

# ЭЛЕКТРИФИКАЦИЯ И АВТОМАТИЗАЦИЯ ГОРНЫХ ПРЕДПРИЯТИЙ

---

DOI: 10.21440/0536-1028-2020-6-109-120

## Rating the speed of the shearer's electric motor drive load automatic control

Dmitrii M. Shprekher<sup>1\*</sup>, Gennadii I. Babokin<sup>2</sup>, Evgenii B. Kolesnikov<sup>3</sup>,  
Aleksandr V. Zelenkov<sup>1</sup>,

<sup>1</sup> Tula State University, Tula, Russia

<sup>2</sup> National University of Science and Technology MISIS, Moscow, Russia

<sup>3</sup> Novomoskovsk Institute (branch) of Dmitry Mendeleev University of Chemical Technology of Russia,  
Novomoskovsk, Russia

\*e-mail: shpreher-d@yandex.ru

### Abstract

**Introduction.** It is possible to improve productivity, effectiveness, and cost-efficiency of coal extraction due to the efficient use of physical resources, technical upgrade of mechanized longwall equipment, and introduction of advanced technologies and control methods. The existing method of shearer electric motor drive automation based on the automated load controller of Uran type has a significant drawback of low speed. In case the actuator (A) meets solid rock and the shearer's (S) speed is not changed, it may result in heavy shock loads on A and its transmission, therefore, increased wear of the cutter or machine's breakage, leading to production loss due to the reduced speed of travel along the face. The foregoing demands higher standards of the load controller's speed, making the task of improving the control system's development a relevant scientific task.

**Research aim** is to synthesize the neural tuner for the coefficients of the proportional-integral controller (PI controller) in the control system of a shearer with increased speed as compared to the existing standard controllers. The research also aims to estimate its efficiency by the method of mathematical simulation.

**Methodology.** Mathematical model has been developed which has made it possible to compare the performance of standard controllers with an adaptive PI controller. The structure and parameters of the neural network underlying the controller have been substantiated. The proposed controller was compared to the standard PI controller and to the MPC controller (microprocessor-based speed controller) by the method of simulation experiment.

**Research results.** The adaptive PI controller has been synthesized based on the neural network which allows changing the coefficients of the PI controller as soon as coal strength changes.

**Summary.** The simulation experiment has shown that the PI controller with the neural network tuner for its coefficients in the control system will make it possible to increase the load controller's speed by 1.5 to 3 times on average as compared to the classical controller. Therefore, it is going to be possible to avoid critical overload and breakage of mechanical parts in the shearer's transmission in case of the sudden contact of its actuator with solid inclusion.

**Key words:** shearer; PI controller; MPC controller; coal strength; modelling; neural network; speed.

**Introduction.** It is possible to improve productivity, effectiveness, and cost-efficiency of coal extraction due to the efficient use of physical resources, technical upgrade of mechanized longwall equipment, and introduction of advanced technologies and control methods.

Fig. 1 represents the block diagram of the shearer's (S) automated control [1].

The cutting drive includes an uncontrolled asynchronous electric motor M1 which rotates the actuator (A) equipped with cutters through the reducer. The feeding unit is the frequency-controlled asynchronous electric drive which consists in a frequency changer (FC) which feeds asynchronous motors (M2 and M3) activating propulsion devices D1 and D2 and the chainless feeder (CF). In order to provide full load of the cutting electric motor in the shearer's electric drive (ED) control system, the load controller (LC) is used. It is aimed at maintaining the cutting electric motor M1 nominal power by changing the shearer's travel speed along the face  $V_f$ . Cutting electric motors load is determined by the thickness of the chip cut by the screws and broken coal strength which changes in a rather wide range.

In the diagram in fig. 1 to the input of the LC from the comparison element, a mismatch signal  $e$  is supplied, equal to the difference between the reference cutting current  $i_r$  and its actual value  $i_c$ .

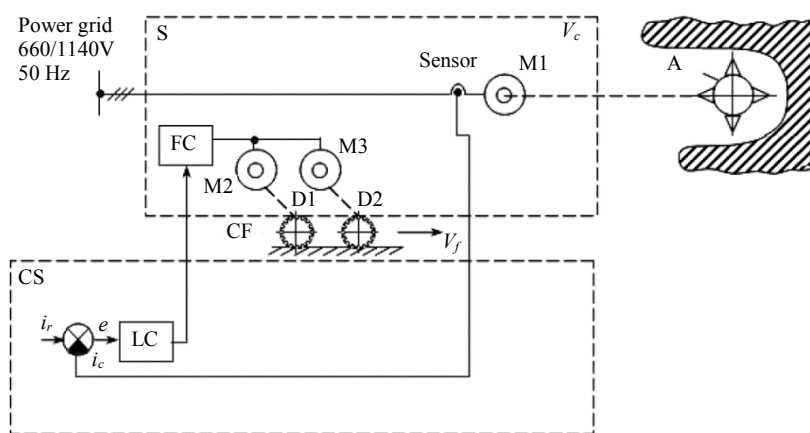


Fig. 1. Block diagram of the shearer's automated control  
Рис. 1. Структурная схема автоматического управления ОК

The existing method of shearer electric motor drive automation based on the automated load controller of Uran type [2] has a significant drawback of low speed. System's speed in this case is determined by the time of transition. It is a well-known fact that shearer drive load depends on the coal strength, solid inclusions, cutters blunting, etc. If the actuator (A) meets solid rock and the shearer's (S) feed speed is not changed, it may result in heavy shock loads on A and its transmission, therefore, causing increased wear of the cutter or machine's breakage, leading to production loss due to the reduced speed of travel along the face [3].

The foregoing demands higher standards of the speed of the load controller. So the task of developing an adaptive load controller of the shearer's electric drive ensuring maximum speed of the control system is a relevant scientific task.

**Analysis of literature on the subject.** Scientific publications of native and foreign scientists are dedicated to problems in the field of shearer's operation modes automation. Work [4] described the study of the shearer with the remote feed system based on the slip coupling; research [5] investigated into the problems of dynamics and optimization of carrying system parameters of the shearers under random load; [6, 7] made an attempt of predicting the load acting on the drive of the cutter-loader. Works [8, 9] engineered the devices for coal shearers automated control. Works [10, 11] were dedicated to the problem of controlling complex technical objects by building their mathematical models which further determined the algorithm of control. [12] resulted

in the suggestion to use smart controllers in the shearer's control system based on fuzzy logic and neural networks (NN). [13] made some attempts in realizing the control by smart controllers with fuzzy logic, while [14] tried to do it with standard neural controller Matlab. However, all works considered the shearer in a simplified way, by one or several dynamical elements the coefficients of which were constant. In reality, it is a complex object with a large number of nonlinearities.

**Research aim** is to synthesize the neural tuner, which will solve the problem of the input data generalization and provide the optimal, earlier obtained by the expert, coefficients of the PI controller in the conditions of changing controlled object parameters in order to ensure the required quality of transition.

**Subject matter. Control systems with classical PI controllers.** The majority of industrial controllers apply the PI algorithm. They are so popular due to simple design, ease of use, clear functioning, ability to solve the majority of practical tasks, and low cost [15].

**Table 1. Parameters of PI controller coefficients at various values of coal resistance to cutting**

**Таблица 1. Параметры коэффициентов ПИ-регулятора при различных значениях сопротивления угля резанию**

Coal resistance to cutting, N/mm	Proportional coefficient $K_p$	Integral coefficient $K_I$
150–300	0.45	3.8
300–350	0.36	3.2
350–400	0.32	2.8
400–450	0.3	2.6
450–500	0.28	2.4
500–550	0.25	2.2
550–600	0.23	2.0
600–650	0.22	1.8
650–700	0.21	1.7
700–750	0.2	1.6
750–800	0.19	1.45
800–850	0.185	1.4
850–900	0.175	1.35
900–950	0.172	1.32
950–1000	0.169	1.26

PI controller uses current and past data on the error of control to manage the system with a feedback; proportional coefficient is responsible for the current information; integral coefficient answers for past information storage and further accounting [16]. PI controller continuously computes error  $e(t)$ , which represents the difference of the signal (setpoint)  $r(t)$  and the measured output of the system  $y(t)$ , and forms the control action  $u(t)$  for the system based on the proportional  $P$  and integral  $I$  items  $e(t)$ . Mathematically it is written as follows:

$$u(t) = K_p e(t) + K_I \int_0^t e(\tau) d\tau, \quad (1)$$

where  $K_p$  and  $K_I$  are proportional and integral coefficients.

For variations in coal resistance to cutting with the help of the Ziegler–Nichols method, the PI controller was tuned by the criterion of transition minimum time. The results are presented in table 1.

The analysis of the table showed that the PI controller allowable for a particular mode is unfitted for the other mode. PI controller's coefficients therefore should possess parameters which drift over time, and due to that once tuned PI controller won't be able to reach the aim of control in the process of the controlled object (CO) operation. As a result, constant tuning of PI controller's coefficients is required [17].

Besides, the majority of real controlled objects have nonlinear characteristics which change in the process of operation, while they are overwhelmingly controlled by linear PI controllers. The coefficients of such controllers are often selected especially for the particular state of the object. However, in case the object transfers into other states (for instance, change in coal strength or shearer's actuator contact with solid inclusion) these values of the coefficients no longer make for obtaining the required quality of transitions. The foregoing results in the reduced quality of control [18], speed reduction and increased dynamic load in transmission.

**Model predictive control (MPC).** This method consists in searching for an optimal control in the bounded interval.

The main aim the model predictive control may be pictured as follows: there is control input of the object  $u(t)$  and the output controlled variable  $y(t)$ , and  $r(t)$  is the desired amount (dependence) of the controlled variable change.

The gist of the method is to find some sequence of the controlled variable values  $u(t)$ , which will make it possible to ensure the best trajectory for the controlled variable  $y(t)$ . Estimated control actions sequence length  $u(t)$  is a fixed quantity called the control horizon. The desired sequence of control action values is found as a result of a particular optimization problem.

The following objective functional is used for optimization [19]. The functional contains the quadrature misalignment between the predicted output variable of the controlled object  $y(t)$  and the desired trajectory  $r(t)$ . When selecting optimal values of the controlled variable  $u(t)$  the controller aims at minimizing the functional which is presented by the expression

$$J = \sum_{i=k}^{k+he} [r(i) - y(i)]^2 + \sum_{i=k}^{k+hu} [u(i) - u(k)]^2,$$

where  $k = 1, 2, \dots, \infty$ ;  $he$  is the number of steps in the prediction of the controlled variable  $y(t)$  behavior (prediction horizon);  $hu$  is the length of control action future values sequence  $u(t)$  (control horizon).

After the computed optimal control action  $u(t)$  is fed to the controlled object, at the next step the whole procedure is repeated again with the account of new information received.

**Adaptive controller based on the neural network.** Artificial neural networks (ANN) can be used in various configurations in control. It is connected with the fact that NN possess nonlinear properties and the ability to learn which gives adaptive properties to neural control systems.

Adaptive two-level circuits are of a great interest [20] with a base PI controller at the lower level and a tuner which coordinates the operation of the base controller at the upper level.

A block diagram of such control is shown in fig. 2.

Let us transform the continuous PI controller described by equation (1) into a discrete form by substituting an integration operator for a finite sum [18]. Then

$$u(k) = K_p e(k) + K_i \sum_{j=0}^k e(j),$$

where  $k$  is a time step (simulation step),  $e(k)$  is a control error in discrete time,  $u(k)$  is a control signal in discrete time.

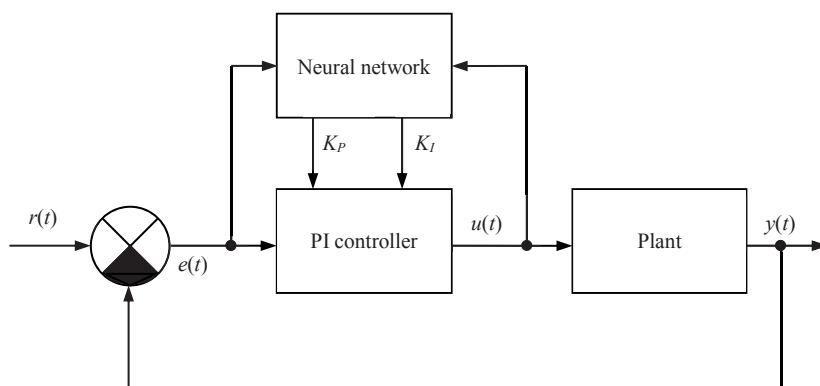


Fig. 2. Block scheme of the adaptive tuner for PI controller's coefficients based on NN

Рис. 2. Структурная схема адаптивного настройщика коэффициентов ПИ-регулятора на базе НС

Then control signal correction (change) is

$$\Delta u(k) = K_p [e(k) - e(k-1)] + K_i e(k).$$

At the same time  $\Delta u(k) = u(k) - u(k-1)$ . Then

$$u(k) - u(k-1) = K_p [e(k) - e(k-1)] + K_i e(k),$$

and

$$u(k) = K_p (e(k) - e(k-1)) + K_i e(k) + u(k-1). \quad (2)$$

In other words, PI controller, according to (2), has to actually have some information on mismatch in real time, mismatch at the moment a step back, and on the control signal a step back. Consequently, NN under consideration must have 3 inlets and 2 outlets (fig. 3). Inlets are selected working conditions of the system; coefficients  $K_p$  and  $K_i$  of the PI controller are the outlets.

The neurons number of the NN shown in fig. 3 equals correspondingly to:  $j$  – for an input layer,  $i$  – for an inner layer and  $l$  – for an output layer.

Inner layer neurons behavior is described by the following equations [20]:

$$O_u^{(2)} = f(net^{(2)}); \quad net_i^{(2)} = \sum_1^j w_{ij}^{(2)} O_j^{(1)}.$$

Similarly, for the neurons of the output layer we obtain

$$O_l^{(3)} = f_l(\text{net}_l^{(3)}), l = 1, 2; \quad \text{net}_l^{(3)} = \sum_i w_{li}^{(3)} O_i^{(2)},$$

where  $O_j$ ,  $O_i$  and  $O_l$  are the output values of the input, buried and output layers correspondingly;  $w_{li}$  – connection strength between the  $i$ -element of the buried layer and  $l$ -element of the output layer;  $w_{ij}$  – connection strength between the  $j$ -element of the input layer and the  $i$ -element of the buried layer;  $\text{net}_i$ ,  $\text{net}_l$  – weighted sum of buried and output layers correspondingly;  $f_i$  and  $f_l$  are the activation function of the buried and output layers correspondingly.

For the buried layer, let us accept the sigmoid activation function  $f(\text{net}_i^{(2)}) = \frac{1}{1 + e^{-\text{net}_i}}$ , and for the output layer – linear function  $f(\text{net}_l^{(3)}) = \text{net}_l$ .

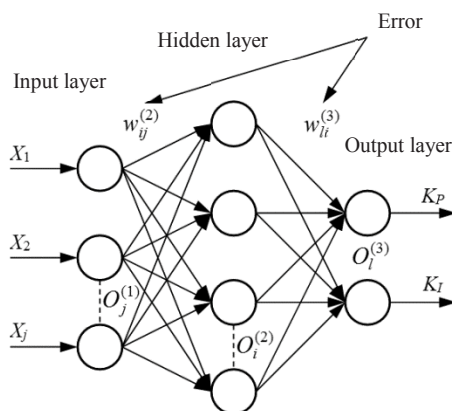


Fig. 3. The structure of the neural network applied to tune the PI controller's coefficients  
Рис. 3. Структура нейронной сети, применяемой для настройки коэффициентов ПИ-регулятора

Neural network was trained with the help of Levenberg–Marquardt algorithm [21]. NN was trained with the help of this method to obtain the minimization of the objective function  $E$  which is generally a mean-square error calculated in the output layer of the network as a half of the sum of differences of desired and actual outputs of output layer elements squared:

$$E(w) = \frac{1}{2} \sum_{i=1}^M [e_i(w)]^2 = \sum_{i=1}^M [d_i - y_i]^2 \rightarrow \min,$$

where  $e_i(w)$  is a function of NN error across the training set,  $d_i$  – the desired output of the  $i$ -element of the output layer;  $y_i$  – the actual output of the  $i$ -element of the output layer, and  $M$  is the number of the inlets.

This method of training was implemented in Matlab software according to the recommendations of work [22]. For the designed network the number of neurons of the buried layer is accepted as equal to 20.

Mathematical model of the shearer as a control object and its full description are presented in [11, 12].

In the course of NN training, material resistance to cutting was simulated by Random Sourcer block which generated evenly distributed random numbers within the range of

250 to 1000 N/mm with an interval of 2 s. Additionally a program has been implemented which compares strength values and proportional and integral coefficients of the PI controller obtained earlier for each discrete strength value. Intermediate coefficients of the controller were calculated by spline interpolation implemented in Matlab Function block.

In order to test the comparative analysis of three options of controllers in the shearer's control system, i.e. the PI controller with constant coefficients, the MPC controller and the PI controller with the neural tuner for its coefficients, a simulation model has been worked out implemented in Simulink and represented in fig. 4.

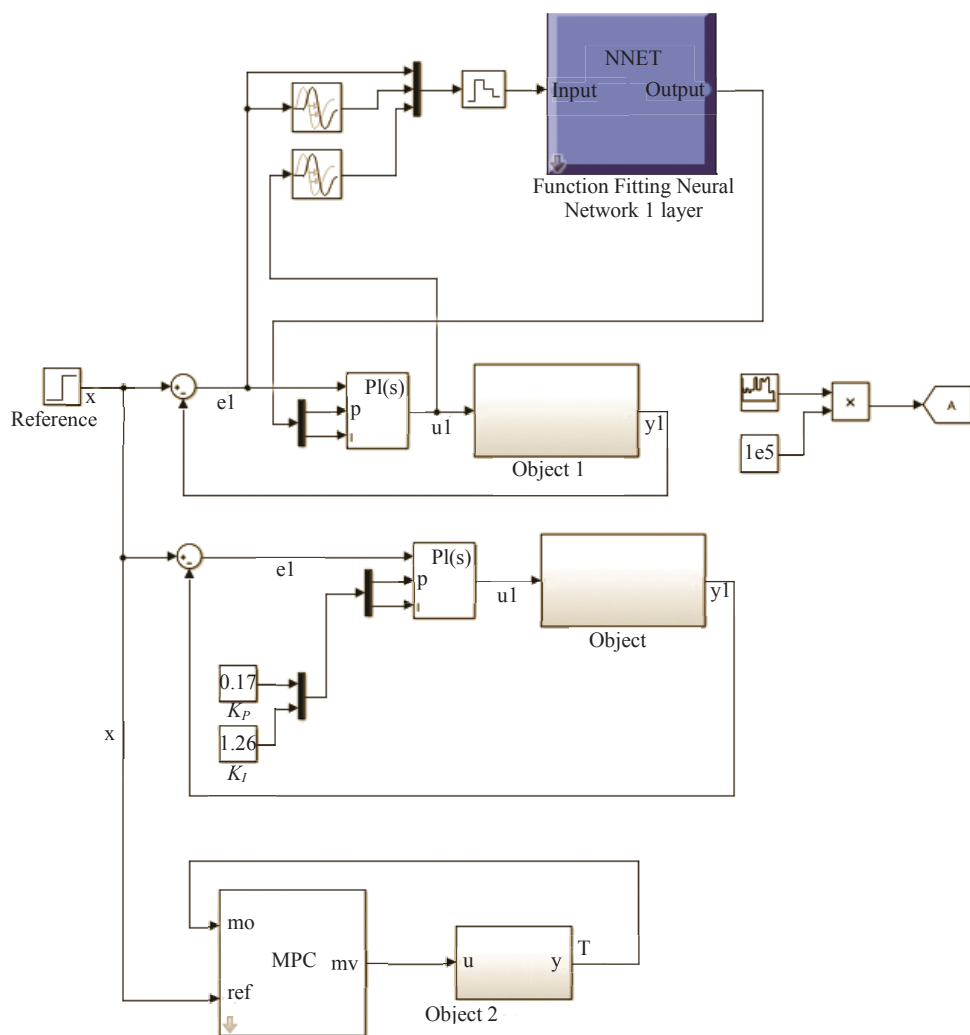


Fig. 4. Simulation model of CS comparison  
Рис. 4. Имитационная модель сравнения систем управления

Fig. 5 presents simulation results. It can be seen from graphs *b* and *c* of fig. 5 that as soon as coal strength changes within 150–450 N/mm, the speed of a typical PI controller has made up 0.97 s with load on and 1.4 s with load-off; as soon as coal strength changes within 400–800 N/mm, the speed of a typical PI controller has made up 0.66 s with load on and 1.25 s with load-off.

MPC controller as compared to typical PI controller does not significantly affect the time of transition, but increases the variability of feed rate in transient modes.

As soon as coal strength changes within 150–450 N/mm, the speed of the PI controller with the neural tuner made up 0.37 s with load-on and load-off; as soon as coal strength changes within 400–800 N/mm, the speed made up 0.43 s with load-on and load-off.

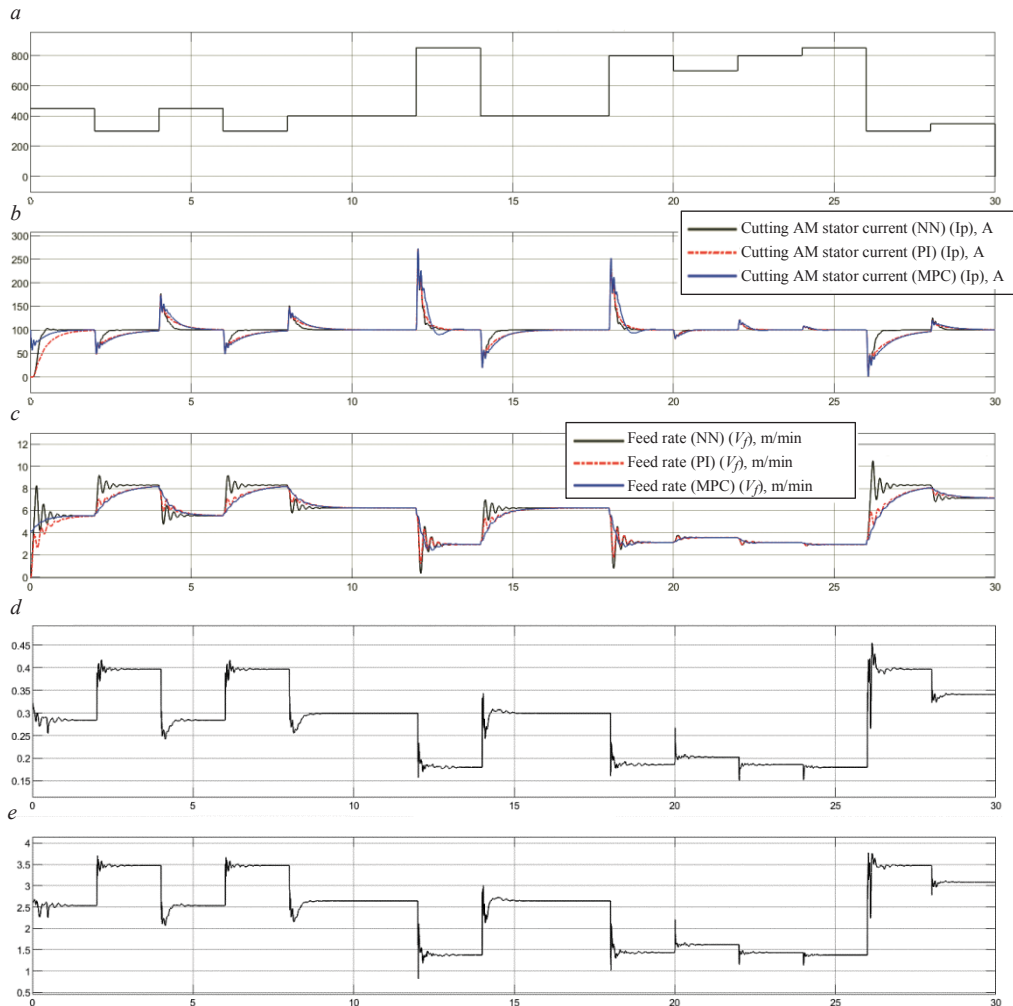


Fig. 5. The results of comparing the classical PI controller and the controller with the neural tuner of its coefficients:

$a$  – material resistance to cutting ( $A$ ), N/mm;  $b$  – cutting AM stator current ( $I_p$ ), A;  $c$  – feed rate  $V_f$ , m/min;  $d$  – proportional coefficient  $K_p$ ;  $e$  – integral coefficient  $K_i$

Рис. 5. Результаты сравнения работы классического ПИ-регулятора и регулятора с нейросетевым настройщиком его коэффициентов:

$a$  – сопротивляемость материала резанию ( $A$ ), Н/мм;  $b$  – ток статора АД резания ( $I_p$ ), А;  $c$  – скорость подачи  $V_f$ , м/мин;  $d$  – пропорциональный коэффициент  $K_p$ ;  $e$  – интегральный коэффициент  $K_i$

It can be seen from graphs  $d$  and  $e$  of fig. 5 that the coefficients of the PI controller which provide the required quality of transition change significantly depending on load variation (coal strength). It is also apparent that their behavior is significantly nonlinear, and it justifies the use of NN to tune the coefficients of PI controller under variable parameters of the control system.

So, the application of the PI controller with the neural tuner will make it possible to significantly improve the speed of the load controller by 1.5 to 3 times on average, thus



ensuring the reduction of dynamic load in the shearer's transmission when working at solid inclusions and during possible arrest of an actuator, increase in the time of the cutting electromotor nominal operation mode and so improve the shearer's reliability and capacity.

**Summary.** Within the framework of this research it has been proposed to apply the PI controller the coefficients of which will adapt to the outer conditions of the shearer's operation under sudden load change (coal strength) in order to improve the speed of the control system. Correct operation of the synthesized controller was checked with the help of computer simulation.

The quality of transition under the operation of three controllers has been compared: classical PI controller with constant coefficients, MPC controller, and adaptive PI controller with neural tuner of its coefficients.

PI controller with neural tuner has shown the best result which will make it possible to improve the speed of the load controller by 1.5 to 3 times on average as compared to the classical controller, and consequently, eliminate critical overloads and possible breakage of mechanical parts in the shearer's transmission in case of its actuator's sudden contact with a solid inclusion.

The proposed approach may be used when solving other practical tasks as well, where the controlled object is nonlinear and the control algorithm has to adapt to changing state of the object. The obtained results are meant to be further used to improve shearer's control system.

#### REFERENCES

1. Babokin G. I., Gnatiuk T. A. Estimating the robustness of shearer electric motor drive control system for various load tuners. *Izvestiia Tulskogo gosudarstvennogo universiteta. Tekhnicheskie nauki = Proceedings of the Tula State University. Engineering Sciences*. 2013; 2: 10–15. (In Russ.)
2. Starikov B. Ia., Azarkh V. L., Rabinovich Z. M. *Asynchronous electric drive of shearers*. Moscow: Nedra Publishing; 1981. (In Russ.)
3. Liu C., Qin D., Liao Y. Electromechanical dynamic analysis for the drum driving system of the long-wall shearer. *Advances in Mechanical Engineering*. 7(10): 2015.
4. Dubinin S. V. *Reducing dynamic load and increasing the efficiency of shearer remote feed: abstract of PhD in Engineering diss.* Donetsk; 1991. (In Russ.)
5. Boiko N. G. *Optimizing the parameters of shearer carrying systems*. Donetsk: DonSTU Publishing; 2012. (In Russ.)
6. Gorbatov P. A., Perinskii M. V. Mathematical models predicting maximum loads in the subsystems of shearer drive based on simulation modeling. In: *Mechatronic mining equipment – 2010: Proceedings of International Science and Technology Conference*. Donetsk: DonSTU Publishing; 2010. p. 25–34. (In Russ.)
7. Zubarev S. G. Improving the system of coal shearer feed by predicting the load. *Tekhnologicheskii audit i rezervy proizvodstva = Technology Audit and Production Reserves*. 2014; 6; 4(20): 17–20.
8. Ivanov A. S. *Developing the nonlinear system of mining machine cutting electric motor drive load control system: PhD in Engineering diss.* Novokuznetsk: 2010. (In Russ.)
9. Kolesnikov E. B. *Developing and studying the feed mechanism of the shearer with variable-frequency drive: abstract PhD in Engineering diss.* Moscow: 1996. (In Russ.)
10. Tkachev V. V., Bublikov A. V. *Using simulation modeling to investigate the automatic control system of the cutter-loader*. Dnepropetrovsk: Dnipro University of Technology Publishing; 2015. (In Russ.)
11. Babokin G. I., Shprekher D. M., Kolesnikov E. B. Mathematical modeling of electric drive of the coal combine with the built-in system of movement. *Izvestiia Tulskogo gosudarstvennogo universiteta. Tekhnicheskie nauki = Proceedings of the Tula State University. Engineering Sciences*. 2019; 3: 645–651. (In Russ.)
12. Shprekher D. M., Babokin G. I., Kolesnikov E. B., Zelenkov A. V. Study loading dynamics for adjustable electric drive of shearer loader. *Izvestiia Tulskogo gosudarstvennogo universiteta. Tekhnicheskie nauki = Proceedings of the Tula State University. Engineering Sciences*. 2020; 2: 514–525. (In Russ.)
13. ZhaoYi-Hui. Constant power automatic control system of electric haulage shearer based on fuzzy control. *Coal Mine Electromechanical*. 2012; 12: 41–43.
14. Zhou Yuan-Hua, Ma Hong-Wei, Wu Hai-Yan, Zhao You-Jun. Constant cutting-power control of shearer based on neural network model predictive control. *Switzerland. Trans. Tech. Publication*. 2013; 823: 340–344.
15. Åström K. J. and Hagglund T. *Advanced PID Control*. ISA, Boston, 2006.
16. Kiam Heong Ang, G. Chong, and Yun Li. *PID control system analysis, design, and technology*. 2005; 13: 559–576.

17. Aleksandrov A. G., Palenov M. V. Adaptive PID controllers: state-of-the-art and future developments. *Avtomatika i telemekhanika = Automation and Remote Control*. 2014; 2: 16–30. (In Russ.)
18. Eremenko Iu. I., Poleshchenko D. A., Glushchenko A. I., Iarmurati D. Iu. On PID controller intellectual adaptation parameters to reduce control process energy usage. In: *Scientific Gazette. Ser. History. Political science. Economics. Information science*. 2013; 22(165); 28: 210–217. (In Russ.)
19. Nadezhdin I. S., Goriunov A. G., Manenti F. Control systems of a non-stationary plant based on MPC and PID type fuzzy logic controller. *Upravlenie bolshimi sistemami = Analysis and Synthesis of Control Systems*. 2018; 75: 50–75. (In Russ.)
20. Zhenyu Jia, Kim Byeongwoo. Direct torque control with adaptive PI speed controller based on neural network for PMSM drives. *International Conference on Electrical Engineering, Control and Robotics*. Chengdu, China, January 12–14, 2018. doi.org/10.1051/mateconf/201816002011
21. Osovskii S. *Neural networks for data processing: translation from Polish*. Moscow: Finansy i statistika Publishing; 2002. (In Russ.)
22. Medvedev V. S., Potemkin V. G. (ed.) *Neural networks. Matlab 6*. Moscow: Dialog-MIFI Publishing; 2001. (In Russ.)

Received 25 May 2020

**Information about authors:**

**Dmitrii M. Shprekher** – DSc (Engineering), Associate Professor, professor of the Department of Electrical Engineering and Electrical Equipment, Tula State University. E-mail: shprekher-d@yandex.ru

**Gennadii I. Babokin** – DSc (Engineering), Professor, professor of the Department of Energy Industry and Energy Efficiency, Mining Institute of the National University of Science and Technology MISiS. E-mail: babokinginov@yandex.ru

**Evgenii B. Kolesnikov** – PhD (Engineering), Associate Professor, associate professor of Industrial Power Supply Department, Novomoskovsk Institute (branch) of Dmitry Mendeleev University of Chemical Technology of Russia. E-mail: kolesnikov55@mail.ru

**Aleksandr V. Zelenkov** – PhD student, Department of Electrical Engineering and Electrical Equipment, Tula State University. E-mail: sashazelnkv@mail.ru

УДК 62-83-52.001.5;075.8

DOI: 10.21440/0536-1028-2020-6-109-120

**Оценка быстродействия системы автоматического регулирования нагрузки электропривода очистного комбайна****Шпрекхер Д. М.<sup>1</sup>, Бабокин Г. И.<sup>2</sup>, Колесников Е. Б.<sup>3</sup>, Зеленков А. В.<sup>1</sup>**<sup>1</sup> Тульский государственный университет, Тула, Россия.<sup>2</sup> Национальный исследовательский технологический университет «МИСиС», Москва, Россия.<sup>3</sup> Новомосковский филиал (институт) Российского химико-технологического университета, Новомосковск, Россия.**Реферат**

**Введение.** Эффективное использование материальных ресурсов, техническое перевооружение очистных механизированных комплексов, внедрение прогрессивных технологий и способов управления дают возможность повысить производительность, эффективность и экономичность выемки угля. Существующий способ автоматизации электропривода горных комбайнов, основанный на автоматическом регуляторе нагрузки типа «Уран» обладает существенным недостатком, заключающимся в низком быстродействии. В случае, если исполнительный орган (ИО) встретит твердую породу и скорость подачи очистного комбайна (ОК) не будет быстро изменена, это может привести к большим ударным нагрузкам на ИО и его трансмиссию. Как следствие, повышенный износ режущего инструмента или поломка комбайна, а значит, потеря добычи за счет уменьшения скорости перемещения вдоль линии забоя. Изложенное предъявляет повышенные требования к быстродействию регулятора нагрузки. Поэтому повышение эффективности разработки его системы управления является актуальной научной задачей.

**Цель работы.** Синтез нейросетевого корректора коэффициентов пропорционально-интегрального регулятора (ПИ-регулятора) в системе управления ОК, обладающего повышенным быстродействием по сравнению с существующими типовыми регуляторами, и оценка его эффективности методом математического моделирования.

**Методология.** Разработана имитационная математическая модель, позволяющая сравнить результаты работы типовых регуляторов и адаптивного ПИ-регулятора, обоснована структура и параметры нейронной сети, которая лежит в основе такого регулятора. Проведено сравнение методом модельного эксперимента предложенного регулятора с типовым ПИ-регулятором и МРС-регулятором (микропроцессорный регулятор скорости).

**Результаты.** Синтезирован адаптивный ПИ-регулятор, в основе которого лежит нейронная сеть, позволяющая изменять коэффициенты ПИ-регулятора при изменении такого параметра, как крепость угля.

**Выводы.** Модельный эксперимент показал, что ПИ-регулятор с нейросетевым подстройщиком его коэффициентов в системе управления позволит повысить быстродействие регулятора нагрузки в среднем от 1,5 до 3 раз по сравнению с классическим регулятором, а значит, избежать критических перегрузок и возможной поломки механических частей в трансмиссии ОК при внезапной встрече его ИО с твердым включением.

**Ключевые слова:** очистной комбайн; ПИ-регулятор; MPC-регулятор; крепость угля; моделирование; нейронная сеть; быстродействие.

#### БИБЛИОГРАФИЧЕСКИЙ СПИСОК

1. Бабокин Г. И., Гнатюк Т. А. Оценка робастности системы управления электроприводом комбайна для различных регуляторов нагрузки // Известия Тульского государственного университета. Технические науки. 2013. № 2. С. 10–15.
2. Стариков Б. Я., Азарх В. Л., Рабинович З. М. Асинхронный электропривод очистных комбайнов. М.: Недра, 1981. 281 с.
3. Liu C., Qin D., Liao Y. Electromechanical dynamic analysis for the drum driving system of the long-wall shearer // Advances in Mechanical Engineering. Vol. 7. Issue 10. 2015. P. 1–14
4. Дубинин С. В. Снижение динамических нагрузок и повышение эффективности вынесенной системы подачи очистного комбайна: автореф. дис. ... канд. техн. наук. Донецк, 1991. 209 с.
5. Бойко Н. Г. Оптимизация параметров силовых систем очистных комбайнов. Донецк: ДонНТУ, 2012. 214 с.
6. Горбатов П. А., Перинский М. В. Математические модели для прогнозирования максимальных нагрузок в подсистемах привода очистных комбайнов на основе имитационного моделирования // Мехатронное горное оборудование – 2010: науч. тр. междунар. науч.-техн. конф. Донецк: ДонНТУ, 2010. С. 25–34.
7. Зубарев С. Г. Совершенствование системы подачи угольного комбайна путем прогнозирования нагрузки // Технологический аудит и резервы производства. 2014. Т. 6. № 4(20). С. 17–20.
8. Иванов А. С. Разработка нелинейной системы управления нагрузкой электропривода резания проходческого комбайна: дис. ... канд. техн. наук. Новокузнецк, 2010. 160 с.
9. Колесников Е. Б. Разработка и исследование механизма подачи очистного комбайна с частотно-регулируемым электроприводом: автореф. дис. ... канд. техн. наук. Москва, 1996. 20 с.
10. Ткачев В. В., Бубликов А. В. Использование имитационного моделирования для исследования системы автоматического управления добычным комбайном. Днепропетровск: НГУ. 2015. 182 с.
11. Бабокин Г. И., Шпрехер Д. М., Колесников Е. Б. Математическое моделирование электропривода очистного комбайна с встроенной системой перемещения // Известия Тульского государственного университета. Технические науки. 2019. № 3. С. 645–651.
12. Шпрехер Д. М., Бабокин Г. И., Колесников Е. Б., Зеленков А. В. Исследование динамики нагружения регулируемого электропривода очистного комбайна // Известия Тульского государственного университета. Технические науки. 2020. № 2. С. 514–525.
13. Zhao Yi-Hui. Constant power automatic control system of electric haulage shearer based on fuzzy control // Coal Mine Electromechanical. 2012. Vol. 12. P. 41–43.
14. Zhou Yuan-Hua, Ma Hong-Wei, Wu Hai-Yan, Zhao You-Jun. Constant cutting-power control of shearer based on neural network model predictive control // Switzerland. Trans. Tech. Publication. 2013. Vol. 823. P. 340–344.
15. Åström K. J. and Hagglund T. Advanced PID Control. ISA, Boston, 2006.
16. Kiam Heong Ang, G. Chong, and Yun Li. PID control system analysis, design, and technology. 2005. No. 13. P. 559–576.
17. Александров А. Г., Паленов М. В. Состояние и перспективы развития адаптивных ПИД-регуляторов // Автоматика и телемеханика. 2014. № 2. С. 16–30
18. Еременко Ю. И., Полещенко Д. А., Глущенко А. И., Ярмуратий Д. Ю. Об интеллектуальной адаптации параметров ПИД-регулятора для снижения энергопотребления управляемого процесса // Научные ведомости. Сер. История. Политология. Экономика. Информатика. 2013. № 22(165). Вып. 28. С. 210–217.
19. Надеждин И. С., Горюнов А. Г., Маненти Ф. Системы управления нестационарным объектом на основе MPC-регулятора и ПИД-регулятора с нечеткой логикой // Управление большими системами. 2018. Вып. 75. С. 50–75.
20. Zhenyu Jia, Kim Byeongwoo. Direct torque control with adaptive PI speed controller based on neural network for PMSM drives // International Conference on Electrical Engineering, Control and Robotics. Chengdu, China, January 12–14, 2018. doi.org/10.1051/mateconf/201816002011
21. Осовский С. Нейронные сети для обработки информации: пер. с польского. М.: Финансы и статистика, 2002. 344 с.
22. Медведев В. С., Потемкин В. Г. Нейронные сети. Matlab 6: под общ. ред. В. Г. Потемкина. М.: Диалог-МИФИ, 2001. 630 с.

**Сведения об авторах:**

**Шпрехер Дмитрий Маркович** – доктор технических наук, доцент, профессор кафедры электротехники и электрооборудования Тульского государственного университета. E-mail: shpreher-d@yandex.ru

**Бабокин Геннадий Иванович** – доктор технических наук, профессор, профессор кафедры энергетики и энергоэффективности Горного института Национального исследовательского технологического университета «МИСиС». E-mail: babokinginov@yandex.ru

**Колесников Евгений Борисович** – кандидат технических наук, доцент, доцент кафедры электроснабжения промышленных предприятий Новомосковского филиала (института) Российского химико-технологического университета им. Д. И. Менделеева. E-mail: kolesnikov55@mail.ru

**Зеленков Александр Вадимович** – аспирант кафедры электротехники и электрооборудования Тульского государственного университета. E-mail: sashazelinkv@mail.ru

**Для цитирования:** Шпрехер Д. М., Бабокин Г. И., Колесников Е. Б., Зеленков А. В. Оценка быстродействия системы автоматического регулирования нагрузки электропривода очистного комбайна // Известия вузов. Горный журнал. 2020. № 6. С. 109–120 (In Eng.). DOI: 10.21440/0536-1028-2020-6-109-120

**For citation:** Shprekher D. M., Babokin G. I., Kolesnikov E. B., Zelenkov A. V. Rating the speed of the shearer's electric motor drive load automatic control. *Izvestiya vysshikh uchebnykh zavedenii. Gornyi zhurnal = News of the Higher Institutions. Mining Journal*. 2020; 6: 109–120. DOI: 10.21440/0536-1028-2020-6-109-120