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A NEW ALGORITHM FOR ADJUSTING PI CONTROLLER COEFFICIENTS IN SHEARER OPERATION CONTROL

The article considers the control system of shearers designed for breaking and loading rocks onto a scraper conveyor. When cutting a coal seam by a shearer, the external disturbances (coal resistance to cutting), solid inclusions and change in the width of a shearer drum, which vary indefinitely, lead to the deterioration in the quality of transients. A typical cutting process controller in the form of a PI controller with the parameters configured for a specific mode of operation of the shearer is incapable to ensure the optimal functioning of the control system in all modes due to the non-linearity of the controlled object and owing to the random changes in the coal resistance to cutting. To improve the control quality indicators, it is necessary to select the parameters of the PI controller so as to minimize the amplitudes of the current steps of the cutting motor, and thereby to reduce the amplitudes of the torque in the transmission of the cutting drive and to minimize the system settling time. In this paper, we present an adjustment algorithm based on obtaining the values of the controller parameters for each of the possible operating modes of the shearer, identifying the type of a disturbing effect by the response curves of the system available to observation. Furthermore, it is proposed to use of an artificial feed-forward neural network as an operational tool of recognizing a multidimensional response curve in the control loop. The correctness of the obtained results is confirmed by the results of computer modeling.

Keywords: *shearer, recognition reliability, transients, neural network, control system*
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Introduction

Despite the global trend of abandoning hydrocarbon fuels in favor of more environmentally friendly fuel and energy resources, the demand for coal and the development of the coal industry are likely to continue in the coming decades. The underground method of coal mining is currently focused on the use of fully-mechanized longwall mining where the main function—rock cutting and loading on an armored face conveyor—is performed by shearers. With the development of coal mining technologies and increased mine safety requirements, the automation of fully-mechanized coal face control has become an inexorable trend.

The shearer is the main equipment at the coal face, and for this reason its automation is important for the automation of the entire coal mining process. The existing shearers consist of two drive systems—a feed drive and a cutting drive (**Fig. 1**) [1]. The feed drive is designed to move the shearer during its operation with the required traction (pressure) force, as well as for its movement during various maneuvering operations; it consists of an asynchronous feed motor (AFM), a feed gearbox and remote or integrated traveling mechanisms. The cutting drive (CD) is comprised of a cutting motor (CM), a cutting unit gearbox and the cutting tool itself of an auger or a drum type, which, when rotating, cuts into coal and crushes it (see fig. 1).

The processes of rock destruction result from a complex interaction of the medium being broken, the cutting tool, and the dynamic system of the coal mining machine. The load on the cutting drive units is determined by a number of factors and, first of all, by the coal resistance to cutting, which is a random and variable value even within the same longwall [2]. In addition, the rotation speed of the cutting tool in existing shearers is uncontrolled, and therefore, the disadvantages of shearers are the high failure rate and poor adaptability of cutting tools to changing environments (coal resistance to cutting).

When cutting through a coal seam, random in time and amplitude current steps occur in the electric motor of the cutting drive due to the presence of solid inclusions and jumps in coal resistance to cutting. With a stepwise variation in the coal resistance to cutting, in particular, at different levels of surges in resistance and their combinations, the duration of transient processes and current steps also differ. The coal mining costs can be reduced by minimizing the amplitude of current steps and the transient process time after a surge in coal resistance to cutting.

Modern research shows that the load on the cutting tool can be adjusted by changing the speed of movement of the shearer itself by using a variable-frequency electric drive in the shearer feeding system [3]. To accomplish this, a cutting current (load) controller (CCC) is installed in the shearer control system—CCC in the form of a PI controller designed to prevent the overloading or overturning of the cutting drive motor by controlling the operating current parameter of the cutting motor I_c with a signal from the current sensor by changing the feed speed V_f of the shearer when the coal cutting resistance A and the operating conditions of the shearer change. The feed speed V_f can be adjusted by controlling the signal at the output of the frequency converter (FC) by changing the frequency and voltage on the feed motor stator—*f*, *U* (**Fig. 2**). The instability of the parameters of the controlled object without reconfiguring the controller leads to the deterioration in the quality of transient processes, which results, among other things, in an increase in power consumption, deterioration in the extracted coal sizing and in a breakdown of the shearer cutters. But in practice, such a reconfiguration at the mine is usually not carried out due to its labor intensity and high requirements for the qualification of operators.

Therefore, in these conditions, it is essential to develop and employ the controllers, the control action of which is formed to promptly respond to the variations in disturbing and setting actions, ensuring the accuracy and quality of control over the coal mining process within a given range of values.

In the industrial and technical practice of mining engineering, the generic controllers of P, PI and PID types have become predominant. In recent years, the study of the application and adjustment of such controllers has been one of the most relevant areas of the theory of linear systems [4, 5]. There are numerous approaches to the synthesis of systems applicable in the

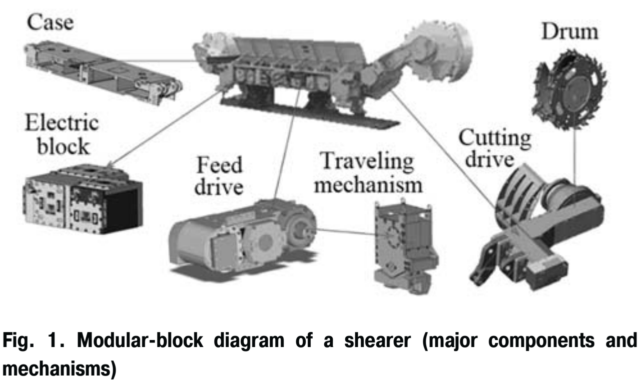

Fig. 1. Modular-block diagram of a shearer (major components and mechanisms)

conditions of random unpredictable changes in rock hardness during coal mining [6–9]. The trend of unmanned coal mining in deep coal seams imposes strict requirements on the reliability and versatility of shearers [10].

An upcoming trend in upgrading the modern systems of control over complex electromechanical objects is the widespread application of artificial intelligence methods and technologies that ensure high efficiency of control processes and a wide range of functionality given the uncertainty of an object model [11, 12]. In article [13], the speed control method for lifting and transporting of mineral hoisting and conveying machinery based on single neuron PID is proposed. In [14], a neural network unit for autotuning the PID controller for power engineering facilities was developed.

Based on the results obtained, it becomes possible to state that in the process of changing the object parameters, the use of a neural network for an autotuning unit has proved its superior efficiency. However, there were no ready-to-implement solutions on the synthesis of neural network control systems for the shearer electric drives.

Method

To prevent the deterioration of the control quality, the controller parameter values for each of the possible modes of the control object operation, including the disturbance compensation, are to be obtained.

To calculate the optimal parameters of the PI controller, it is necessary to know the nature of the change in the coal resistance to cutting, which, in its turn, can be identified by the shape of the initial fragment of the response curve for the load surge.

The PI controller coefficients can be adjusted using an artificial feed-forward neural network (NN) functioning as an operational tool for recognizing a multidimensional response curve in the control loop.

With a sudden change in the coal resistance to cutting, in particular, at different levels of surges and their combinations, the response rate of the cutting current controller (transient process duration) and current steps also differ, and the settling time of the transient varies and depends on the parameters of the controller [15]. To improve the quality of the transient process, the parameters of the PI controller are to be selected to minimize the amplitudes of the current steps, and therefore reduce the amplitudes of the torque in the transmission of the cutting drive and minimize the system settling time (by reducing the duration of the peak torque in the transmission), including with respect to the PI controller in these conditions.

In this manner, the optimal settings of the PI controller, K_p and K_i, are such that, at a given disturbing effect A, ensure a minimum area S under the current curve of the CM stator recorded after the surge (or the first one in a combination of surges).

To solve the above problem, an algorithm is proposed that contains the following sequence of steps.

1. The development of the training sample (**Table 1**) using a computer model of the *PI Controller–Coal Shearer* system created in MATLAB/Simulink [12].

In a sample list of all possible combinations of A, K_P and K_I of volume N, the optimal combinations [A, K_P^* and K_I^*] are determined according to the following criterion: $S \rightarrow \min$.

2. Based on the sample list (see Table 1), a model for recognizing the response of the *PI Controller–Coal Shearer* system is developed. The input and output parameters of the model are given in **Table 2**.

In terms of system engineering, the above refers to L recognition models, where L is the number of combinations of K_P and K_I, i.e. for each combination of K_P and K_I, the readings of a two-dimensional curve [$\{I\}$,$\{V\}$] are applied to the input of the model, and the recognized type of surge A is read off at the output. The sample of the type presented in table 2 is used to train a feed-forward neural network (NN). At the same time, L neural network recognition models can also be applied, each for its own combination of K_P and K_I—the readings of the curve [$\{I\}$,$\{V\}$] are applied to the input, and the recognized type of surge A is read off at the output.

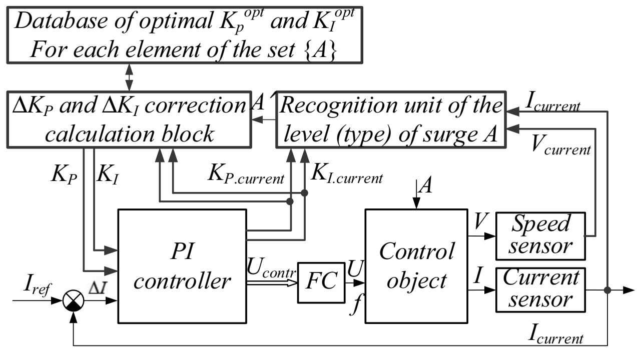

Fig. 2. Generalized scheme for controlling the electric drive of a shearer (common blocks are shown in black, additional implementation blocks of the proposed method are shown in blue)

Table 1. Observation model input and output data

Input data				Output data	
A_1	K_{P1}	K_{I1}	$\{I\}_1$	$\{V\}_1$	S_1
...	...	...	...	...	...
A_N	K_{PN}	K_{IN}	$\{I\}_N$	$\{V\}_N$	S_N

Legend:
Input data:
$A_1 \ldots A_N$ are the single values or the combinations of surges in the coal resistance to cutting; $K_{P1} \ldots K_{PN}$ is a proportional component of the PI controller; and $K_{I1} \ldots K_{IN}$ is an integral component of the PI controller;
Output data:
$\{I\}_1 \ldots \{I\}_N$ are the readings of the current curve of the CM stator recorded after the surge (or the first one in a combination of surges); $\{V\}_1 \ldots \{V\}_N$ are the readings of the curve of the shearer feed speed recorded after the surge (or the first one in a combination of surges); and $S_1 \ldots S_N$ are the areas under the current curve of the CM stator recorded after the surge (or the first one in a combination of surges)

Table 2. Recognition model input and output data

Input data				Output data
K_{P1}	K_{I1}	$\{I\}_1$	$\{V\}_1$	A_1
...	...	...	...	...
K_{PM}	K_{IM}	$\{I\}_M$	$\{V\}_M$	A_M

Legend:
Input data:
$K_{P1} \ldots K_{PM}$ is a proportional component of the PI controller; $K_{I1} \ldots K_{IM}$ is an integral component of the PI controller; $\{I\}_1 \ldots \{I\}_N$ are the first M readings of the current curve of the CM stator recorded after the surge (or the first one in a combination of surges); and $\{V\}_1 \ldots \{V\}_M$ are the first M readings of the curve of the shearer feed speed recorded after the surge (or the first one in a combination of surges);
Output data:
$A_1 \ldots A_M$ are the single values or combinations of surges in the coal resistance to cutting

3. The process of the shearer operation is recorded or modeled in the setting of unpredictable types of surges (if the surges are unpredictable in time and level, then a complete Markov process is obtained as a generalization of the Bernoulli scheme). The PI controller has the initial values of the coefficients: K_P^1 and K_I^1. The start of the surge and the first M readings of the transient process are recorded. The readings of the identified curve after the surge at an interval of 1.25 of the CM stator current and feed speed are shown in figs. 3*a* and 3*b*, respectively; parameters: $A = 6$; $K_P = 0.21$; $K_I = 2.5$.

In real environmental conditions, the information systems of most technical facilities operate in the presence of noise and distortion. Therefore, the first M readings of the two-dimensional signal [$\{I'\}$,$\{V'\}$] are applied to the input of the recognition model being distorted (with matched low-frequency noise) and noisy (white Gaussian noise). At the output of the model, an

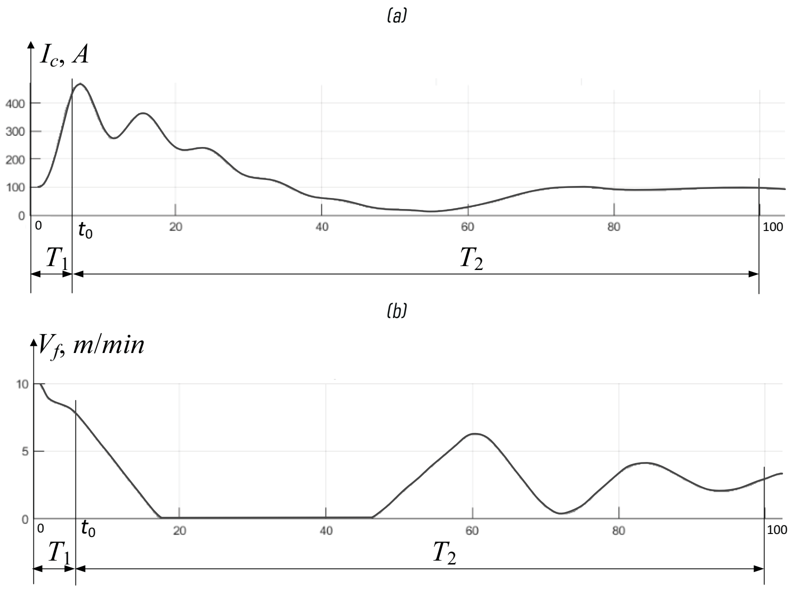

Fig. 3. Formation of a fragment of the first readings of (*a*) the CM stator current, and (*b*) the feed speed of the shearer

estimate of the recognized class of the A' surge type is made. The class A generally characterizes the levels and sequence of a series of step approximations of changes in the coal resistance to cutting. The first M readings of the transient process are recorded within the duration T_1. The total duration of the transient process is $T_1 + T_2$ (**Fig. 3**).

In parallel, the optimization problem of selecting the ratio of T_1/T_2 intervals is solved. At this ratio, on the one hand, the stable recognition process is ensured in the presence of interference and noise, and on the other hand, there is still a gain in optimal control associated with the anticipatory correction of the PI regulator coefficients for the recognized class of the surge in the coal resistance to cutting.

4. For the recognized type of the surge A', according to Table 1, the optimal combination of K_P^{opt} and K_I^{opt} is determined, for which $S \to \min$.

5. The parameters of the PI controller are corrected as follows:

$$\begin{cases} \Delta K_P = \left(K_P^1 - K_P^{opt}\right)\left(\dfrac{S_1}{S_1 + S_2}\right); \\ \Delta K_I = \left(K_I^1 - K_I^{opt}\right)\left(\dfrac{S_1}{S_1 + S_2}\right), \end{cases} \tag{1}$$

where S_1 and S_2 are the areas under the branches of the observation and forecast curves, respectively, for the durations T_1 and $(T_1 + T_2)$ (see fig. 3).

With limited computing resources of the controller, the correction formulas can be simplified:

$$\begin{cases} \Delta K_p = \left(K_p^1 - K_p^{opt}\right)\left(\dfrac{T_1}{T_1 + T_2}\right); \\ \Delta K_I = \left(K_I^1 - K_I^{opt}\right)\left(\dfrac{T_1}{T_1 + T_2}\right), \end{cases} \tag{2}$$

where T_1 and T_2 are the durations of the curve recording at the input of the recognition model and the remaining duration of the transient process, respectively.

6. At the time t_0, or, more precisely, $(t_0 + Dt)$, where Dt is the time spent for the recognition and correction, the new values are assigned to the PI controller coefficients:

$$\begin{cases} K_P^2 = K_P^1 + \Delta K_P; \\ K_I^2 = K_I^1 + \Delta K_I. \end{cases} \tag{3}$$

Then the generalized scheme of regulation by the electric drive of the combine is supplemented with new blocks—Fig. 2 (new blocks in the regulation system are shown in blue).

In general, n sections of a multidimensional response curve available for observation can be used as the data sources for identifying the type of a disturbing effect on the controlled unit (**Fig. 4**). The curve recognition algorithm is to be scalable relative to n, and to satisfy the constraints related to the expeditious solving of an electromechanical system control problem, since it is necessary to recognize a surge before the transient process reached the peak current step (see fig. 3).

Implementation of the PI controller setting method with neural network

The PI controller coefficients can be adjusted using an artificial feed-forward NN functioning as an operational tool for recognizing a multidimensional response curve in the control loop of the controller parameters.

The controlled object, or the source of data on transient processes in the observation model, is the simulation model of the UKD300 shearer operation implemented in the Simulink system [16].

A discrete level of the surge in the coal resistance to cutting A is applied to the input of the observation model.

It is assumed that the internal state of the observation object with a degree of approximation sufficient for the reliable recognition is described by two scalar values: the proportional component of the PI controller of the CM current K_P; and the integral component of the PI controller of the CM current K_I.

The discrete readings of the two-dimensional curve $[\{I\},\{V\}]$ are taken at the output of the observation model, where I is the CM current, and V is the shearer feed speed.

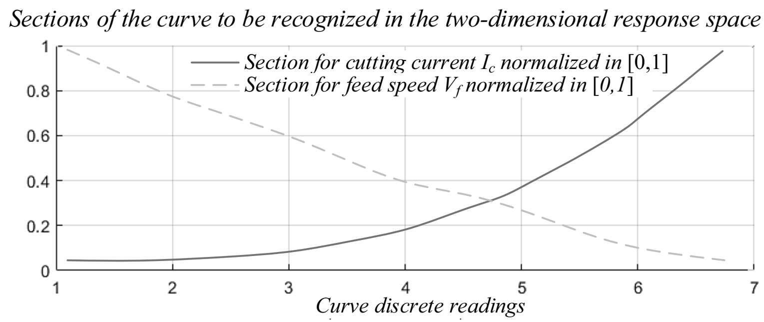

Fig. 4. Two sections of a fragment of a two-dimensional curve applied to the input of the recognition algorithm

The generation of a training sample consists in the sequential execution of the following steps:

1. Setting the conditions for the initial level of the surge $A = A_1$ and the initial values of the components of the PI controller of the CM current K_P^1 and K_I^1.

2. Starting the shearer operation simulation model.

3. Registration and recording in a two-dimensional array of implementations of the response curve $[\{I\}, \{V\}]_1$ for the surge A_1.

4. Consistent variation of the conditions of the shearer operation $[A_1,\ldots,A_n]$, $[K_P^1,\ldots,K_P^m]$, $[K_I^1,\ldots,K_I^k]$ with launching the operation simulation model and registering $M = nmk$ response curves in a three-dimensional array.

The recognition task consists in estimating the level of the surge A_i, $i = 1,\ldots,M$, based on a fragment (initial readings) of the two-dimensional curve $[\{I\},\{V\}]_i$, at the specified values of K_P^i and K_I^i.

The input vector of the training sample contains the first L readings of the recognized curve and, due to different ranges of the curve for current [1, 100] and speed [1, 10] s_i, is normalized to the interval $s_i^{norm} \in [0,1]$:

$$s_i^{norm} = \frac{s_i - s_{i,\min}}{s_{i,\max} - s_{i,\min}}(b-a)+a, \quad (4)$$

where a and b are the limits of the normalized range (a=0, b=1); $s_{i,\min}$ and $s_{i,\max}$ are the maximum and minimum values in the normalization interval.

The output variables of the training sample characterize a scalar value—the level of the surge in the coal resistance to cutting A, and therefore the normalization / denormalization of the output vectors is inexpedient.

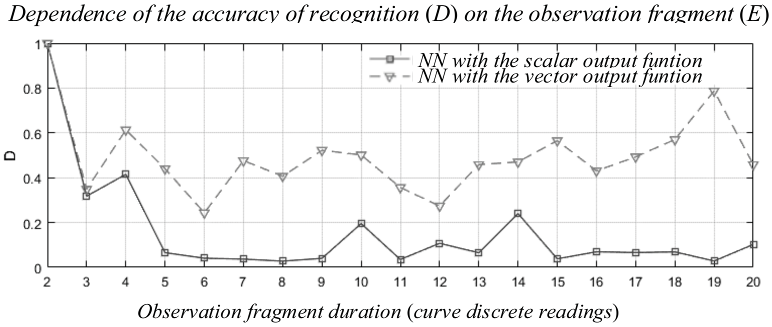

Fig. 5. Dependence of the accuracy of recognition of the current step type on the observation fragment duration

Consequently, it is possible to use a multilayer feed-forward neural network of two architectures. The first NN, with the so-called scalar output function, has the $\{L, X_1,\dots X_N\}$ architecture, where L is the size of the input layer, $X_1,\dots X_N$ are the sizes of the hidden layers, and the number of hidden layers is 1. The input signals will be the fragments of the section of the cutting current curve $\{S_1{}^1,S_{L1}{}^1\}$ and the fragments of the section of the shearer feed speed curve $\{S_1{}^2,S_{L2}{}^2\}$, and the output e_j consists of one neuron and corresponds to the type of the surge A. The second NN, with the so-called vector output function, has the $\{2L, X_1,\dots X_N\}$ architecture.

The input signals are identical to the first NN, and the number of output neurons corresponds to the number of possible values (variants) of A. The number of hidden layers is 2.

The weighted output values of $w_{ij}\cdot f(s_i)$ neurons are calculated in accordance with the expression below, taking into account the maximum number of layers:

$$c_j = f_j^{[3]}\left(\sum_{m=1}^{n_3} w_{mj}^{[3]}\left(f_m^{[2]}\left(\sum_{h=1}^{n_2} w_{hm}^{[2]}\left(f_h^{[1]}\left(\sum_{i=1}^{n_1} w_{ih}^{[1]} s_i\right)\right)\right)\right)\right), \; j=\overline{1,n_3}, \quad (5)$$

where n_2, n_3 are the numbers of neurons in hidden layers, n_3 is the number of neurons in distribution layer, s_i is the i-th input of the NN; w are the weighting coefficients for layers with indices i,h,m; f are activation functions for layers with indices h,m,j.

In experiments, all the transfer functions of neurons are identical:

$$f^{[s]}(x) = \frac{e^{\alpha^{[s]}x} - e^{-\alpha^{[s]}x}}{e^{\alpha^{[s]}x} + e^{-\alpha^{[s]}x}}, \quad (6)$$

where a is the parameter of the hyperbolic tangent slope; and x is the weighted sum of neuron inputs.

A quasi-Newtonian algorithm, or a second-order procedure including both the first-order and the second-order derivatives, has been chosen as the training algorithm for both NN architectures [17, 18].

Figure 5 shows the dependences of the accuracy of recognition of a surge in the coal resistance to cutting by two types of NNs (with the scalar and vector output functions) on the number of the first readings of the fragment of the curve used in the recognition process. In numerical experiments, from 10 to 1000 examples of a training sample have been used, in which the normalized values of the coal resistance to cutting A varied from 1 to 10 with a uniform pitch from 1 to 0.01.

The dependencies indicate a higher interference immunity of recognition when using NNs with a vector output function and the price to be paid for that is by an order more time-consuming and longer training.

An NN with a vector output function applies in the NN output layer a weighted code of the form

$$\underset{1,\ 2,\ \dots\ ,\ j,\ \dots\ ,M}{[-1,-1,\dots,1,\dots,-1]} \to C_j, j=\overline{1,M}. \quad (7)$$

In other words, the presence of a single level of the j-th neuron output signal in combination with the negative levels of other neurons in the target vector indicates the A_j-th surge in the coal resistance, where the number of a neuron with the maximum level output indicates the number of the desired curve template and, consequently, the desired level of surge A. With a large amount of samples, the NN with two hidden layers was used. The number of neurons of the first and second hidden layers was 85 and 35, respectively.

Conclusions

1. As a part of this work, in order to increase the control rate, it was proposed to use a PI controller with the coefficients adapting to the external operating conditions of the shearer in case of sudden changes in the load (coal resistance to cutting).

2. As a result of studying the methods for adjusting the PI controller coefficients, the possibility of using a feed-forward NN functioning as an operational tool for recognizing a multidimensional response curve in the control loop of the shearer controller parameters has been confirmed. To increase the noise immunity of recognition, a specialized NN architecture with a vector output function has been applied. The target training vectors of such NN are formed by a weighted code indicating the type of the recognized load surge (change in the coal resistance to cutting).

3. The approach proposed in the article can be employed for solving other applied problems with nonlinear controlled objects where the control algorithm needs to adapt to the changing state of the object. The results obtained are planned to be used to further improve the shearer load control system.

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INFLUENCE OF PICK BLUNTING ON HYDRAULIC BREAKER CAPACITY IN FRACTURE OF GRANITE BLOCKS

The necessary condition for the operation of crushers in the production of crushed granite is feeding of the crushers with granite fragments of a certain size. At the same time, granite fragmentation after blasting does not always meet the required size for the crushers and needs additional destruction by blasting or disintegration directly on site. Hydraulic breakers are most often used in disintegration of oversizes. For example, in quarries in Vietnam, JCB HM380 hydraulic breakers with a fracture energy of up to 2.5 kJ are widely used. The working tools of the hydraulic breakers are steel picks of various diameters and shapes. The operation of this tool is accompanied by its intensive wear due to the impact-abrasive action of rocks; the pointed part of the tool gets gradually blunted, which affects the rate of penetration of the pick in rock. In this regard, it is relevant to determine the influence exerted by the degree of wear of the pick on the performance of the hydraulic breaker, and to find out whether replacement or re-sharpening of the pick is expedient.

In this paper, based on the previously determined crack propagation velocity in granite and the impact time, the length of the fracture is calculated. The dimensions of a crack in a granite block are calculated depending on the degree of blunting of the pick at a certain number of blows per cycle. At the same time, the limiting value of a crack that causes chipping of a piece from rock mass was considered as the fracture length to free surface at different degrees of pick blunting. Based on these calculations, the average productivity and energy input of disintegration process were determined.

It is shown that for a tool with a completely worn tip, the decrease in the productivity and the increase in the energy input of fracture reach two times compared with a sharpened pick. In this regard, from the point of view of increasing the hydraulic breaker capacity, it is advisable to replace or re-sharpen the pick after complete wear of its tip.

Keywords: *hydraulic breaker pick, degree of blunting, capacity, granite, oversize crushing*
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Introduction

A considerable amount of a state budget comes from the mineral mining sector. For instance, according to [1], in the period between 2005 and 2018, the Vietnamese mining industry replenished the amount of the state treasury by 9.39% of GDP. To achieve gains, the mineral production needs advanced technologies, including high-performance machines and equipment [2–8], environmental mitigation [9–12], as well as process automation and digitalization [13, 14]. One of the fields that demands much mineral resources is construction, and the main construction material is crushed granite. Granite enjoys wide application in concrete manufacturing, in construction of roads, buildings and structures, etc. By estimates, granite reserves in quarries in Vietnam average 30 Bm^3.

One of the common methods of mineral mining remains drilling and blasting, and its efficiency largely depends on the drilling equipment and tools in operation [4, 15]. Yet, some operations require only the hammer blow (breaking of oversizes, chipping, etc.). The oversize breaking tool is prone to fast wear, which brings a big drop in productivity and a jump in expenses connected with new tool purchase. The service life extension of a tool is a relevant research issue which includes the tool re-designing, the use of new materials and their manufacturing techniques [16–25].

Granite quarries in Vietnam have a low capacity—around 300 thousand tons per year. Such poor performance is due to inaccessible transportation and low-productive crushing-and-screening plants. The maximum allowable size of material to be broken should never exceed 480 mm. In fragmentation by blasting, approximately 10–12% of fragments exceed the maximum