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MODEL-BASED DESIGN OF A CONE CRUSHER ADAPTIVE CONTROL SYSTEM

Purpose. The purpose of the article is to develop a methodology for creating cone crusher adaptive control system based on the model-based design method for automated software generation of microprocessor controllers.

Methodology. A method based on a block-oriented predictive model was used to generate control signals for the cone crusher. The parameters and structure of this model were identified in real time using measured data from the plant. A prototype of the control system was created in MATLAB/Simulink. Then, the model-based design method was used to generate software for digital signal processors. Mathematical statistics methods were employed to analyze the experimental results.

Findings. A method of model-based design of an adaptive control system for a cone crusher has been developed. This system uses a predictive model of a block-oriented structure. This model adjusts the predictive controller's structure and parameters directly during operation. This approach makes it possible to divide the functions of identifying the process model and generating controls between the two digital controllers. Consequently, the average computational time is reduced while ensuring the stabilization of the degree of homogeneity of ore crushing and separate output of the control size class, with respective standard deviation coefficients not exceeding 3.42 and 1.83 %, respectively.

Originality. The regularity of the effect of the closed-side setting and the eccentric speed on the particle size distribution of crushed ore has been established. This shows that high homogeneity of the crushed product is ensured by simultaneously adjusting these input coordinates. We propose a new method for synthesizing an adaptive cone crusher control system based on a model-based design approach. This method provides automated real-time generation of software for microprocessor-based controllers, allowing the system to quickly adjust to changes in rock mass characteristics and other disturbances.

Practical value. A hardware and software implementation of an adaptive control system for a cone crusher is proposed. This system is based on a block-oriented predictive model. The model ensures the stabilization of the required ore particle size distribution. This stabilization is achieved by adjusting the closed-side setting and the eccentric speed. The system is based on 16-bit, low-cost digital signal processors. A prototype of the system was tested in a crushing plant at a metallurgical enterprise.

Keywords: *cone crusher, adaptive control system, model-based design, implementation*

Introduction. The ever-increasing cost of mining and mineral processing, particularly iron ore, requires a constant search for ways to improve the technological processes performance at the ore dressing plants. Crushing and grinding are among the most energy- and resource-intensive processes at such enterprises. In total, the share of multi-stage ore preparation in crushers and mills is more than 60 % of the company's total power consumption. At the same time, it is possible to increase the energy efficiency of production in general by obtaining homogeneous ore of the required size at the crushing stage.

Today, cone crusher control systems at Ukrainian ore dressing plants do not allow for high-quality crushed ore particle size distribution (PSD) control. This is due to the use of outdated crushers that are not equipped with automated control of the main control variables, which include the closed-side setting (CSS), eccentric speed, or feeder capacity [1]. The ore crushing process can be improved by replacing outdated technological equipment, primarily cone crushers, with more modern ones or by introducing new approaches to controlling existing crushers. The first solution requires significant capital expenditures, so in the short term, it is advisable to give preference to the second option.

Available approaches to the design of automated control systems (ACS) for the crushing process do not allow for sufficiently effective of the crushed ore PSD control under disturbances. Therefore, the development of an adaptive ACS that ensures high PSD under the conditions of varying in ore properties, changes in technological equipment parameters, and the noise presence in data transmission channels is a current scientific task.

To date, a large number of studies have been conducted on the development of crushing process control systems [2]. However, all of them are mostly theoretical in nature and hardly consider the practical implementation of the synthesized systems. Given that there are adequate mathematical models of the crushing process that qualitatively describe the nonlinear behavior of a dynamic object, it is therefore advisable to apply a model-based approach to the design of real controllers [3], namely their hardware and software parts, thereby automating the development process and ensuring that this method can be used to upgrade control systems for cone crushers of any configuration.

Implementing the resulting control systems will increase profits from existing equipment operations by reducing ore processing costs [4].

This work is a logical continuation of the research presented in articles [5, 6] and utilizes the primary results of these studies to develop a cone crusher control system.

Literature review. When controlling the crushing processes, the following criteria are used: stabilization of the PSD of the finished product at constant or maximum crusher productivity, and stabilization of the crusher productivity while minimizing the size of the finished product [7]. Currently, there are several studies dedicated to the development of control systems for the crushing process that implement these management principles. However, as noted earlier, to improve the efficiency of grinding at a mineral processing plant, the crushing process must ensure the production of ore with the most uniform PSD. An analysis of the crushing process control systems will be conducted considering this specific feature of ore preparation technology for grinding.

A cone crusher control system with a local PSD control loop is presented in [8]. As a control action, the authors consider the closed side setting. The control is performed using a modified PID controller. A comparative analysis was performed between the closed-loop system and an open-loop system that maintains a constant closed-side setting (CSS). Uncontrolled disturbances include the moisture content and PSD of the input material, as well as feed productivity. Analyzing the results of the computational experiment, the authors established that the open-loop system does not stabilize the PSD of the finished product under disturbances compared to the feedback system. The peculiarity of the proposed system is the absence of consideration of the influence of the cone revolution speed on the PSD. Adjusting this parameter allows for achieving a more uniform finished product and more flexible compensation for uncontrolled disturbances.

In [9], an extremum control system for the productivity and PSD of a cone crusher is proposed. It is based on the unimodality of the productivity dependence on the rotational speed of the mantle and closed-side setting. The extremum of the target function is sought by estimating the gradient using the synchronous detection method with an extended Kalman filter. However, the work does not provide a justification for choosing this solution. Based on the results of simulation modeling, a comparative analysis of the developed algorithm with a synchronous detector based on a band-pass filter was performed. The harmonic excitation parameters applied to the input of the plant were taken as identical for both systems. The author notes that both systems exhibit the same convergence speed. The use of the extended Kalman filter allows for a reduction in the frequency of output oscillations of the plant relative to the operating point.

However, implementing the proposed method for determining the eccentric rotation speed in real-world conditions is challenging. This is primarily due to low resistance to noise and disturbances, resulting from the inability to accurately estimate the gradient of the target function. Consequently, the productivity oscillations of the crusher increase significantly. Additionally, the extremum control system does not provide stabilization of the crushed ore PSD to the absence of a subsystem for regulating the closed side setting.

A potential decrease in crushing quality also will lead to an increase in circulating load, significantly reducing process control efficiency. The rigid attachment of the control system to the plant real parameters results the speed calculation algorithm instability due to drifting extremums under rapidly changing disturbance conditions and noisy data transmission channels from sensors. While noise can be compensated for using technical means such as filters, to eliminate disturbance fluctuations, it is necessary to improve the control algorithm. This limitation hinders the applicability of the system in its proposed form for ore preparation.

A multidimensional approach to crushing cycle control is proposed in [10]. The authors consider the control efficiency of a cone crusher using two input coordinates simultaneously – the eccentric speed and the closed-side setting. By means of modeling, based on experimental data the influence of these control actions on the particle size distribution of crushed ore, productivity, and power of the crusher is determined. The obtained response surfaces in the range of input parameters have global maxima. The authors note that this approach makes it possible to optimize the operation of the closed crushing cycle and ensure a high level of crushing performance with the required particle size distribution at acceptable energy costs. The authors see the main problem with this control approach in the insufficient quality of rock mass flow control [10, 11].

To determine the PSD of crushed ore, devices implementing both contact and non-contact methods for controlling the PSD of bulk material can be used. Non-contact control is based on irradiating the ore with acoustic waves [12], ultrasonic waves [13] and X-ray [14]. However, the most promising method is considered to be optical control [15, 16]. The last one allows determining the particle size distribution of crushed ore by processing images of a moving conveyor belt loaded with ore obtained from a video camera or laser profiler [17]. This approach has become very widespread due to the use of machine learning methods [18, 19] for segmentation [20, 21] and analysis [22, 23] of segmented crushed ore images.

Considering that the PSD is represented by the mass distribution curve of ore by size, the weight of each particle-size class is determined by volume under the assumption of constant ore density.

Thus, it can be concluded that most of the reviewed crushing process control systems, despite their technical capability to control PSD, do not allow for prompt response to changing operating conditions due to uncontrolled disturbances. Some control systems ensure maximum productivity of individual units and crushing stages as a whole without considering the qualitative characteristics of the final product. Control systems for PSD share a common disadvantage: the spatial separation of the control device for the regime parameter from the technological object. The resulting delays prevent these systems from adapting to disturbance fluctuations, especially high-frequency ones. A drawback of systems implementing multidimensional control with multiple regulation loops is the lack of coordination between them, which reduces the system's efficiency in achieving its control objectives.

Therefore, one of the research tasks is the development of a multidimensional control system for the quality of crushed ore with adaptation to the influence of disturbances.

Main material presentation. ***Substantiation of the methods used.*** An adaptive control method based on a model predictive control scheme was used to generate control actions for the cone crusher's closed-side setting and eccentric speed. The predictive model (Wiener, Hammerstein or Hammerstein-Wiener [24]) and parameters were estimated online using the crushing process parameters measurement data. The prototype control system was created as a simulation model in MATLAB/Simulink. Then, using the model-based design method [3], software for several digital signal processors was generated. These processors implemented the logic of the model-predictive control scheme and the cone crusher's electric and hydraulic drives control systems. The efficiency of the system was verified by conducting an active experiment at the crushing plant on an experimental cone crusher. Mathematical statistics methods were used to process the results of experimental studies.

Results and discussion. ***Development of a functional diagram of the control system for a cone crusher.*** Fig. 1 shows the block diagram cone crusher control system at a mining and processing plant. The system includes the following units, elements, and blocks: *1* – hopper feeder with an electromechanical vibrator mounted on its capacity (not indicated on the diagram); *2* – scraper conveyor of the feeder; *3* – cone crusher CH880 EEF; *4* – conveyor for transporting ore to the vibrating screen; *5* – vibrating screen GIT-51; *6* – ore bins of the ore dressing plant; *7* – eccentric electric drive; *8* – hydraulic drive pump; *9* – electric drive of the hydraulic system pump for the CSS control; *10* – uncontrolled electric drive of the feeder conveyor; *11* – digital signal processor for eccentric electric drive speed control; *12* – digital signal processor for the CSS control; *13* – digital signal processor that implements the process control algorithm based on the predictive model; *14* – personal computer that performs digital image processing and control system model-based design; *LT* – ultrasonic level sensor with remote data transmission; *ST* – digital rotational speed sensor of the motor shaft with remote data transmission; *GT* – digital tensometric sensor for measuring the lifting height of the crushing cone with remote data transmission; *QT* – laser profilometric sensor for determining the PSD of crushed ore with remote data transmission.

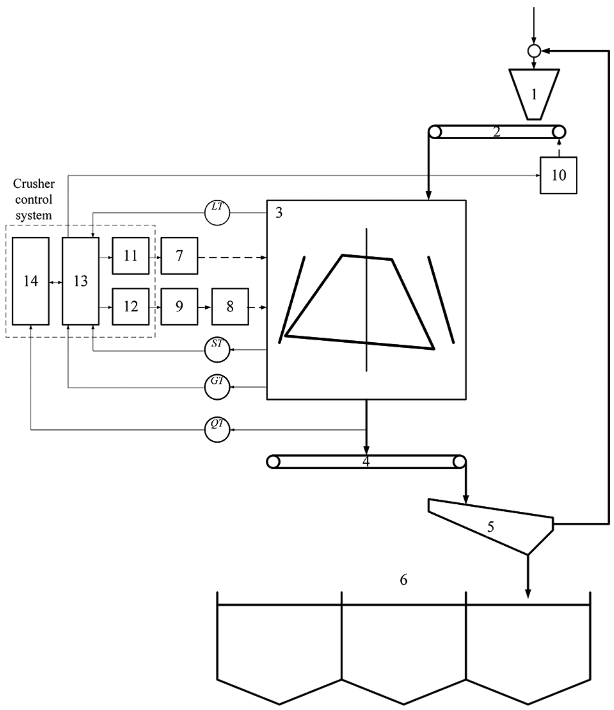

Fig. 1. Adaptive cone crusher control system

Solid thick lines on the diagram indicate the path of ore movement along the technological chain. Dashed lines represent channels for the transmission of electrical, hydraulic, and mechanical energy. Thin solid lines indicate information communication lines transmitting data on the current values of physical quantities from sensors to control units, as well as control signals from the controller to the control systems of actuators.

The crusher *3* starts when the working space of the crusher is empty. The predictive controller *13* generates setpoint signals based on the eccentric speed and the CSS according to the basic requirements of the technological process. It should be noted that, unlike the rotational speed, which is directly determined using the digital shaft rotation frequency sensor ST with a correction for the gearbox ratio, the closed side setting is indirectly determined through the force applied to the strain gauge sensor, corresponding to the plunger position that changes the height of the crushing cone lift. Until the speed and CSS stabilize, the crusher *3* continues to operate in idle mode, while the electric motor *10* of the feed conveyor *2* is turned off. Upon completion of the crusher startup, the predictive controller *13* generates a permission signal to the motor *10* and the conveyor *2*, which begin to feed ore into the working area of the crusher.

In real time, the digital signal processor *13* receives data from the speed (ST) and pressure (GT) sensors and sends it to the PC *14* via a communication interface. At the same time, data from the laser profilometer (QT) is sent directly to the PC (*14*), where a specialized digital image processing module analyzes it to determine the current ore PSD. This data is then transferred to MATLAB.

Based on the aggregated data from QT, GT, and ST, the crusher model is parametrically identified. The model is built until the identification accuracy, as determined by mean square error (MSE), reaches a specified value. The final mathematical description is used as a predictive model when designing the cone crusher's predictive controller. Next, MATLAB is used to analyze step response parameters of the resulting predictive controller. If the controller's quality meets the requirements, the controller is used as a prototype, and firmware is generated automatically and loaded into the digital signal processor *13* program memory using a programmer.

At the next stage, hardware-in-the-loop simulation is carried out for software testing and verification. In the absence of errors, the digital signal processor begins to function as a digital controller of the PSD of the crushed ore with a predictive model. The digital controller *13* generates CSS and eccentric speed setpoint and sends them to the digital controllers of the drives *11* and *12* via the communication interface.

The eccentric and the oil pump of the cone lifting mechanism induction motors speeds are regulated by a variable-frequency drives (VFD-IM) [25, 26]. Changing the AC motor stator voltage frequency makes it possible to adapt the operation of electric motors to changing technological conditions. This is achieved using power semiconductor converters with a controlled voltage inverter implemented on insulated-gate bipolar transistors (IGBTs). The choice of frequency control is determined by its high regulation accuracy and energy efficiency [27, 28]. The use of the VFD-IM combination to adjust the working oil pressure in the hydraulic system of the closed side setting regulation mechanism is necessitated by the need for precise control of the cone lift speed to promptly respond to fluctuations in feed quality and emergency situations involving the entry of non-crushable objects into the crushing chamber. Moreover, this approach allows the use of identical circuit design solutions and embedded software for digital controllers *11* and *12*, as well as identical power converters of drives *7* and *9*, differing only in the power of the semiconductor devices. This significantly simplifies design, data exchange between controllers *11*, *12*, and *13*, as well as subsequent maintenance and diagnostics.

Digital signal processors *11* and *12* are designed to generate control pulses and adjust the duration of the open state of the power semiconductor switches in converters of drives *7* and *9* according to the pulse-width modulation law as a function of the control action from the digital predictive controller *13*.

Data from the ST and GT sensors are sent to the predictive controller *13*, which provides feedback to the control system. Additionally, control parameter values are transmitted via the communication interface to the personal computer *14* for forming a test sample for adaptive identification of the control plant model. The process of model refinement is continuous to reduce the speed of prototyping the predictive control system, provided there is a significant discrepancy between the responses of the plant and its mathematical model to the same control signals during system operation.

Controller *13* also performs two-position relay control of the crusher loading level with ore to protect it from jamming. For this purpose, an ultrasonic level sensor LT is installed in the scheme. When the maximum allowable loading limit is reached, the digital controller *13* stops the motor *10* of the feeder *1*, *2*, and ore feeding is halted. Once the ore level drops to the required value, the operation of the feeder *1*, *2* resumes.

The proposed functional diagram of the cone crusher predictive control system uses a laser profilometer to reduce transport delays that the traditional PSD measurement method (sieve analysis) has. The processing of 3D-profilometer images, the prototyping of the predictive controller, and its physical implementation are carried out by separate digital devices. This system design is intended to improve performance.

The use of the discussed algorithm for determining particle size characteristics further reduces computational load and enables obtaining operating parameter values at a frequency that corresponds to the control system's sampling rate. The rationale for selecting the quantization interval, in terms of the inertia of the crushing process, is discussed in previous sections. It is also proposed to implement the control systems for the actuators using separate hardware-software modules based on microcontroller devices, which prevents overloading the digital predictive controller with additional calculations.

Hardware-software implementation of a model predictive control system. According to the proposed method for controlling the ore crushing using predictive models, it is intended to be implemented by digital control devices. The schematic diagram of the digital predictive control system is shown in Fig. 2. The predictive digital controller is based on a 16-bit digital signal processor dsPIC30F6015 (DD1), whose core is optimized for high-speed matrix calculations.

In the communication channels discussed in previous section, data received from sensors about the current values of the cone crusher's eccentric speed and closed side setting is transmitted from the digital signal processor to the personal computer. In the reverse direction, information about the PSD of the crushed ore is received after image processing from the laser scanner located above the conveyor belt.

The second universal asynchronous transmitter-receiver (UART2) of the dsPIC30F6015 is used for polling the sensors for the rotational speed of the drive motor shaft and the closed side setting. To match the logic levels between the DD1 controller and the RS-485 interface bus, through which polling occurs, an RS485/RS422 transceiver with a limited voltage rise rate and low power consumption, MAX487 (element DD4), is used. Unlike the rest of the circuit, DD4 is powered by +12 V from the LM78L12 voltage controller (DA2).

Considering the need for real-time adjustment of predictive control algorithms and their coefficients, which is related to the adaptive parametric identification of the plant model, connector X7 is provided. A programmer is permanently connected to it for loading code generated by the MATLAB/Simulink environment.

The development of the control device software is based on the method of model-based design. The process of implementing the adaptive predictive control system for the crushing process using this approach is shown in Fig. 3. The first step in building the prototype (step 1) is determining the parameters of the technological object model with a known structure based on orthonormal Laguerre functions [4]. For this purpose, a software implementation of the modified adaptive recursive least-squares algorithm is used together with MATLAB/System Identification Toolbox.

Next, the predictive control system model (step 2) is built using standard blocks from the MATLAB/Simulink library, MATLAB Function user-defined functions, configuration blocks for the dsPIC30F6015 digital signal processor, and emulation of its peripheral modules via MPLAB 16-bit Device Blocks for Simulink. At this stage, the system's operability, transient process quality, and other characteristics are analyzed. Based on the results, design errors are identified and corrected.

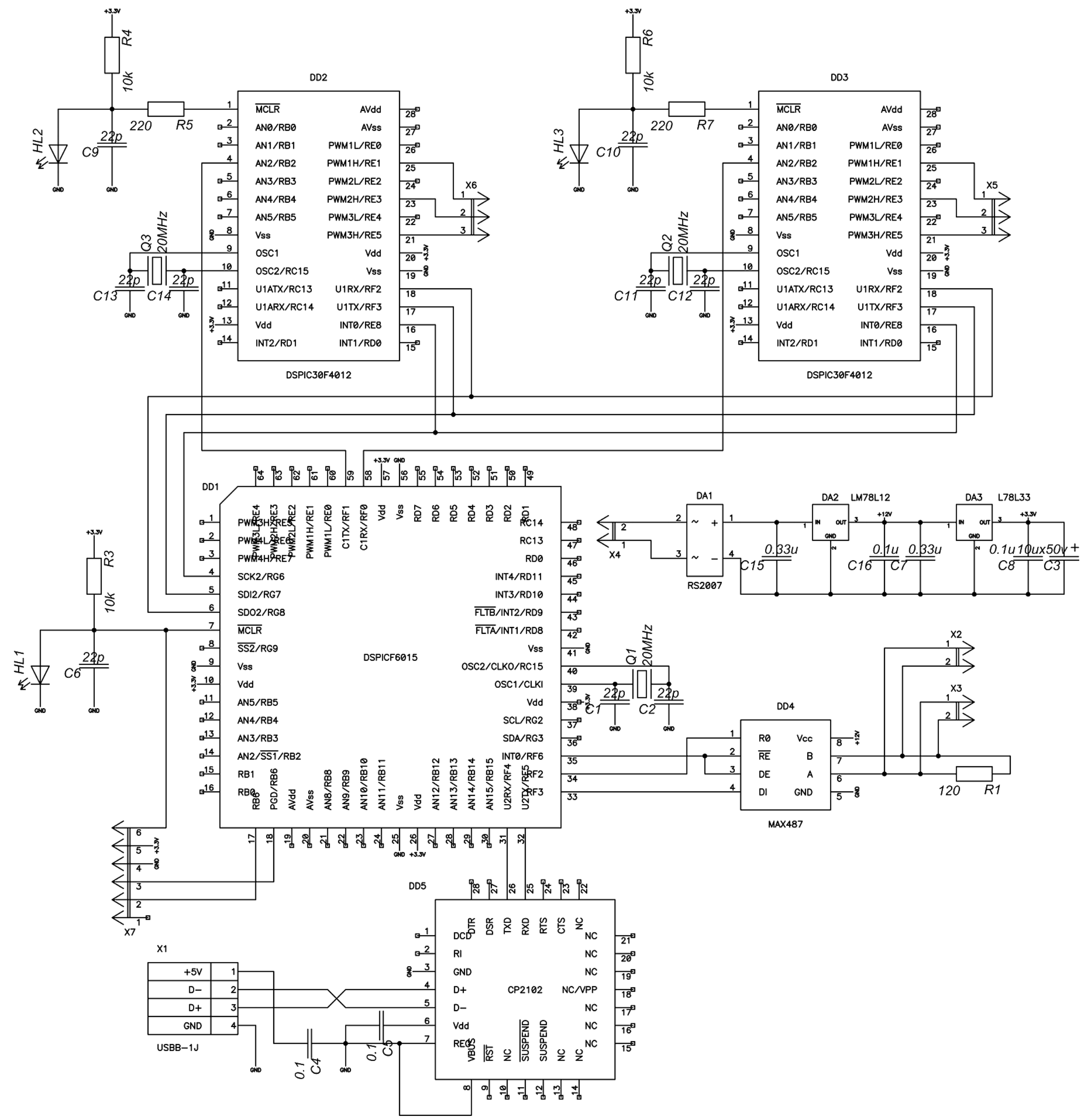

Fig. 2. Schematic diagram of the microprocessor predictive control system

After simulations are completed, real-time modeling must be performed. For this purpose, based on the *.slx model file, the control device's program code in *.c and *.h formats is automatically generated (step 3). The code is then compiled (step 4) into a hexadecimal object file *.hex and subsequently loaded into the microcontroller (step 5).

Considering that testing the predictive controller in an industrial setting on a cone crusher is expensive and unsafe, the program code generated from the technological object model is loaded into a dsPIC30F4012 signal processor connected to the target dsPIC30F6015 via the SPI bus. As a result, testing of the control system in real-time mode occurs through data exchange between the two digital signal processors.

If no errors are found in the operation algorithm of the physical device, the dsPIC30F4012 microcontroller is programmed with the control system software for the corresponding actuator (step 7), and the hardware complex is ready to connect to the real plant (step 6). During operation, the control device queries the sensors for the eccentric speed and the closed side setting via RS-485 (step 8) and transmits the received values via the USB-UART channel to a personal computer for updating the model parameters (step 1), which may have changed due to external disturbances.

Fig. 4 presents the predictive controller model in the MATLAB/Simulink. It serves as the basis for generating the program code for the digital signal processor.

In the general case, solving the control problem involves determining the control trajectory that minimizes a quadratic cost function [29]

$$J=(R-\widehat{Y})^T Q(R-\widehat{Y})+\Delta\widehat{U}^2 S\Delta\widehat{U}, \tag{1}$$

with constraints

$$\{\widehat{U}\in R^2 \mid \widehat{U}_{\min}\le\widehat{U}\le\widehat{U}_{\max}\}\forall\{k\in N \mid 1\le k\le N_c-1\};$$

$$\{\widehat{Y}\in R^2 \mid \widehat{Y}_{\min}\le\widehat{U}\le\widehat{Y}_{\max}\}\forall\{k\in N \mid 1\le k\le N_p\},$$

after block-oriented system applying

$$\widehat{U}=\Xi(U);\quad \widehat{Y}=\Upsilon(C^T\Lambda), \tag{2}$$

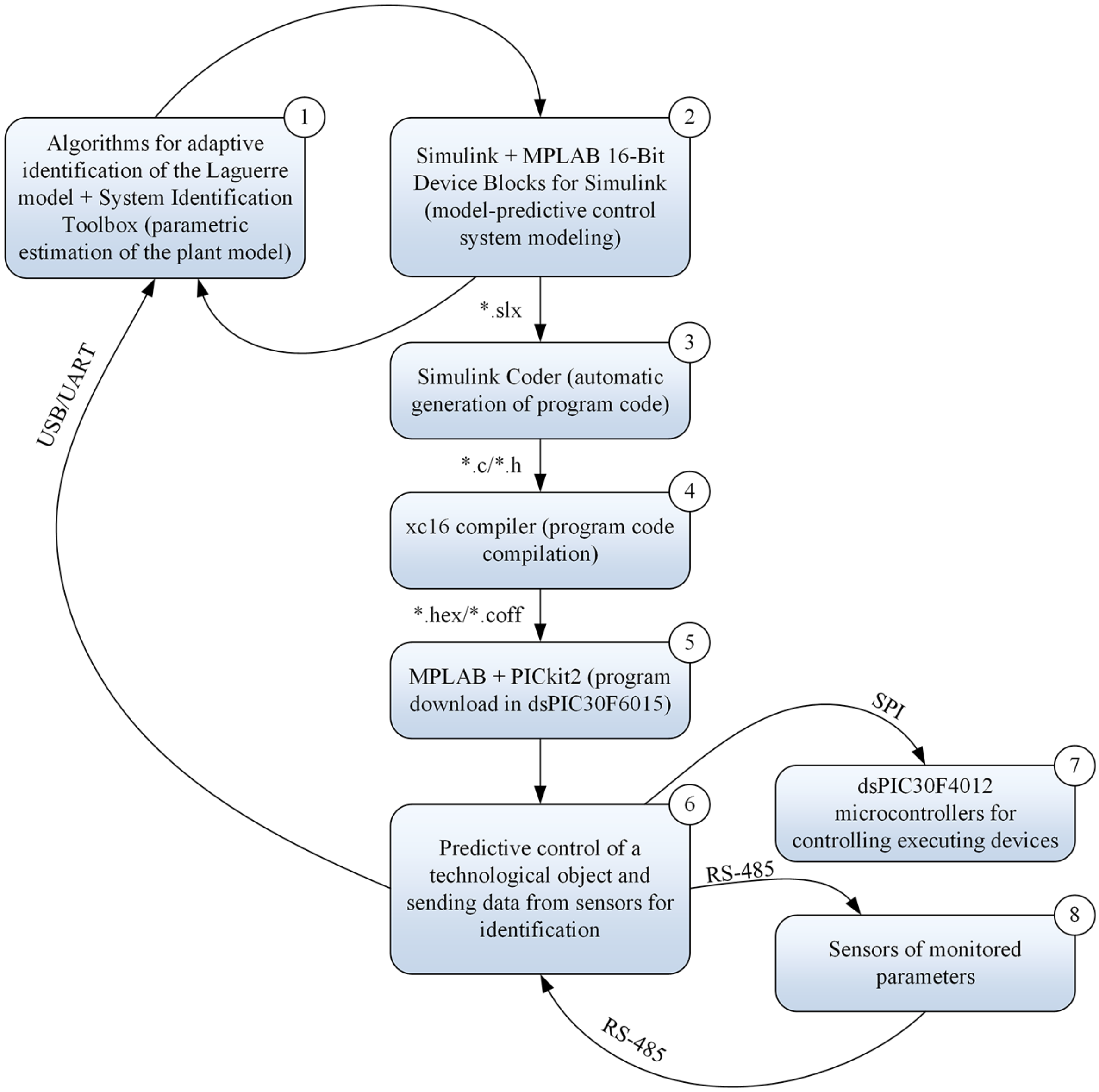

Fig. 3. Algorithm of model-based design of the control system with a predictive model based on the dsPIC30F6015 digital signal processor

where N_c, N_p are control and prediction horizons; Q, S are weight matrices for inputs and outputs; $\Xi(\cdot)$, $\Upsilon(\cdot)$ are block-oriented system nonlinear functions; R is a reference vector

$$R = [r[k+1\,|\,k]\,r[k+2\,|\,k]\ldots r[k+N_p\,|\,k]]^T;$$

U is an input vector

$$U = [u[k+1\,|\,k]\,u[k+2\,|\,k]\ldots u[k+N_c-1\,|\,k]]^T;$$

$\Delta\widehat{U}$ is a control vector

$$\Delta\widehat{U} = [\Delta\hat{u}[k+1\,|\,k]\,\Delta\hat{u}[k+2\,|\,k]\ldots\Delta\hat{u}[k+N_c-1\,|\,k]]^T;$$

$\widehat{Y}$ is a predicted output vector

$$\widehat{Y} = [\hat{y}[k+1\,|\,k]\hat{y}[k+2\,|\,k]\ldots\hat{y}[k+N_p\,|\,k]]^T,$$

$\widehat{Y}_{\min}, \widehat{Y}_{\max}, \widehat{U}_{\min}, \widehat{U}_{\max}$ are output and control constraints.

Microchip Master, Compiler Options and UART Configuration blocks are used to set the parameters of the target microcontroller to ensure the proper generation of program code by the Simulink Coder package. To correctly transmit the control action values from the predictive controller on the dsPIC30F6015 processor to the actuator control processors dsPIC30F4012, the communication parameters for each SPI channel are configured using the BUS SPI and BUS SPI1 blocks, where it is also specified that the dsPIC30F6015 acts as the master relative to the slave dsPIC30F4012 processors.

The blocks Weight Matrices Generator, Laguerre Generator, System Matrices Generator, MPC Constraints Calc, Hessian Calc, Gradient Vector Calc, Quadratic Programming Procedure, and Control Calc represent the steps of the algorithm for forming control actions by the predictive controller. The developed model structure allows for an investigation of the control system's quality characteristics under various predictive controller parameters.

After the control actions are calculated by the Control Calc block, their values are inverted by the Inverse

Input Nonlinearity and Inverse Input Nonlinearity1 blocks and applied to the cone crusher via actuators – namely, the electromechanical systems for the eccentric bowl drive and the hydraulic pump regulating the height of the movable cone. Simultaneously, the output value of the technological plant model (State and Output Calc) is calculated and stored in the Memory y block until the next calculation moment. During the next computation interval, data on the cone crusher's response is received through the RS-232 receiver (UART Rx block), processed by the Inverse Output Nonlinearity1 block, and subtracted from the previous model output value (Memory y block). This determines the control error. If the error exceeds the permissible value, the Sys Ident Enable block signals the need for parameter identification of the control plant model.

To control the rotational speed of the actuator motors for the crusher's eccentric bowl drive and the hydraulic pump regulating the closed side setting, the designed scheme includes two specialized digital signal processors, dsPIC30F4012 (DD2 and DD3), with hardware modules for generating three-channel PWM signals. During predictive control, after the control actions are formed by the DD1 chip, data on their values is transmitted via the Serial Peripheral Interface (SPI) to DD2 and DD3. This alters the duty cycle and period of the PWM signals, which correspond to the required speed.

The power section of the regulated asynchronous electric drive is implemented as a VFD-IM system with double conversion.

Controlling actuators with separate hardware and software modules prevents the digital predictive controller from being overloaded with additional computations. Using frequency-based control for the rotational speeds of the crusher's working body drive motors and the hydraulic pump for CSS adjustment provides flexible speed regulation, reduces the design time for hardware and software components of the controllers, and simplifies diagnostics and troubleshooting during operation. An additional advantage is the use of identical component bases, which reduces the range of spare parts needed for repairs. The difference lies only in the power section, nominal currents, and voltages of the semiconductor elements of the frequency converter.

Experimental study of the cone crusher control system performance. Practical testing of the proposed algorithmic and hardware-software developments was conducted during commissioning work at the crushing plant of the mining department of PJSC "ArcelorMittal Kryvyi Rih". The following equipment was used: for prototyping the predictive control system – an Intel Core i5-8500 16 Gb RAM OS x64; a predictive controller board based on dsPIC30F6015 and dsPIC30F4012 microcontrollers; and for controlling the PSD of crushed ore – a laser profilometer of the SICK-IVP Ruler E4111 type with a maximum field of view of 88 × 185 mm. The non-contact size analyzer was connected to the PC via an Ethernet interface. Image processing from the profilometer, the estimation of PSD, the calculation –9 + 7 mm particle-size class, and the uniformity index were performed using software developed in MATLAB. This allowed the calculation of operating parameter values and the identification of the crushing process model in a single software package without requiring additional interfacing modules.

To determine the homogeneity of the ore, the coefficient of variation (CV) is used

$$CV = \sqrt{\frac{\sum_{i=1}^{n} f_i (m_i - \bar{X})^2 / 100}{\bar{X}}}; \quad \bar{X} = \frac{\sum_{i=1}^{n} f_i m_i}{100}, \qquad (3)$$

where n is the number of particle size classes; m_i is the midpoint of the i^{th} particle size class; f_i is the frequency corresponding to the i^{th} class.

Experimental studies on industrial equipment were conducted over 2 hours and 42 minutes. To achieve

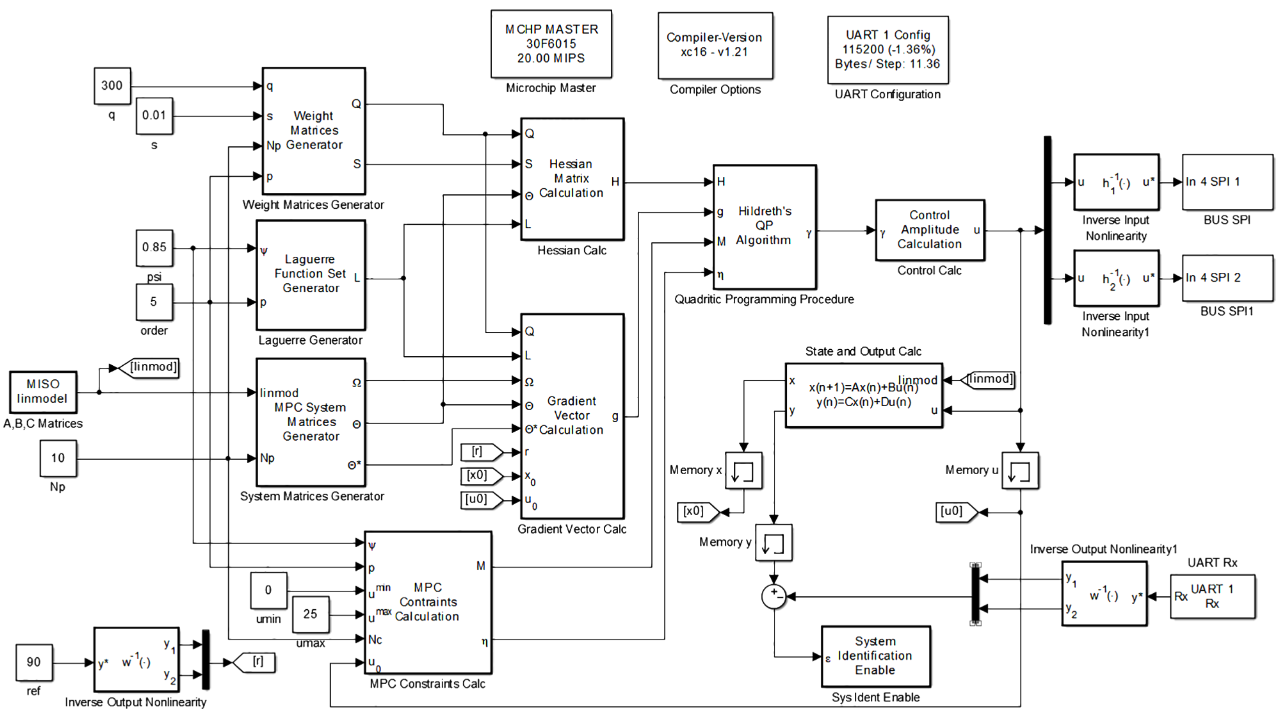

Fig. 4. Block diagram for prototyping the digital control system with a predictive model in MATLAB/Simulink

qualitative results, the testing interval was divided into 10 time segments of 1,000 seconds each. At the start of each interval, the parameters of the models predicting the plant's behavior and approximating control trajectories were reset. Upon completion of the regulation, the coefficient of variation of the root-mean-square error CV(RMSE) between the output values and the setpoint signals were calculated for the uniformity index (*CV*) of the crushed product and the specific output of the control particle-size class (γ).

CV(RMSE) formula is

$$CV(RMSE) = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i}}{\sum_{i=1}^{n} \hat{y}_i / n}, \qquad (4)$$

where y_i is the observed value; $\hat{y}_i$ is the predicted value; n is the total number of observations.

After completing the series of experiments, the average CV(RMSE) values were computed. The setpoint signals for the operating parameters: crushed ore uniformity index $r_{CV} = 0.5$ and main particle-size class $r_\gamma = 20$ % were maintained constant throughout all the stages of the experiment.

The first series of experiments was conducted using the baseline control system employed at the industrial enterprise, which regulates the closed side setting. The stabilization process is shown in Fig 5.

The graphs clearly illustrate the impact of disturbances in data transmission channels and changes in the characteristics of the ore mass and technological equipment parameters on the plant's performance. It is worth noting that the stabilization process of the operating parameters with the proposed controller settings is relatively inertial (Figs. 5, *a*, *b*). At the same time, the high-frequency fluctuations in speed exhibit insignificant amplitude (Fig. 5, *d*), making it unnecessary to impose additional constraints on control increments. As a result, the average quality stabilization indices across 10 experiments were $CV(RMSE_{CV})$ = 5.54 % and $CV(RMSE_\gamma)$ = 6.27 %.

At the next stage, a hardware-software prototype of the adaptive predictive control system was used to stabilize the operating parameters, and a series of ten experiments was conducted again.

The predictive controller parameters were configured as follows. The MPC-controller weight coefficients were: for the coefficient of variation of particle size distribution – Q_{CV} = 1,200 (input weight), S_{CV} = 0.005 (output weight); for the separate output of the –9 + 7 mm class – Q_γ = 600, S_γ = 0.005. The prediction horizon was set to N_p = 20. Constraints on control amplitudes were: $u_{\omega\,min}$ = 6 rps, $u_{\omega\,max}$ = 12 rps, u_θ$_{min}$ = 8 mm, $u_{\theta\,max}$ = = 13 mm. Constraints were applied only to the first component of the control trajectory. The stabilization process graphs for this scenario are shown in Fig. 6.

As we can see, changing the settings resulted in higher-quality stabilization of the controlled values. The average coefficients of variation of the root mean square errors decreased to $CV(RMSE_{CV})$ = 3.42 % and $CV(RMSE_\gamma)$ = 1.83 %, corresponding to reductions by factors of 1.41 and 2.61, respectively. It is worth noting that the quality control indicator decreased more significantly for the specific output of the control size class (Fig. 6, *b*).

Attempts to achieve better stabilization of the uniformity of the crushed product by adjusting the weighting coefficients Q_{CV} and S_{CV} resulted in an increase in the amplitude of fluctuations in the rotational speed of the crusher cone, which worsens the operating conditions of the drive motor. From the perspective of process control quality requirements for crushing, the value of 3.42 % is entirely acceptable. Therefore, no additional changes to the control algorithm or restrictions on the increment of control actions were introduced.

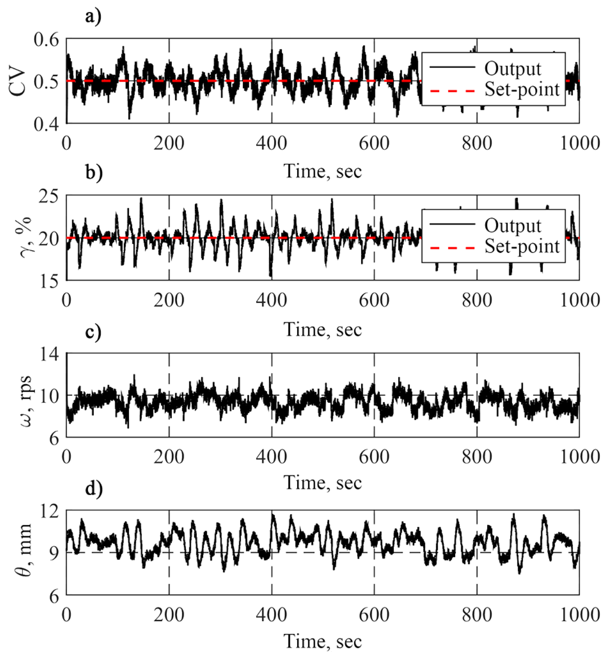

Fig. 5. Cone crusher particle-size distribution stabilization without a predictive controller

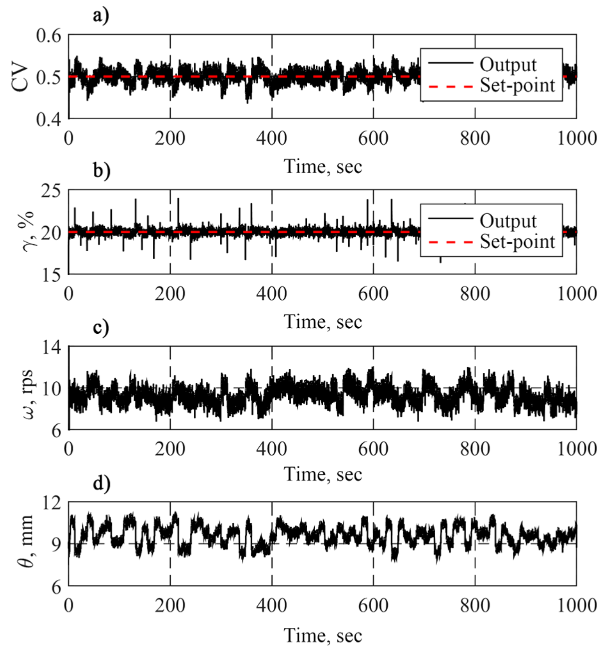

Fig. 6. Cone crusher particle-size distribution stabilization using a predictive controller

In summary, the results of the experimental studies demonstrated that the developed model-based design method for cone crusher automated control system building is viable and can be applied under ore preparation conditions at mining and processing plants. The high control quality and responsiveness of the proposed algorithms allow for improved performance of the technological process under uncontrolled disturbances due to the input raw iron ore physical parameters variations, as well as noisy data transmission channels from process parameter monitoring tools.

Conclusions. The methodology for model-based design of the adaptive cone crusher control system aimed at stabilizing the crushed ore particle size distribution was presented. The proposed approach is based on the use of a predictive block-oriented model that adapts to changes in rock mass characteristics and other disturbances in real time.

A hardware-software complex implementing model identification and predictive control algorithms for ore crushing processes has been developed. The use of digital signal processors (DSPs) as control devices, which support multiple reloading of embedded software, enables the model-oriented design of control systems. Thus, all stages of development – from building the plant model to software implementation of the predictive controller's algorithms – are carried out without active interference in the technological process.

Industrial testing of the purposed cone crusher control system under the disturbances (due to the iron ore parameters variations and noisy data transmission channels), showed that with appropriate controller settings, coefficient of variation of the root mean square error of stabilization can be achieved at 3.42 % for the uniformity indicator and 1.83 % for the specific output of the control size class.

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Модельно-орієнтоване проєктування адаптивної системи керування конусною дробаркою

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Мета. Полягала в розробці методики синтезу адаптивної системи керування процесом дроблення руди на базі методу модельно-орієнтованого проєктування для автоматизованого генерування програмного забезпечення мікропроцесорних регуляторів.

Методика. Для формування керуючих дій конусної дробарки використовувався метод керування на базі прогнозуючої блочно-орієнтованої моделі. Параметри та структура цієї моделі визначалися в реальному часі шляхом ідентифікації із використанням виміряних на об'єкті даних. Прототип системи керування створювався у MATLAB/Simulink. Далі із використанням методу модельно-орієнтованого проєктування відбувалася генерація програмного забезпечення для цифрових сигнальних процесорів. Для обробки результатів експериментів використовувалися методи математичної статистики.

Результати. Розроблено метод модельно-орієнтованого проєктування адаптивної системи керування конусною дробаркою, котра використовує прогнозуючу модель блочно-орієнтованої структури. У даній моделі здійснюється налаштування структури й параметрів прогнозуючого регулятора безпосередньо під час керування. Такий підхід дозволяє розділити функції ідентифікації моделі процесу й формування керувань між двома цифровими контролерами. У результаті скорочується середній час обчислювальних операцій при забезпеченні стабілізації ступеню однорідності дроблення руди та окремого виходу контрольного класу крупності із коефіцієнтами варіації середньоквадратичної похибки не вище 3,42 і 1,83 % відповідно.

Наукова новизна. Визначена закономірність впливу ширини розвантажувальної щілини й частоти обертання ексцентрику конусної дробарки на гранулометричний склад дробленої руди, яка показує, що шляхом одночасного регулювання цих вхідних координат забезпечується висока однорідність продукту дроблення. Запропоновано новий метод синтезу адаптивної системи керування конусною дробаркою на базі модельно-орієнтованого підходу, котрий забезпечує автоматизовану генерацію програмного забезпечення для мікропроцесорних регуляторів у режимі реального часу, що дозволяє системі оперативно підлаштовуватися під зміни характеристик гірської маси та інші збурення.

Практична значимість. Запропонована апаратно-програмна реалізація адаптивної системи керування конусною дробаркою на базі нелінійної блочно-орієнтованої моделі, що забезпечує стабілізацію необхідного гранулометричного складу руди шляхом регулювання ширини розвантажувальної щілини дробарки й частоти обертань ексцентрикового стакану. Система побудована на базі 16-ти розрядних цифрових сигнальних процесорів низької вартості. Прототип системи випробувано в умовах дробарної фабрики металургійного підприємства.

Ключові слова: *конусна дробарка, адаптивна система керування, модельно-орієнтоване проєктування, реалізація*

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