RLS	12,5	0,51

Fig. 2b shows the time series of the plant and block-oriented models outputs that provide the minimum CV($RMSE_{\gamma}$).

As you can see from the graphs, the Hammerstein-Wiener model with the LMS algorithm does not adequately describe the inertia of the ore crushing process and has the highest error of the steady-state of $e_{cm\,\gamma}$ = 3,9 % compared to other models that are given. In contrast, all Wiener models are acceptable to simulate the dynamics of a plant. The best accuracy in steady-state for the Wiener structures is achieved with a RLS algorithm of parametric identification $e_{cm\,\gamma}$ = 0,53 %, and worst – with the NLMS algorithm $e_{cm\,\gamma}$ = 0,64 %.

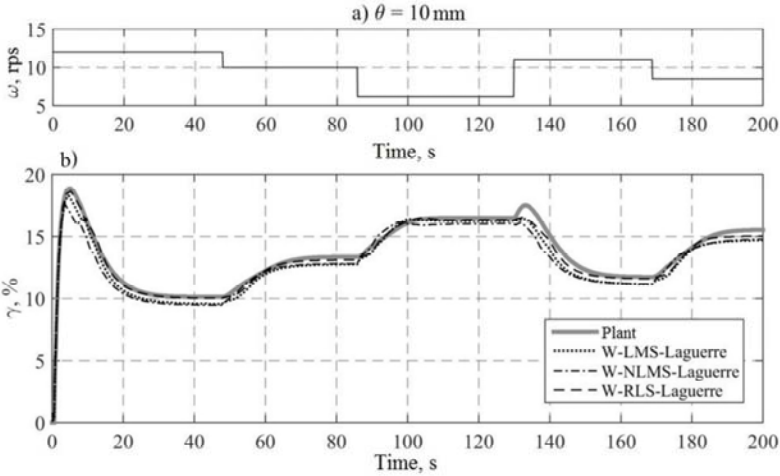

Fig. 2. Time series of the plant and Wiener models outputs

On the other hand, for the coefficient of variations of size density function, the Hammerstein-Wiener model is more accurate than the Wiener structure (table 1, fig. 3b).

The maximum accuracy of simulation of the mode parameter is a model with a recursive algorithm for determining the linear dynamic part CV($RMSE_{CV}$) = 0,51 %. The dynamics of the ore crushing process by all three Hammerstein-Wiener models is described adequately. The average error in steady-state is $e_{cm\,CV}$ = 0,24 %, $e_{cm\,CV}$ = 0,6 % and $e_{cm\,CV}$ = 0,16 % adapting the models using the algorithms of the usual and normalized least squares, and the recursive least squares algorithm, respectively.

Consequently, in this case, the best accuracy have a model with a recursive algorithm of linear block parameters estimation. This adaptive algorithm (so one source program in controller) can be used to estimate the model parameters on other channels. This will reduce the controller memory load.

Using the Wiener nonlinear structure and the LMS algorithm identifying the Laguerre system parameters, there is oscillation in dynamics and the error in steady-state is $e_{cm\,\mathrm{CV}}$=0,59 %.

We also note that for both parameters the worst identification accuracy was demonstrated by Hammerstein's models, regardless of the adaptive parameter estimation algorithm. In this case, the use of the LMS algorithm leads to deterioration in the modeling of the process behavior by the coefficient of variation of size density function 17.86%.

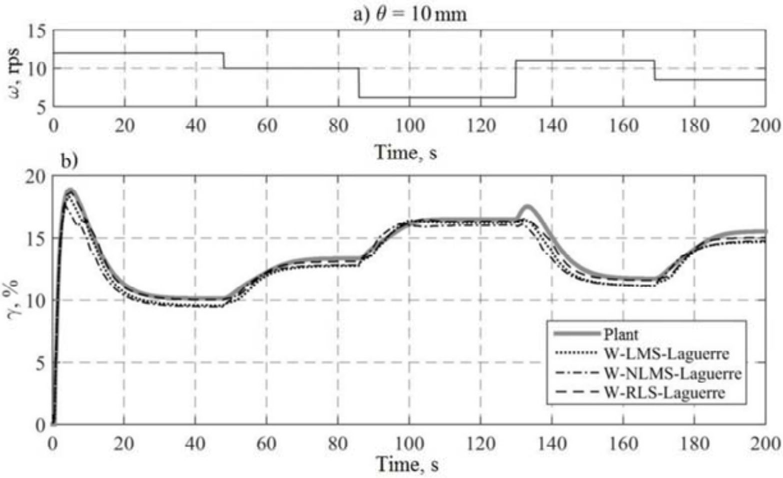

Fig. 3. Time series of the plant and Hammerstein-Wiener models outputs

We perform a comparison of the received block-oriented models that provide the minimum value of the approximation quality index, with the typical nonlinear structures used in the theory of system identification. Third-order Volterra, Wiener, and Hammerstein-Wiener models have a linear part of the "output-error" structure (W-OE, H-W-OE), as well as the nonlinear autoregressive model (NARX).

Simulation of the influence of external disturbances and noise in data transmission channels was carried out by applying to the output of the plant additive interference, which is represented by a sequence of random variables with normal distribution. Computational experiments were performed at various values of the distribution standard deviation σ. With each change of standard deviation, the structural identification of the models W-OE, H-W-OE and NARX was carried out by direct sampling of the parameters n_a, n_b, n_f, n_k. In order to determine the stability of the parametric identification process, for each value of σ and defined sets of model parameters, calculations were made 30 times. The averaged CV(RMSE) values are summarized in table 2, 3.

According to the obtained data (fig. 4b, table 2), the Hammerstein-Wiener with Laguerre (HW-RLS-Laguerre) models and the "output-error" structure provides the best approximation of the crushing process reaction by the coefficient of variation of size density function on the cone rotational speed changes.

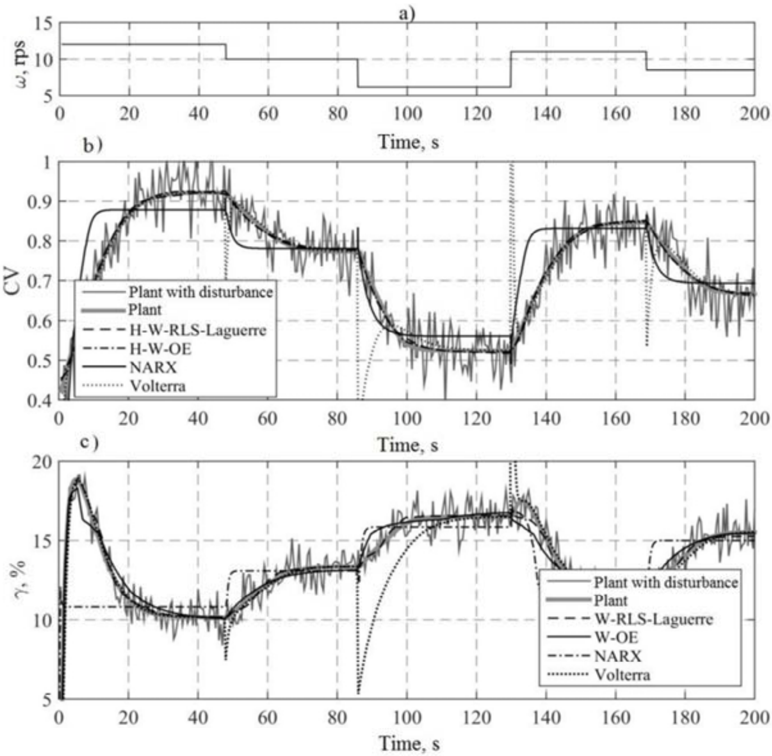

Fig. 4. Time series of the plant and nonlinear models outputs

In this case, the structure with the Laguerre model has 9.8% greater accuracy with σ = 0,005 and at 2.1%, with σ = 0.1 in relative terms. It should also be noted that the error of the stable mode of the proposed block-oriented system is only $e_{cm\,\mathrm{CV}}$ = 0,18 %. For comparison, in W-OE and H-W-OE models with "output-error" structure, this value is $e_{cm\,\mathrm{CV}}$ = 2,17 % and $e_{cm\,\mathrm{CV}}$ = 2,26 %, respectively.

The worst quality of simulation was shown by NARX. The spread of values of the variation coefficient of the root-mean-square error with a consistent increase σ shows the instability of the process parameters estimating. The polynomial structure inadequately reflects the inertia of the ore crushing process and, in general, the behavior of the plant in steady-state.

Table 2

The accuracy of nonlinear models identification of the process of fragmentation by the coefficient of variation of the grain size characteristic

Standard deviation σ, %	CV(RMSE), %				
	H-W-RLS-Laguerre	W-OE	H-W-OE	NARX	Volterra
0,005	1,02	2,17	1,12	9,75	9,23
0,01	1,27	2,39	1,54	8,73	9,29
0,025	2,97	3,64	3,15	14,4	9,72
0,05	5,89	6,34	6,11	17,37	11,07
0,075	8,85	9,18	9,25	22,5	12,94
0,1	11,84	12,1	12,09	20,05	15,22

The average deviation of the output of this model in a steady0state relative to the output of the plant without additive disturbance is $e_{cm\,\mathrm{CV}}$ = 17,9 %, that is the worst among considered nonlinear structures. Unlike NARX, the 3rd order Volterra system has a better accuracy of steady-state description. The error of the steady-state is, at the same time interval $e_{cm\,\mathrm{CV}}$ = 0,013 %. However, in the simulation of the transition process, such system loses stability. As a result, for its, the coefficient of variation of the root-mean-square error is quite high. At the same time, it changes by only 5.99% in the range of standard deviations of additive disturbance

$\{\sigma \in \mathrm{R} \mid 0,005 \le \sigma \le 0,1\}$. For comparison, with the increase of σ from 0.005 to 0.1, the accuracy of the Hammerstein-Wiener model with Laguerre OBF drops by 10.82%. At the same time, all the BOMs, regardless of the type of linear model, are quite stable.

A comparative analysis of the modeling results of the behavior of the ore crushing process by the control size class output (table 3, fig. 4c) shows that the best overall accuracy of the Wiener structure with Laguerre OBF (W-RLS-Laguerre). Its accuracy is higher by 3,02% at σ = 0,05 and 11,98% at σ = 1 than in the W-OE structure, which also showed a fairly high quality of approximation, especially with slight disturbances.

The Wiener model with Laguerre OBF best describes the steady-state process $e_{cm\,\gamma}$ = 0,61 % of the three block-oriented structures. For comparison, the steady-state errors of the W-OE and HW-OE systems make up $e_{cm\,\gamma}$ = 1,39 % and $e_{cm\,\gamma}$ = 1,64 %, respectively. It should be noted that the W-OE system is unstable. At the same time, CV(RMSE) increases by a maximum of 2.67%, so loss of stability can be considered as not significant.

Table 3

The accuracy for identification of nonlinear models of the splitting process for the partial execution of the size class –9.1+6.7 mm

Standard deviation σ, %	CV(RMSE), %				
	W-RLS-Laguerre	W-OE	H-W-OE	NARX	Volterra
0,05	2,07	5,09	10,17	13,2	15,1
0,075	2,12	5,29	12,84	14,9	15,15
0,1	2,19	5,51	10,07	39,14	15,17
0,25	2,93	5,46	10,95	28,18	15,28
0,5	4,7	19,73	21,8	23,9	15,81
0,75	6,72	18,53	21,1	30,25	16,58
1	8,81	20,79	22,91	32,5	17,64

As with the simulation of the variation coefficient of the size density function, the impossibility of practical application of the NARX model proves low quality of identification (accuracy and stability). The 3rd order Volterra system demonstrated the best modeling accuracy of the ore crushing process in steady-state. The steady-state error is only $e_{cm\,\gamma} = 0{,}012\,\%$. However, as before, it remains unstable in dynamics. The coefficient of variation of the root-mean-square error of the Volterra system increases by only 2.54% in the range of mean-square deviations of the additive disturbances $\{\sigma \in \mathrm{R} \mid 0{,}05 \le \sigma \le 1\}$. Under the same conditions, the general accuracy of the Wiener modeling with the Laguerre linear model increases by 6.74%.

Thus, as a result of the research, it was found that the best quality of the ore crushing process dynamics modeling has a hybrid block-oriented structure consisting of Hammerstein-Wiener and Wiener models, in which an orthonormal basis Laguerre functions system is used as a linear block (see fig. 5).

In addition to analyzing the quality of the ore crushing process simulation an investigation of the identification speed was additionally performed. Due to the high convergence rate of the adaptive RLS algorithm for identifying the Laguerre model, the total time of evaluating the characteristics of block-oriented structures on its basis was significantly lower than in standard nonlinear systems.

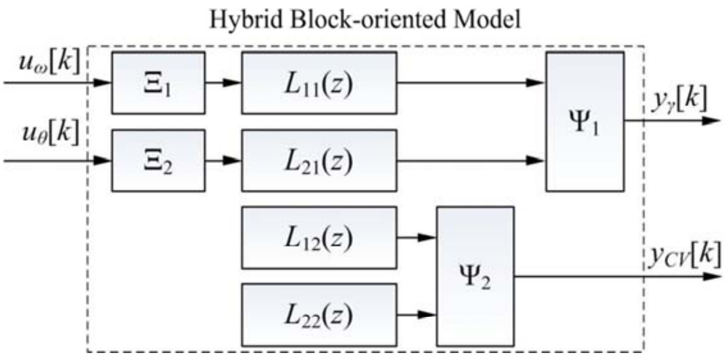

Fig. 5. Hybrid block-oriented model of ore crushing process

However, due to the determination of the parameters of static nonlinearities through the sequential use of three algorithms for nonlinear programming at one step, the total time of identification of the hybrid model was 153 milliseconds, which exceeds the system sampling period. Therefore, to reduce the identification time only the

Gauss-Newton algorithm was used, which reduced the time to 42.7 milliseconds without significant loss of accuracy.

Task formalization of multidimensional predictive control of ore crushing process based on hybrid block-oriented model

Given the nonlinearity of the hybrid model in the formation of controls, it is necessary to use methods and algorithms for nonlinear programming (NMPC), which, firstly, are complex in implementation and require significant memory resources of controller, and, secondly, have low performance through its iterative character [24]. Therefore, it is advisable to explore the possibility of using an alternative model predictive control method based on finding the block-oriented models static nonlinearities inverse functions.

In general, the solution of the model prediction control problem is to determine the trajectory of the controls, which minimizes the quadratic criterion of the form:

$$J = \left(R - \hat{Y}\right)^T Q \left(R - \hat{Y}\right) + \Delta \hat{U}^T S \Delta \hat{U}, \qquad (8)$$

Subject to:

$$\begin{gathered} \left\{\hat{U} \in \mathbf{R}^n \mid \hat{U}_{\min} \le \hat{U} \le \hat{U}_{\max}\right\} \forall \left\{k \in \mathbf{N} \mid 1 \le k \le N_c - 1\right\}; \\ \left\{\hat{Y} \in \mathbf{R}^n \mid \hat{Y}_{\min} \le \hat{Y} \le \hat{Y}_{\max}\right\} \forall \left\{k \in \mathbf{N} \mid 1 \le k \le N_p\right\}, \end{gathered} \qquad (9)$$

Applying a block-oriented model:

$$\hat{U} = \Xi\left(U\right); \hat{Y} = \Upsilon\left(C^T \Lambda\right),$$

where N_p, N_c – prediction and control horizons; Q, S – matrix of input-output weighing coefficients; $\Xi(\cdot)$, $\Upsilon(\cdot)$ – nonlinear input-output functions; U – vector of input actions $U = \left[u[k] \quad u[k+1] \quad \cdots \quad u[k+N_c-1]\right]^T$; $\Delta\hat{U}$ – control trajectory $\Delta\hat{U} = \left[\Delta\hat{u}[k] \quad \Delta\hat{u}[k+1] \quad \cdots \quad \Delta\hat{u}[k+N_c-1]\right]^T$; $\hat{Y}$ – vector of predicted output values $\hat{Y} = \left[\hat{y}[k+1 \mid k] \quad \hat{y}[k+2 \mid k] \quad \cdots \quad \hat{y}[k+N_p \mid k]\right]^T$; R – reference signal $R = \left[r[k+1 \mid k] \quad r[k+1 \mid k] \quad \cdots \quad r[k+N_p \mid k]\right]^T$; $\hat{Y}_{\min}$, $\hat{Y}_{\max}$, $\hat{U}_{\min}$, $\hat{U}_{\max}$ – constraints on output and control amplitudes.

Inversion of the hybrid model static nonlinear input-output functions allows us to reduce the problem (8) and (9) to the quadratic programming problem in the following form [11]:

$$J = \left(R^* - \hat{Y}^*\right)^T Q^* \left(R^* - \hat{Y}^*\right) + \Delta\hat{U}^{*T} S^* \Delta\hat{U}^*,$$
$$R^* = \Upsilon^{-1}(R); \hat{Y}^* = \Upsilon^{-1}\left(\hat{Y}\right); \hat{U}^* = \Xi^{-1}\left(\hat{U}\right), \quad (10)$$

Subject to:

$$\left\{\hat{U}^* \in \mathbf{R}^n \mid \hat{U}^*_{\min} \le \hat{U}^* \le \hat{U}^*_{\max}\right\} \forall \left\{k \in \mathbf{N} \mid 1 \le k \le N_c - 1\right\};$$
$$\left\{\hat{Y}^* \in \mathbf{R}^n \mid \hat{Y}^*_{\min} \le \hat{Y}^* \le \hat{Y}^*_{\max}\right\} \forall \left\{k \in \mathbf{N} \mid 1 \le k \le N_p\right\}, \quad (11)$$

where Q^*, S^* – matrix of input-output factors weight; $\Xi^{-1}(\cdot)$, $\Upsilon^{-1}(\cdot)$ – inverse nonlinearities of the input-output; $\Delta\hat{U}^*$ – inverted control trajectory $\Delta\hat{U}^* = \left[\Delta\hat{u}^*[k] \quad \Delta\hat{u}^*[k+1] \quad \cdots \quad \Delta\hat{u}^*[k+N_c-1]\right]^T$; $\hat{Y}^*$ – inverted vector of predicted output values of the block-oriented model $\hat{Y}^* = \left[\hat{y}^*[k+1|k] \quad \hat{y}^*[k+2|k] \quad \cdots \quad \hat{y}^*[k+N_p|k]\right]^T$; R^* – reference on prediction horizon $R^* = \left[r^*[k+1|k] \quad r^*[k+2|k] \quad \cdots \quad r^*[k+N_p|k]\right]^T$.

In order to find the inverse functions, it is proposed to use the ZEROIN algorithm tested in [25, 26].

It should also be noted that the computing load of a digital controller is influenced by the length of the prediction N_p and the control N_c horizons, which determine the size of the system matrices and the number of control trajectory elements to be evaluated. It is proposed to investigate the appropriateness of the Laguerre OBF control trajectory approximation to reduce the number of parameters to be estimated.

Taking into account the considerations discussed above, a block-diagram of the ore crushing process control system was compiled with the predictive model presented in fig. 6.

It consists of three main units: the control plant – a cone crusher, a hybrid predictive model and a controller. The structure of the predictive model includes two pairs of Wiener and Hammerstein-Wiener systems.

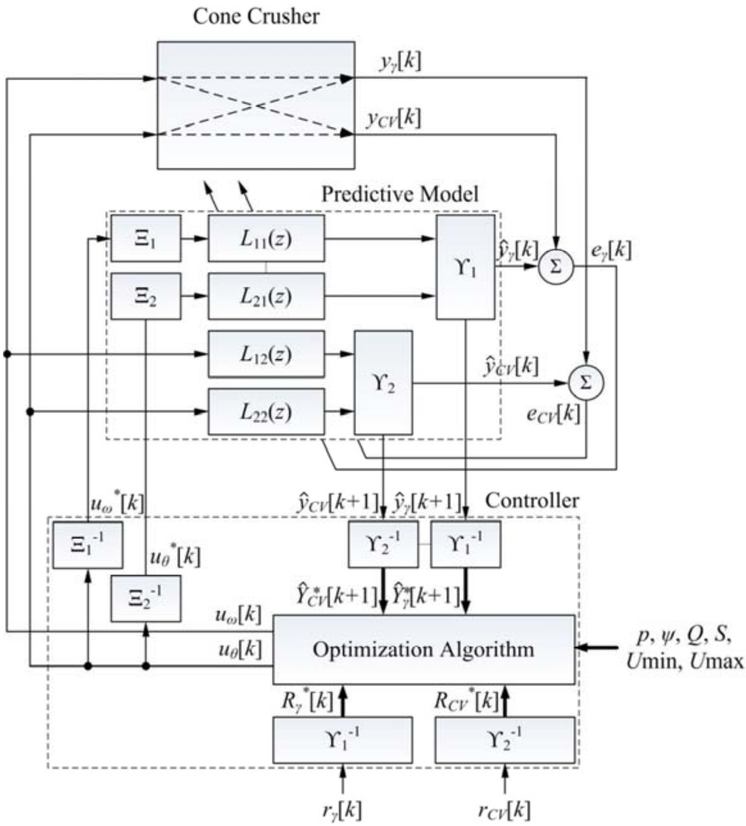

Fig. 6. Block-diagram of the crushing process model predictive control system

Note that the static nonlinearities at the output of the model Υ_1 and Υ_2 have a combined form. This is due to the fact that in the multidimensional system the output signals of the linear models $L_{11}(z)$, $L_{21}(z)$ i $L_{12}(z)$, $L_{22}(z)$ are added either before or after the nonlinear block and the number of values of the combination during the inverting is directed to infinity, that is, it can be argued that the inverse function does not exist. The features of the identification process of the combined nonlinearities of block-oriented models and their subsequent inverting are considered in [27, 28]. The controller consists of blocks of inverse nonlinear functions Ξ_1^{-1}, Ξ_2^{-1}, Υ_1^{-1}, Υ_2^{-1}, as well as a block that minimizes the criterion by one of the quadratic programming methods.

On the input of a closed system signals are given for control size class output and the coefficient of variation of the size density function $r_{\gamma}[k]$, $r_{CV}[k]$, the matrix of weight coefficients Q, S, the constraints on the controls amplitude $U_{\min}$, $U_{\max}$, the order p and the scale factor ψ of Laguerre model, which approximates the control trajectory.

The symbol "*" denotes the scalar and vector inverse values of the corresponding actions. The totally thick line is indicated by vector signals.

Simulating the MIMO adaptive control system of the ore crushing process based on a hybrid block-oriented predictive model

To evaluate the efficiency of the ore crushing process model predictive control system which using inverse nonlinear functions and Laguerre OBF parameterizing the control vector (the iLMPC system), we perform a series of computational experiments. In order to carry out a comparative analysis of the dynamics quality and the computational load, we additionally perform the simulation of the predictive controller operation with the nonlinear sequential quadratic programming algorithm for identifying control trajectory elements (NMPC). The length of the prediction trajectory N_p, the number of controls N_c and the weight coefficients matrices values Q, S are assumed to be the same for both systems.

The simulation was performed for 1000 samples with sampling interval $\Delta t = 0.5$ c. So, the experimental time lapse was $\{t \in \mathbf{R} \mid 0 \le t \le 500\}$ seconds. The reference signals were submitted to the input of both systems, and change according to the same law. The reference signal by the variation coefficient of size density function r_{CV} in the beginning of the calculation increases to 0.7, and then in 90 seconds – to 1.2. Next, the value of r_{CV} is reduced to 0.8 on 190 seconds and to 0.4 on 290. The reference for a control size class output r_{γ} after the start of the experiment steps from 0 to 9% and then to 15% and 18% at 140 and 240 seconds respectively. Then in 340 seconds signal is reduced to 11%.

The controllers are configured as follows. The prediction horizon for N_p is 20 counts. The matrixes of input-output weights were chosen arbitrarily with the following values: for the coefficient of variation $Q_{CV} = 600$, for the control size class output $Q_\gamma = 300$, for the input of the cone rotational speed S_ω=0,01 and for entering the closed side setting S_θ=0.01. The NMPC system has a 10-point control horizon. The amplitudes of the control vectors first components are imposed by the constraints of $\{\omega \in \mathbf{R} \mid 6 \le \omega \le 12\}$ revolution per second and $\{\theta \in \mathbf{R} \mid 8 \le \theta \le 13\}$ mm.

In the real cone crusher the induction motor is used to rotate the cone. It is expedient to adjust the speed by influencing the supply voltage frequency. To simulate the dynamics of the executing mechanism along the channel "voltage frequency–rotation speed" we use the linearized model of the induction motor [30]:

$$\begin{cases} \dfrac{d\omega}{dt} = \dfrac{1}{J}\left(M - M_c\right); \\ T_e \dfrac{dM}{dt} = \beta\left(\omega - \omega_0\right); \\ \omega_0 = \dfrac{2\pi f}{p}, \end{cases} \quad (12)$$

where $\beta = 2M_{\max} / \omega_0 s_{\max}$ – mechanical stiffness module; $T_e = 1/\omega_0 s_{\max}$ – the equivalent electromagnetic time constant of the stator and rotor circuits; f – voltage frequency; p – the number of poles pairs; M – engine torque; M_c – static torque; $M_{\max}$ – critical torque; $s_{\max}$ – critical slip; ω – motor speed; ω_0 – synchronous motor speed; J – moment of inertia.

The CH880 EEF cone crusher has motor with nominal parameters: $P = 600$ kW, $\omega_0 = 78.5$ rad/s, $\eta = 0.935$, $\cos\varphi = 0.85$, $J = 1600 \cdot 10^{-2}$ kg·m^2, $p = 4$, $\lambda_{\max} = 2$. According to the motor, the missing model parameters are calculated: $s_{\max} = 0.049$; $\beta = 8125$ H·m·s; $T_e = 0.262$ s.

The closed side setting dynamics can be approximated by the nonlinearity of the type "limiting the speed of the signal change". The analysis of the obtained experimental data shows that the level of speed restriction with signal growth is 0.1047 mm/s, with decrease –0.6059 mm/s.

Perform the research of controller qualitative characteristics exposing the plant of external uncontrolled disturbances. We will perform the models for two disturbances: high-frequency interference with low amplitude that is characteristic of channels for transmitting data from sensors to a control device and low frequency with high amplitude due to fluctuations in granulometric and physical-mechanical properties of the mountain mass. To model the first action we use a sequence of random numbers that change on each step in the normal distribution with the mean square deviations $\sigma_{\mathrm{CV}1} = 0.01$ and $\sigma_{\mathrm{CV}2} = 0.05$ for the coefficient of variation of size density function $\sigma_{\gamma 1} = 0.1$ % and $\sigma_{\gamma 2} = 0.5$ % for the control size class output –9.1+6.7 mm. The simulation of low frequency oscillations will also be accomplished by using a sequence of random numbers with mean square deviations $\sigma_{\mathrm{CV}2} = 0.2$ and $\sigma_{\gamma 2} = 2.2$ %, varying at each 60th samples. The results of modeling the work of predictive controllers are presented in fig. 7 and in table 4.

Starting up in the considerated systems the dynamics quality decreases with the control size class output in comparison with the system without interference. In the iLMPC system appears overshoot $\delta_{CV} = 12.7\%$, and the NMPC increases the settling time with less overshoot ($\delta_{\gamma} = 10.2\%$). On the other hand, while controlling the homogeneity, the qualitative characteristics of the iLMPC and NMPC systems do not significantly deteriorate. Overall, the CV(RMSE) for the systems under consideration was: iLMPC for CV12.1%, for γ 7.9%, NMPC for CV 16.5%, for γ 9.3%.

Table 4

Control errors during operation of various predictive controllers

Predictive controller	Control error, %		Computational time, ms	
	Disturbance $\sigma_{CV} = 0{,}01$ i $\sigma_{\gamma} = 0{,}1$ %	Disturbance $\sigma_{CV} = 0{,}05$ i $\sigma_{\gamma} = 0{,}5$ %	Disturbance $\sigma_{CV} = 0{,}01$ i $\sigma_{\gamma} = 0{,}1$ %	Disturbance $\sigma_{CV} = 0{,}05$ i $\sigma_{\gamma} = 0{,}5$ %
iLMPC	0,31	0,87	1,14	1,19
NMPC	2,53	3,48	168,34	195,16

We note that the speed of the iLMPC controller does not significantly change compared to the undisturbed system and averaged 1.19 milliseconds, while the computational speed of the NMPC system is reduced to 195.16 milliseconds that is on 15.9%.

Thus, it can be stated that the model predictive controller with the inversion of static nonlinearities and the approximation of the Laguerre OBF paths has the best dynamics qualitative characteristics, in particular, the speed, accuracy and computational load compared to the usual nonlinear model predictive controller. Taking into account the time of the adaptive parameters identification of the hybrid predictive model, the total calculation time is 43.84 milliseconds, which is much less than the sampling interval.

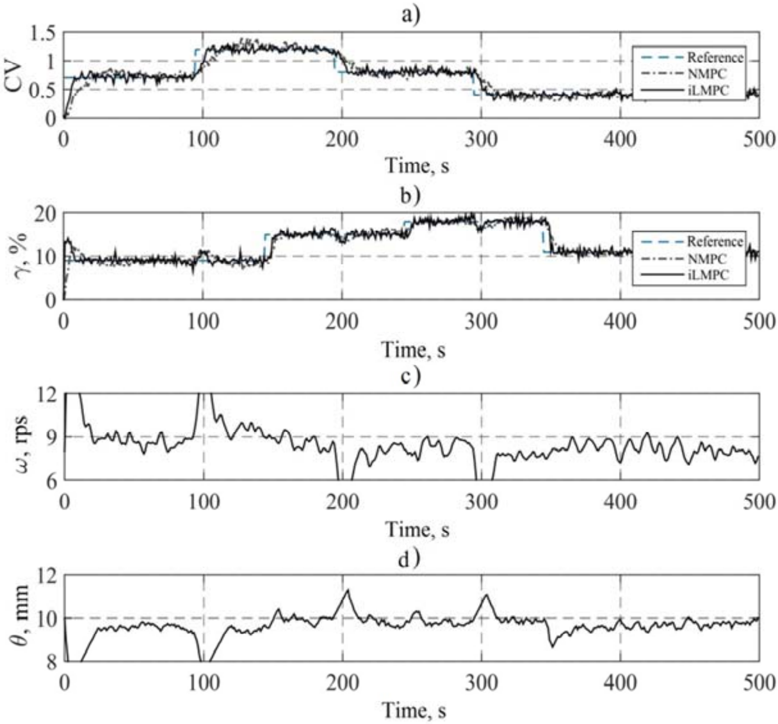

Fig. 7. Time series of the ore crushing process adaptive MPC control system with disturbances (σ_{CV} = 0,05 and σ_{γ} = 0,5 %)

This feature allows you to carry out the entire computer cycle in the interval between obtaining data on the current value of the operational process parameters of drainage from the corresponding sensors and ADC. Consequently, the proposed control system can be used in real conditions of ore preparation at ore mining and processing plants.

Conclusions. Thus, the conducted studies confirm the appropriateness of the use of block-oriented structures, which include Laguerre OBF, in the tasks of design and practical implementation of automated high-accuracy controllers. The high level of reconstruction of the technological object output signal allows the use of these nonlinear models in the real conditions of mining and concentrating production, where the plant is affected by uncontrolled disturbances caused by fluctuations of technological parameters, properties of iron ore raw materials, obstacles in data transmission channels and so on.

The method of model predictive control formation of the ore crushing process is proposed, which is based on inverting the static nonlinearities of the input-output of the block-oriented model and approximating the control trajectories by orthonormal basis Laguerre functions. This approach allows us to reduce the predictive control problem to the quadratic programming problem, and thus reduce the time of computational operations.

A comparative analysis of the control quality and performance of the system implementing the proposed method, with the system of nonlinear model predictive control, was conducted. It is established that with the same settings of comparable controllers and identical disturbances, the developed system allows to provide 12.5% and 11.9% less overshoot by the coefficient of variation of size density function and control size class output, at 6.3 and 14.7 seconds, the shorter settling time under the corresponding regime parameters and in 164 times (1.19 milliseconds) the lower time of control forming. It should be noted that the proposed control system has a lower steady-state error.

Further research will be devoted to the practical implementation of the proposed adaptive control system for the ore crushing process.

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