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MODEL-BASED PREDICTIVE CONTROL OF THE WELL DRILLING PROCESS

Purpose. Improving the quality and efficiency of well drilling process management by applying a model-predictive control (MPC) strategy.

Methodology. The following methods were used in the work: analysis of scientific and practical solutions; methods of analytical synthesis; methods of computer modeling for the synthesis and analysis of mathematical models; and statistical methods for processing the results of experimental studies.

Findings. The researched method of controlling a drilling rig based on an MPC controller involves the use of adjustable variables such as bit rotation speed (RPM), bit load (weight) (WOB), and pressure in the well cleaning system (P). The purpose of control is to maintain the rate of penetration (ROP) at a nominal set value corresponding to the estimated physical and mechanical properties of the rock being drilled (PMP). In traditional control systems, proportional-integral-derivative (PID) controllers generate control actions based on historical data without predicting the state of existing systems and cannot take constraints into account. The use of the MPC strategy allows the formation of a multivariable system that takes into account constraints and includes various elements, such as nonlinear, higher-order, interrelated, etc. MPC uses a physical model to predict future system states, thereby facilitating informed decisions that optimize current and future system performance.

Originality. The automated drilling rig control system has been improved by using two levels in its structure. The lower level is represented by closed loops of proportional-integral-derivative control of the load on the drill bit, its rotation speed, and the pressure in the well cleaning system. The upper level uses model-predictive control for dynamic adjustment of the set values of the specified controlled variables, the magnitude of which is determined by operational estimates of the characteristics of mineralogical and technological varieties of ore.

Practical value. The technology described in the has been tested and can be recommended for improving the efficiency of drilling operations in iron ore quarries. The use of the proposed approach to forming a model-predictive control system for the technological process of drilling wells allows improving the quality of control, reducing the time of transitional processes, increasing the speed of drilling, and reducing energy consumption.

Keywords: *controlling, control actions, modeling*

Introduction. The mining industry is developing in the direction of technological optimization and information digitalization. The development and promotion of innovative computer-integrated technologies are necessary to make mining profitable and to enable information to be fed back into the process for continuous improvement. Monitoring tools, measurement technologies, and computational tools can now form a bank of useful information that was previously only the subject of speculation [1, 2].

These achievements are particularly useful for use in ore extraction and processing control systems. Recently, particular attention has been paid to advanced control strategies, in particular model predictive control (MPC) and nonlinear control, which offer forecasting capabilities and adaptability to nonlinear dynamics, respectively [3]. MPC uses a model of the controlled object to predict future states of the system, thereby facilitating informed decisions that optimize current and future system performance, taking into account constraints [4].

A transition from traditional proportional-integral-derivative (PID) structures to the implementation of advanced control strategies eliminates the shortcomings inherent in PID controllers, which generate control actions based on historical data without predicting future system states and are unable to take constraints into account [5].

This approach requires a more complex reference model that uses a cost function that balances multiple objectives, taking into account factors such as control smoothness and acceleration to ensure an optimized and smooth response.

Literature review. Well drilling speed is a key indicator of process efficiency. A higher rate of penetration (ROP) means better drilling rig performance, so ROP modeling and prediction are important for optimizing drilling operations [6].

Many drilling models have been proposed to simulate the impact of drilling rig parameters, environmental properties, and geology on ROP. The first models were based on RWN equations (ROP, WOB – bit load, and RPM – bit rotation speed), which were mainly driven by empirical indicators multiplied by proportionality constants to account for influencing variables. Later, experimental tests showed that RWN equations provide reliable results only under ideal well-cleaning conditions [7].

Existing ROP models are undergoing continuous modifications, and research and development are ongoing, but one of the most comprehensive ROP models is the BYM model proposed by Bourgoine and Young, which takes many factors into account and allows each of them to be adjusted by fitting coefficients [8].

The BYM ROP model defines the main variables of the well drilling process. The mathematical expression of this model consists of eight functions that have a significant impact on ROP [7, 8].

$$ROP = f_1 \cdot f_2 \cdot f_3 \cdot f_4 \cdot f_5 \cdot f_6 \cdot f_7 \cdot f_8.$$

Table 1 provides a description of these functions.

The following symbols are used in the above functions: TVD is a true vertical depth; TVD_N is a normalized value of the true vertical depth; EPP is an actual equivalent pore pressure gradient; EPP_N is an actual normalized value of equivalent pore pressure; ECD is an actual equivalent circulating density; WOB_{sf} is a measured weight on the chisel; OD_{bit} is an outer diameter of the drill bit; $\left(\dfrac{WOB_{sf}}{OD_{bit}}\right)_N$ is a normalized weight value on the chisel; RPM_{sf} is a measured surface rotation speed of the drill string; $(RPM_{sf})_N$ is a normalized value of drill string rotation speed; h is an assessment of partial wear of the drill bit; F_j is an impact force of a hydraulic jet; a_1 is a coefficient of formation strength and drilling fluid properties; a_2 is a compaction trend coefficient; a_3 is an undercompaction coefficient and pore pressure; a_4 is a differential pressure coefficient; a_5 is a constant depending on drilling modes and WOB; a_6 is an A constant that depends on drilling conditions and bit rotation speed; a_7 is a bit tooth wear coefficient; a_8 is a hydraulic coefficient.

The coefficients used in the expressions given in Table 1 are determined by taking into account boundary conditions, and their final values are obtained as a result of modeling related to specific scenarios for which the relevant data were collected.

Thus, the drilling model is a function of many variables that cannot be predicted and applied in advance, and only some of them (e.g., WOB and RPM) can be changed by the drilling operator or the corresponding automated control system.

As shown in [9, 10], three phases of drilling efficiency can be observed for different types of drill bits, related to the ROP response to changes in WOB and RPM. During the drilling process, load is applied to the bit, causing the cutters to continuously cut into the rock. In addition, the rotation of the bit causes lateral movement of the cutters, resulting in rock destruction.

Phase I is typical for inefficient drilling due to insufficient load on the bit [11]. At low WOB values, the bit does not penetrate deep enough into the rock, which causes higher friction. That is, in this phase of drilling, the scraping mechanism prevails; low load on the bit, together with higher friction, leads to wasted energy and

Table 1

Characteristics of the BYM ROP model functions

No.	Function	Expression
1	The effect of formation strength	$f_1 = e^{2.303 \cdot a_1}$
2	Depth and compaction effect	$f_2 = e^{2.303 \cdot a_2 \cdot (TVD_N - TVD)}$
3	The effect of pore pressure	$f_3 = e^{2.303 \cdot a_3 \cdot TVD^{0.69} \cdot \left(EPP - EPP_N\right)}$
4	The effect of pressure drop	$f_4 = e^{2.303 \cdot a_4 \cdot TVD \left(EPP - ECD\right)}$
5	The influence of bit diameter and WOB	$f_5 = \left[\dfrac{\dfrac{WOB_{sf}}{OD_{bit}} - \left(\dfrac{WOB_{sf}}{OD_{bit}}\right)_t}{\left(\dfrac{WOB_{sf}}{OD_{bit}}\right)_N - \left(\dfrac{WOB_{sf}}{OD_{bit}}\right)_t}\right]^{a_5}$
6	The effect of rotation speed	$f_6 = \left[\dfrac{RPM_{sf}}{\left(RPM_{sf}\right)_N}\right]^{a_6}$
7	The effect of drill bit wear	$f_7 = e^{-a_7 \cdot h}$
8	The effect of the impact force of the hydraulic drill bit	$f_8 = \left[\dfrac{F_j}{(F_j)_N}\right]^{a_8}$

low ROP, indicating the inefficiency of the drilling process [9, 10, 12].

Phase II is typical for efficient drilling, where there is a linear relationship between WOB and ROP. In this phase, thanks to adequate, sufficiently high WOB values, several drilling mechanisms are involved, including chipping, crushing, and scraping, which reduces the work expended on friction and leads to higher ROP rates. Energy in this phase is effectively used to destroy rock.

With a further increase in ROP, when a large volume of rock is drilled in a short period of time, it is not possible to remove all the drilling mud before it re-enters the bit. In phase III, as WOB increases, the relationship between WOB and ROP deviates from a linear response due to insufficient cleaning of the bottom hole. The transition of the drilling process to phase III is also facilitated by changes in lithology, the mechanism of bit engagement with the rock, vibration, etc. This phase, like phase I, is also characterized by low efficiency in the use of energy [12].

Therefore, the task of controlling the drilling process is to form control influences that ensure the maintenance of the specified and achieved optimal drilling speed when numerous disturbing factors change.

Automating the drilling process requires a systematic approach that integrates real-time well and surface data with previous drilling experience and models. An automated control system (ACS) changes operating parameters such as a bit load, a bit rotation speed, etc., depending on changing operating conditions. In addition, the ACS updates the model using real-time data, essentially simulating the decisions of an experienced driller, adapting to the results of imperfect predictions. The level of integration between surface and down hole systems varies significantly and is limited by the capabilities of sensors near the bit and along the drill string, as well as the bandwidth of the communication channel for transmitting measurement results and commands [13].

Currently, there are various methods for optimizing drilling parameters [14]. In particular, many methods have been proposed that optimize parameters with a single goal (single-purpose methods): minimum specific mechanical energy [15], minimum drilling cost [16, 17], and maximum drilling speed [18, 19]. However, in real drilling operations, different optimization goals often conflict with each other, and increasing one goal is often accompanied by a decrease in others. Therefore, for synergistic optimization of drilling parameters, it is advisable to use several target indicators simultaneously.

In [20], maximization of ROP and minimization of MSE are proposed as the optimization objective function. This is achieved by searching for the appropriate WOB and RPM parameters. Maximizing ROP and minimizing the risk of stick-slip vibration using controlled parameters WOB, RPM, and GPM (flow rate per minute generated by a hydraulic pump) is proposed in [21]. The parameters of bit durability and maximum ROP are selected as the objective function in [22]. Optimization is performed using the parameters WOB and RPM. The same approach is used in [23], but PP (hydraulic pump pressure) is added to the parameters used for optimization. As an additional target function to ROP, the study [24] minimizes the non-productive time (NPT) of the drilling rig. In this case, GPM is added to the usual parameters that are optimized.

This multi-parameter approach provides better results than optimization based on a single criterion. In other words, the method of multi-parameter optimization of drilling parameters, taking into account boundary conditions, can be considered more reasonable and promising.

Model predictive control (MPC) is a feedback control approach that uses model-based optimization to calculate control inputs. In MPC, the system model, together with the current state (measured or estimated), is used to predict the future behavior (states) of the system for a short period of control input sequence. The predicted behavior is characterized by a cost function, which is a function of the predicted state and control sequence. An optimization algorithm is then used to find a control sequence that optimizes the predicted behavior or cost function. The first element of the control sequence is applied to the system, which gives the next state, and the algorithm is repeated at the next time step, resulting in a receding horizon scheme.

MPC, which originated from the optimal control approach, has the following advantages: it uses closed-loop control schemes, whereas traditional optimal control mostly results in open-loop control schemes; it handles complex systems, such as nonlinear, higher-order, multivariable, etc.; and it takes constraints into account [4, 5, 25].

The input variables of the MPC controller are controlled variables (CV) and measured disturbance variables (DV). They are provided by measuring instruments or soft sensors. MPC algorithms are mainly implemented on special computers that exchange data with the process control system via the OPC interface. PLS provides an OPC server, and the MPC software system provides an OPC client. For MPC controllers with fewer controlled and controlled variables, there are also MPC function blocks in selected process control systems that run directly on PLS components related to the process [25, 26].

Therefore, bearing in mind that the control of a multivariable nonlinear drilling process requires an appropriate multi-loop structure capable of taking into account its specific features, it is advisable to use model predictive control methods to solve the problem.

Purpose. The purpose of the study is to improve the quality and efficiency of well drilling process management by applying a model-predictive control strategy. The results of the study show that a drilling rig, as a control object, is a dynamic nonlinear structure with interrelated variable parameters. Traditional automated control systems do not allow predicting their future state and are not able to take into account restrictions on controlled variables. Another problem is determining the optimal structure of the control system based on MPC controllers and their interaction with existing traditional PID controllers. A separate task is to determine a set of controlled variables that ensure the maintenance of the optimal drilling speed in the presence of disturbances and interference in the measured signals.

Methods. In general, the predictive control algorithm solves the problem of optimal control in real time, taking into account system dynamics and variable constraints.

The system model can be represented as follows [25, 28].

$$x(k+1) = Ax(k) + Bu(k) + Gd_p(k);$$
$$y(k) = Cx(k) + Du(k) + Hd_m(k),$$

where $x(k) \in \mathbb{R}^{n_x}$ is a state; $u(k) \in \mathbb{R}^{n_u}$ is a controlled input; $y(k) \in \mathbb{R}^{n_y}$ is measured outputs.

Vectors $d_p(k)$ and $d_m(k)$ are unmeasurable disturbances in state dynamics (process noise) and outputs (measurement noise), respectively. The controller predicts the future behavior of the actual system over a time interval defined by the lower and upper prediction horizons, denoted by N_w and N_p respectively.

The optimal input for the plant is calculated by minimizing the cost function defined along the forecast horizon, which is defined as the sum of the quadratic future errors between the reference trajectory and the predicted plant output and the predicted control adjustment [28].

$$J(k) = \sum_{i=N_w}^{N_p} \left\| \hat{y}(k+i/k) - r(k+i) \right\|_{Q(i)}^2 + \\ + \sum_{i=0}^{Nu-1} \left\| \Delta u(k+i/k \right\|_{R(i)}^2 .$$

Taking into account the restrictions set for inputs, outputs, and input increments

$$u_{\min} \le u(k) \le u_{\max};$$
$$y_{\min} \le y(k) \le y_{\max};$$
$$\Delta u_{\min} \le \Delta u(k) \le \Delta u_{\max},$$

where $Q(i)$ is a positively defined matrix of error weight coefficients; $R(i)$ is a positively semi-definite matrix of control weight coefficients; $\hat{y}(k+i/k)$ is a vector of predicted output signals; $r(k+i)$ is a vector of future development; $\Delta u(k + i/(k))$ is a vector of future controlling influences.

We implement feedback measurement and a receding horizon strategy to account for the presence of obstacles and the incompatibility of the installation/model. This means that only the first element of the calculated control sequence is applied to the installation. At the next sampling interval, both the control horizon and the prediction horizon are moved one step forward, and the entire cycle of state estimation, output prediction, and optimization is repeated using the new measurement.

To model the structure represented by expressions (2) and (3), we used the capabilities of the Simulink® /MATLAB® platform and the Model Predictive Control Toolbox MATLAB® [25].

A model of a control system for a drilling rig based on an MPC controller is shown in Fig. 1. In the model, the input data are represented by the vector $u(t)$, which contains the manipulated variables (mv):

u_1 – load (weight) on the drill bit (WOB);

u_2 – pressure in the well cleaning system (P);

u_3 – rotation speed of the drill bit (RPM).

These variables, as well as the ROP, form the state of the model and are located in the vector $x(t)$.

The purpose of control is to maintain the rate of penetration (ROP) at the nominal set value corresponding to the established assessment of the physical and mechanical properties of the rock (PMP) being drilled. This assessment is determined in accordance with the procedure described in [28].

The model shown in Fig. 1 uses the following blocks: *1* – MPC Controller block from the Simulink Model Predictive Control Toolbox TM library; control object model block (Subsystem), which includes *2* – Demux blocks from the Simulink/Signal Routing library; *3–6* – Transfer Fcn blocks from the Simulink/Continuous library; *7–9* – Fcn blocks from the Simulink/User-Defined Functions library; *10–12* – Transport Delay blocks from the Simulink/Continuous library; *13*, *14* – Sum blocks from the Simulink/Math Operations library; *15*, *16* – To Workspace blocks for outputting information to the MATLAB workspace (out.y and out.u) from the Simulink/Sinks library; *17*, *18* – Step blocks from the Simulink/Sources library; *19*, *20* – Scope blocks from the Simulink/Commonly Used Blocks and Simulink/Sinks libraries.

The Transfer F_{cn} block models a linear structure using the transfer function of variable s in the Laplace domain. The Fcn block applies a specified mathematical expression to its input data and is used to model nonlinearity in a specific control loop. The Transport Delay block delays the input signal for a specified time.

The MPC controller block receives the current measured output signal (mo) and the reference signal (ref). The block calculates the optimal controlled variable (mv) by solving a quadratic programming problem using the standard KWIK solver [25].

When the controller is operating, it uses its current state x_c, as the basis for predictions. By definition, the state vector is as follows [25, 29]

$$x_c^T = \left[x_p^T \; x_{id}^T \; x_{od}^T \; x_n^T \right],$$

where x_c is a controller status containing $n_{xp} + n_{xid} + n_{xod} + n_{xn}$ state variables; x_p is a vector of the state of the object model with length n_{xp}; x_{id} is a vector of the state of the input disturbance model with length n_{xid}; x_{od} is a vector of the state of the initial disturbance model with length n_{xod}; x_n is a vector of the state of the noise model measurement length n_{xn}.

The combination of these models gives the observer of the state [28]

$$x_c(k+1) = Ax_c(k) + Bu_o(k);$$
$$y(k) = Cx_c(k) + Du_0(k).$$

The MPC controller uses an observer to estimate the values of unmeasured states as a basis for predictions and to predict how the controller's proposed adjust-

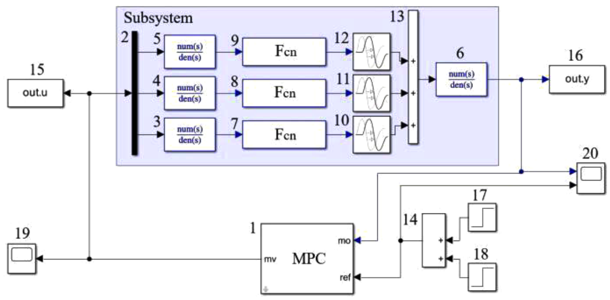

Fig. 1. Model of a drilling rig control system based on an MPC controller

ments to the MV will affect future values of the output variable.

The observer's input signals are dimensionless input data of manipulated and measured variables, as well as white noise input data for disturbance and noise models

$$u_o^T(k)=\left[u^T(k)\ v^T(k)\ w_{id}^T(k)\ w_{od}^T(k)\ w_n^T(k)\right].$$

The observer outputs are n dimensionless outputs of the object model.

The observer parameters are defined as follows [28]

$$A=\begin{bmatrix} A_p & B_{pd}C_{id} & 0 & 0 \\ 0 & A_{id} & 0 & 0 \\ 0 & 0 & A_{od} & 0 \\ 0 & 0 & 0 & A_n \end{bmatrix};$$

$$B=\begin{bmatrix} B_{pu} & B_{pv} & B_{pd}D_{id} & 0 & 0 \\ 0 & 0 & B_{id} & 0 & 0 \\ 0 & 0 & 0 & B_{od} & 0 \\ 0 & 0 & 0 & 0 & B_n \end{bmatrix};$$

$$C=\begin{bmatrix} C_p & D_{pd}C_{id} & C_{od} & \begin{bmatrix} C_n \\ 0 \end{bmatrix} \end{bmatrix};$$

$$D=\begin{bmatrix} 0 & D_{pv} & D_{pd}D_{id} & D_{od} & \begin{bmatrix} D_n \\ 0 \end{bmatrix} \end{bmatrix}.$$

The models of the controlled object disturbances and output disturbances are changed so that the measured outputs precede the unmeasured outputs.

The controller setpoint generation block is used to generate a step signal whose amplitude changes over time to study the corresponding response of the controller's MPC, taking into account the characteristics of the control object model.

The setpoint signals are combined and connected to the "ref" input of the MPC controller. The outputs of the MPC controller, together with the disturbance variables, form the inputs of the control object model. The outputs of the model are returned to the "mo" input of the MPC controller. The setpoint and actual values of the controlled variables are displayed by Scope blocks and exported to the MATLAB main memory using "To Workspace" blocks. A special feature of the Simulink model is that the model of the linear transfer function of a controlled system with several variables processes or generates deviations from the operating point. However, the values of the physical operating point are predefined in the MPC controller by the MPC Designer program. Thus, the values of the operating point of the controlled variables and disturbance variables are subtracted from the output signals of the MPC controller before processing in the LTI System software module [25]. Similarly, the operating point values of the controlled variables are added to the outputs of the object model before processing in the MPC controller module.

The structure of the drilling rig control system model shown in Fig. 2 allows all its operating modes to be reproduced. Parametric identification of the model was based on the operating characteristics of a pilot industrial drilling rig (Table 1), taking into account the relevant limitations and experimental data obtained.

Results. Experimental studies were conducted using a pilot industrial drilling rig based on the SBSh-250MNA-32 drilling machine, which is widely used for drilling explosive and production wells in open-pit ore mining. The main parameters characterizing the drilling mode are: axial feed force or load on the bit WOB; rotation speed of the drill string (bit) RPM; the required amount of compressed air supplied to the bottom hole to remove the products of destruction Q, which is provided by the corresponding pressure P in the well cleaning system. All manufacturers provide average recommendations for the maximum permissible axial force on the bit WOBmax and the corresponding maximum bit rotation speed RPMmax, at which satisfactory operating conditions are ensured. Table 2 shows the main operating characteristics of the pilot industrial drilling rig used in the experimental studies.

The technical base of the experimental industrial drilling rig allows reproducing various structures of the automated control system and conducting a meaningful analysis of the results obtained from experimental research.

The software implementation of the studied system of predictive control of a drilling rig includes two main stages: determining the object model and synthesizing the MPC controller (Fig. 2).

To determine the relationship between the variables RPM, WOB, and P with ROP, continuous transfer functions from each input to the *plant* TF output are used. The Linearize (model,io) function performs a linear approximation of the nonlinear Simulink® model using the analysis points specified in *io*.

Since a dynamic system model has internal dynamics or memory of past states, such as integrators, delay lines, and transfer functions, a state space transformation is performed using the ss function. The sampling time *Ts* is chosen to be 0.3 s.

The model is converted from continuous time to discrete time by keeping the zero-order *ZOH* on the inputs and the sampling time *Ts*.

Table 2

Main technical characteristics of the pilot industrial drilling rig

No.	Parameters	Meaning
1	Bit diameter, mm	244.5; 269.9
2	Well depth, m, no more than	32
3	Bar length/continuous feed stroke, m	8/8
4	Axial force, kN, max.	300
5	Rotation frequency of the drill bit, s^{-1}	0.2–2.5
6	Torque on the rotator, kN×m	4.2
7	Compressor performance, m^3/s	0.417
8	Compressed air pressure, MPa	0.685
9	Drive type	Low-voltage electric drive
10	Electric motor power, kW: - installed - of the rotator - of the compressor - of the movement	 400 68 200 44

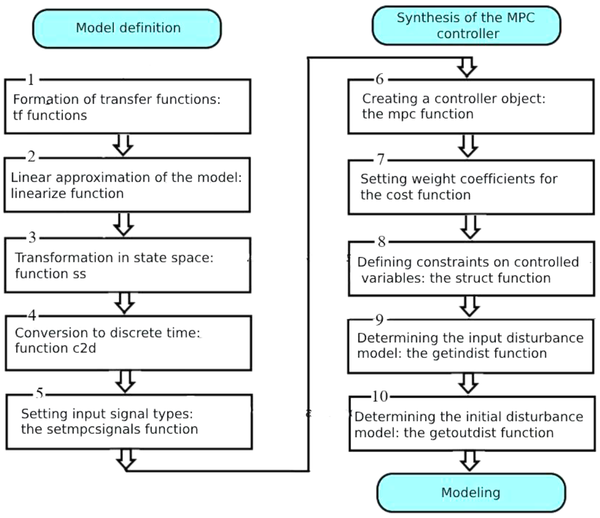

Fig. 2. Basic operations of the software implementation of the modeling and forecasting control system for drilling rigs

To determine the types of input signals of the LTI model of the object as manipulated variables, the *setmpcsignals* function is used (controlled variables, measured and unmeasured disturbances).

When synthesizing the MPC controller, a 7-step forecast horizon and a 3-step control horizon were chosen.

The hard constraints for the controlled variables and the weighting coefficients of the quadratic cost function were selected based on the normalized values of the relevant rig parameters (Table 2).

To determine the dynamic characteristics of the additive input and output unmeasured disturbances, an integrator was used as a disturbance model for each unmeasured interference input and each unmeasured interference acting on each measured output.

A Kalman filter was used to assess the system state.

The results of modeling the formation of control influences in the SAC at the ROP rate when the MRS controller processes the specified values are shown in Fig. 3.

Fig. 4 shows graphs of transient processes in the system when the MRS controller processes the specified ROP (Y) values corresponding to the obtained estimates of the physical and mechanical characteristics of rocks or their mineralogical and technological varieties

The results of Simulink modeling are identical to those obtained in MPC Designer.

Existing traditional drilling rig control systems are based on PID controllers, which have the above-mentioned disadvantages. The transition to a higher level of control using MPC strategies is best achieved using a cascade scheme. In this case, the output or controlled variables (mv) of the MPC controller act on the set values of the existing subordinate PID structures. Such a cascade structure has two advantages: on the one hand, it allows maintenance personnel to control the system in emergency situations using only conventional control means, thus facilitating the implementation of the MPC strategy in practice. On the other hand, it has a linearization effect – the relationships between the setpoints of the subordinate PID controllers and the controlled variables of the MPC tend to behave more “linearly” [5, 26, 28].

The general state space equations describing the plant and the controller are as follows [27].

$$x_p(k+1) = A_p x_p(k) + B_p u(k) + G d_p(k);$$
$$y_p(k) = C_p x_p(k) + D_{pu}(k) + H d_m(\mathrm{k});$$
$$x_c(k+1) = A_c x_c(k) + B_c e(k);$$
$$u(k) = C_c x_c(k) + D_c e(k) + w(k),$$

where $x_p(k)$ and $x_c(k)$ are plant and PID controller status, respectively; $u(k)$ is input data for the plant generated by the low-level controller; $d_p(k)$ and $d_m(k)$ are a process noise and measurement noise; $w(k)$ is a noise in the control signal; $e(k) = r(k) - y(k)$ is the error signal.

The basic structure of a multicircuit drilling rig control system using PID controllers can be performed according to the principles given in [5]. Fig. 6 shows a Simulink model of a three-circuit structure based on an MPC controller for use in a two-level cascade scheme of a drilling rig.

The following blocks are used in the model shown in Fig. 5: *1* – MPC Controller block from the Simulink Model Predictive Control Toolbox TM library; *2* – block of the model of interconnection of variable control channels; *3* – block of the model of the control object; *4* – Demux block from the Simulink/Signal Rout-

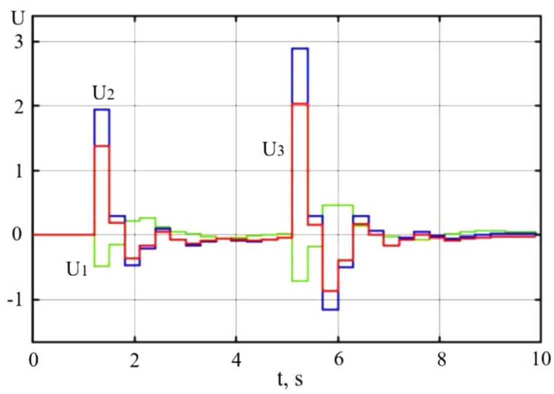

Fig. 3. Results of modeling the formation of control influences in the control system of a drilling rig according to the direct control scheme (normalized values)

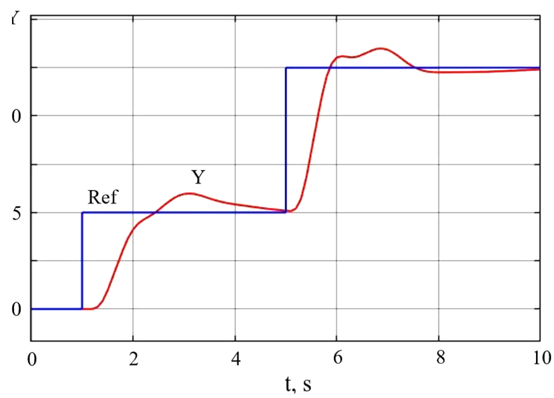

Fig. 4. Graphs of transient processes in the control system when the MRS controller operates at the set values (Ref) of the well penetration rate ROP (Y) (normalized values)

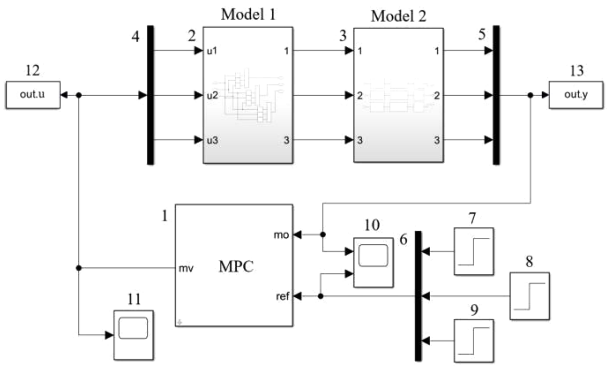

Fig. 5. Schematic diagram of the SAC model using an MRS controller to control parallel interconnected structures (MIMO)

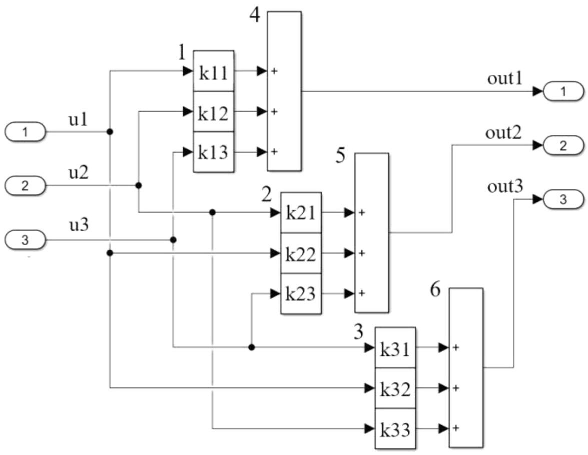

Fig. 6. Scheme for modeling the interconnection of variable control channels

ing library; *5*, *6* – Mux blocks from the Simulink/Signal Routing library; *7–9* – Step blocks from the Simulink/Sources library; *10*, *11* – Scope blocks from the Simulink /Commonly Used Blocks, Simulink/Sinks library; *12*, *13* – To Workspace blocks for outputting information to the MATLAB workspace (out. y and out.u) from the Simulink/Sinks library.

Taking into account the relationships between the variables RPM, WOB, and P, Model 1 was used to model their complex impact on ROP, the structure of which is shown in Fig. 6.

In the model shown in Fig. 6, the following blocks are used in the model: *1–3* – Slider Gain blocks from the Simulink/Math Operations library; *4–6* – Sum blocks from the Simulink/Math Operations library.

The MPC controller was configured using the MPC Designer program. The specific values of the coefficients k1n, k2n, k3n are determined by the results of the correlation analysis of the corresponding variables of the pilot drilling rig.

The results of modeling the formation of control influences in the SAC by a drilling rig using a cascade control scheme when working out changes in the set values of WOB (U_1), P (U_2), and RPM (U_3) are shown in Fig. 7.

Fig. 8 shows the graphs of transient processes in the ACS when the MPC controller operates the set values for each control loop.

The results of computer modeling were used to set up the SAC with a pilot drilling rig. The experimental operation of the rig was carried out at a section of the deposit consisting of 7 mineralogical and technological types of iron ore. The results obtained indicate that the use of a cascade control scheme based on the MPC controller reduced the time of transients in the system by an average of 12–15 %, with the value of the overshoot not exceeding 1.2 ROP values, which was determined to be optimal according to the obtained assessment of mineralogical and technological types of iron ore. Timely assessment of the physical and mechanical properties of the rock and operational adjustment of the drilling rig operating modes with the help of MRS control made it possible to reduce its specific energy consumption by 7–9 %.

Conclusions. The general principles of multi-loop model predictive control (MPC) of a drilling rig as a nonlinear structure with interrelated variables that determine its state are considered. A control system is investigated in which the MPC controller is used both at the level of direct control and in a cascade scheme. Closed-loop control simulation has shown that the use of such a two-level structure has better characteristics compared to classical PID control schemes and allows all constraints to be taken into account. Flexibility in formulating the model predictive control problem allows the use of additional objectives and constraints, such as economic criteria.

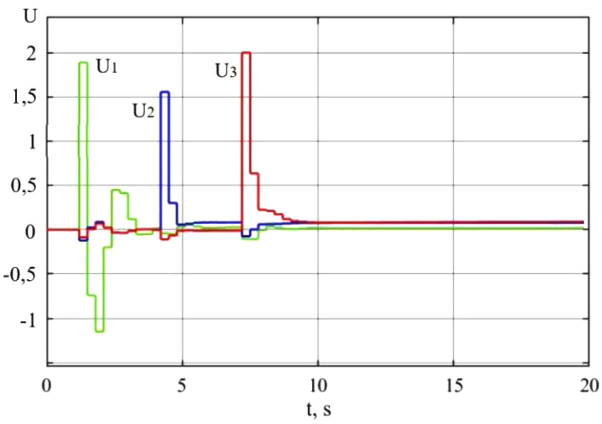

Fig. 7. Results of modeling the formation of control influences (U) according to the cascade control scheme (normalized values)

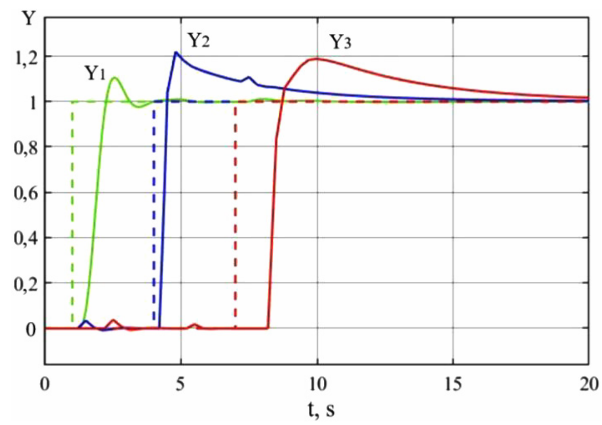

Fig. 8. Graphs of transient processes in the ACS when the MPC controller works out the set values in a cascade scheme (normalized values)

The automated control system for a drilling rig has been improved by using two levels in its structure, the lower of which is represented by closed-loop proportional-integral-derivative control of the load on the drill bit, its rotation speed, and the pressure in the well-cleaning system, while the upper level uses model-predictive control for dynamic adjustment of the set values of the specified controlled variables, the magnitude of which is determined by operational assessments of the characteristics of mineralogical and technological varieties of ore.

The use of a cascade control scheme for the drilling rig based on an MRS controller reduced the transition time in the system by an average of 12–15 % with an overshoot value not exceeding 1.2 times the ROP value, which corresponded to the determined assessment of the mineralogical and technological varieties of iron ore. Operational adjustment using model-predictive control of the drilling rig's operating modes made it possible to reduce its specific energy consumption by 7–9 %.

Further research should focus on studying the structure of the well drilling process control, in which the MPC controller is connected in parallel with existing low-level PID controllers to improve the performance of the closed system, as well as the application of economic control criteria in conjunction with technical ones.

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Модельно-прогнозуюче керування процесом буріння свердловин

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Мета. Підвищення якості й ефективності керування процесом буріння свердловин шляхом застосування стратегії модельно-прогнозуючого керування (MPC).

Методика. У роботі використані такі методи: аналіз наукових і практичних рішень; методи аналітичного синтезу; методи комп'ютерного моделювання для синтезу й аналізу математичних моделей; статистичні методи для оброблення результатів експериментальних досліджень.

Результати. Досліджений метод керування буровою установкою на основі MPC контролера, що передбачає використання в якості регульованих змінних швидкості обертання долота (RPM), навантаження (ваги) на долото (WOB) й тиску в системі очищення свердловин (P). Метою керування є підтримка швидкості проходки свердловин (ROP) на номінальному заданому значенні, що відповідає сформованій оцінці фізико-механічних властивостей гірської породи, що буриться (PMP). У традиційних системах керування пропорційно-інтегрально-диференціальні (ПІД) контролери формують керуючі впливи на основі історичних даних без передбачення стану існуючих систем і не можуть ураховувати обмеження. Використання стратегії MPC дозволяє сформувати багатозмінну систему, що враховує обмеження та включає різноманітні елементи, такі як нелінійні, вищого порядку, взаємопов'язані тощо. MPC використовує фізичну модель для прогнозування майбутніх станів системи, тим самим полегшуючи ухвалення обґрунтованих рішень, що оптимізують поточну й майбутню продуктивність системи.

Наукова новизна. Удосконалена автоматизована система керування буровою установкою шляхом використання в її структурі двох рівнів. Нижній рівень представлений замкнутими контурами пропорційно-інтегрально-диференціального регулювання навантаження на долото, швидкості його обертання й тиску в системі очищення свердловини. На верхньому рівні використовується модельно-прогнозуюче керування для динамічного корегування заданих значень зазначених регульованих змінних, величина яких визначається оперативними оцінками характеристик мінералого-технологічних різновидів руди.

Практична значимість. Наведена в роботі технологія апробована й може бути рекомендована для підвищення ефективності бурових робіт у залізорудному кар'єрі. Використання запропонованого підходу до формування системи модельно-прогнозуючого керування технологічним процесом буріння свердловин дозволяє підвищити якість керування, зменшити час перехідних процесів, збільшити швидкість проходки та знизити енергоспоживання.

Ключові слова: *керування, керуючі впливи, моделювання*

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