New Method for Adjusting Coefficients PI Controller in the Load Control System of the Shearer

D M Shprekher¹, A V Zelenkov²

¹Department of Electrical Engineering and Electrical Equipment, Tula State University, Tula, Russia
²Department of Electrical Engineering and Electrical Equipment, Tula State University, Tula, Russia

E-mail: shpreher-d@yandex.ru, sashazelnkv@mail.ru

Abstract. The paper proposes a method using extrapolator models to predict the parameters of the PI controller. With a sudden change in the resistance of coal to cutting, in particular, at different levels of steps and their combinations, the speed of the cutting current controller and current steps also differ, the quieting time of the transient process also occurs in different times. To implement the adjustment of the coefficients of the PI controller, a feed forward artificial neural network is used, which acts as an operational means of recognizing a multidimensional response curve in the control loop. Neural networks of two architectures were used: with a scalar and vector output function. The recognition result is the estimated level of the step in the coal's resistance to cutting based on the initial counts of the multidimensional response curve at the specified coefficients of the PI controller. The approach proposed in the article can be used in solving other applied problems in which the control object is nonlinear and the control algorithm needs to adapt to the changing unobservable effect on the object.

1. Introduction

The underground method of coal mining is currently focused on the use of mechanized mining complexes, in which the shearer performs the main function - cutting coal and loading it onto the face conveyor. The efficiency and economy of underground coal mining, as well as its safety, depend on the degree of automation of the shearer's operation.

A shearer is a complex electromechanical object consisting of two interacting electromechanical systems: a movement drive and a cutting drive. The movement drive is designed to move the shearer during operation with the required traction (push) force, as well as to move during various shunting operations and, in turn, consists of a movement induction motor, a movement transmission and external or integrated movement mechanisms. The cutting drive contains a cutting induction motor, a cutting transmission and an executive body of a screw or drum type, which, while rotating, cuts into the coal face and carries out its destruction. Thus, the connection of the power and electrical parameters of the cutting drive and the movement drive the shearer when the rock mass is destroyed is carried out through the coal face. At the same time, a moment of resistance to the rotation of the auger (moment of resistance to cutting) acts on the executive body of the shearer from the side of the coal massif; and on
the shearer - the force of resistance to the movement of the shearer. The equations of the mathematical model describing the joint operation of the shearer drives are given in [1].

The only used means for the automation of shearsers with a hydraulic movement drive should include automatic load controllers of the “Uran” type [2], operating according to a program previously established by the operator.

However, this method of automation of the shearer's electric drive has a significant drawback, which is low speed. And in the event that the executive body encounters hard rock and the speed of movement of the shearer is not quickly reduced, this can lead to large shock loads on the executive body and its transmission. As a result, increased wear of the cutting tool or breakdown of the shearer, which means the loss of production due to a decrease in the speed of movement along the coal face line. Thus, the cutting drive is one of the weakest, from the point of view of reliability, parts of the shearer [3].

Recently, the hydraulic travel drive of the shearer is increasingly being replaced by a variable frequency drive, in which the travel speed is controlled by a frequency converter, which supplies power to the drive motor of the movement of the shearer. By controlling the signal at the input of the inverter, it is possible to regulate the angular speed and moment of the output shaft of the movement drive and, therefore, to regulate the speed and force of movement of the shearer.

The main function of a modern automatic load controller is to optimize the shearer's operating mode while ensuring maximum productivity and avoiding dangerous overloads of electric drives of movement and cutting.

The tendency of recent years is to increase the length of the working faces up to 300-400 m and the power of the electric motors in the drives of the shearsers. This means an increase in the mass of the shearer, and, as a consequence, an increase in the time of the transient process when controlling its electric drive of movement, which means that the dynamic loads on the drive of the shearer increase when exposed to external disturbances in the form of a sudden change in the cutting resistance of the rock mass (A). The above increases the requirements for the speed of the load controllers. Therefore, in connection with the need to improve the reliability and productivity of the shearer's operation, increasing the efficiency of developing its control system is an urgent scientific task.

Works of domestic and foreign scientists are devoted to issues in the field of automation of shearer operating modes. For example, in [4], research was conducted about shearer with an external movement system based on a sliding coupling, in [5], the dynamics and optimization of parameters of power systems of shearsers under the influence of random load were studied, and in [6, 7], an attempt was made to predict the load acting on the shearer drive. In [8, 9], devices for automating the control of coal shearsers were developed. Solving the problem of managing complex technical objects based on works [1, 10] are devoted to the development of their mathematical models that determine the control algorithm in the future. The result of the research conclusion [11] there was a proposal to use intelligent controllers in the shearer’s control system based on fuzzy logic and neural networks. Attempts to implement control using intelligent controllers were considered in [12] using fuzzy logic, in [13] using a standard neural network controller Matlab and in [14] using the ANFIS network. However, in all these works, the shearer was considered as a simple first-order transfer function, when in reality it is a complex object with a large number of nonlinearities.

2. Description of the algorithm

Research in the field of improving the control systems of the technological processes with intelligent controllers are highly relevant, since most real control objects have non-linear characteristics that change during operation, while they are controlled, in most cases, using linear PID (PI) controllers. The coefficients of such controllers are often selected optimally for a specific state of the object, but when it transitions to other states (for example, when the executive body of a coal shearer meets with a solid inclusion in the pack of cut coal), these values of the coefficients not allow us to obtain the required quality of transients. This leads to a decrease in the quality of regulation [15]. As you can see, this problem is relevant for the coal mining industry, because long-term fluctuation processes with dynamic
moments greater than the nominal values in the mechanical parts of the transmission can lead to equipment failure.

In our opinion, the most promising method is using extrapolator models to predict the parameters of the PI controller.

Generalized control scheme of a shearer according to the mismatch of the cutting induction motor current under conditions of a suddenly changing coal resistance to cutting (\( A \)), shown in Fig. 1.

If a sudden change coal resistance to cutting, in particular, at different levels of steps and their combinations, the speed of the cutting current controller (duration of transients) and current steps also differ, the time of quieting of the transient process also occurs for different times.

![Figure 1. Shearer control scheme.](image)

To improve the quality of the transition process, it is necessary:

1) minimize current step amplitudes;
2) minimize the system's quieting time, including relative to the classical PI controller under these conditions.

Both requirements can be met by minimizing the integral of the function, calculated by sampling and summing the residual in each sample of the cutting current curve and the setpoint line samples in a given time interval. So, by optimal settings of the PI controller \( K_p \) and \( K_i \) considered are those that, for a given disturbing effect \( A \), provide a minimum of the area \( S \) under the stator current curve of the cutting induction motor, recorded after the step (or the first of a combination of steps).

To solve the above task, we propose a method containing the following sequence of steps.

1) Using a computer model of the shearer control system, implemented in the Matlab/Simulink environment, forming a training sample of the form (Table 1, 2).

In a sample of all possible combinations \( A, K_p, K_i \) by size \( N \) optimal combinations are determined \([A, K_p, K_i] \) by criterion \( S \rightarrow \min \).

| Input Data | Proportional component of the PI controller | Integral component of the PI controller |
|------------|------------------------------------------|---------------------------------------|
| Single values or combinations of steps in coal resistance to cutting | \( K_{p1} \) | \( K_{i1} \) |
| \( A_1 \) | \( K_{p2} \) | \( K_{i2} \) |
| \( … \) | \( … \) | \( … \) |
| \( A_N \) | \( K_{pN} \) | \( K_{iN} \) |

| Output Data | Samples of the cutting induction motor current curve, recorded after a step (or the first of a combination of steps) | Samples of the movement speed curve, recorded after a step (or the first of a combination of steps) | Area under the cutting induction motor current curve, recorded after a step (or the first of a combination of steps) |
|-------------|-------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| \( \{I\}_1 \) | \( \{V\}_1 \) | \( S_1 \) |
Output Data

| Samples of the cutting induction motor current curve, recorded after a step (or the first of a combination of steps) | Samples of the movement speed curve, recorded after a step (or the first of a combination of steps) | Area under the cutting induction motor current curve, recorded after a step (or the first of a combination of steps) |
| --- | --- | --- |
| $\ldots$ | $\ldots$ | $\ldots$ |
| $\{I\}_N$ | $\{V\}_N$ | $S_N$ |

2) Based on the sample (Tables 1, 2) a model is being formed recognition of the shearer’s control system response. Input and output parameters of the model presented in Table 3.

| Input Data | Output Data |
| --- | --- |
| Proportional component of the PI controller | Output Data |
| Integral component of the controller | Single values or combinations of step in coal resistance jumps to cutting |

|  | First $M$ samples of cutting induction motor current curve, recorded after a step (or the first of a combination of steps) | First $M$ samples of the movement speed curve, recorded after a step (or the first of a combination of steps) |
| --- | --- | --- |
| $K_p1$ | $\{I\}_1$ | $\{V\}_1$ | $A_1$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| $K_pN$ | $\{I\}_N$ | $\{V\}_N$ | $A_N$ |

Systemically, we are talking about $L$ recognition models. Where $L$ – number of value combinations $K_p$ and $K_i$. For each combination $K_p$ and $K_i$ samples of a two-dimensional curve are fed to the model input $[\{I\}, \{V\}]$, and the recognized step type $A$ is output. When using neural network methods, a sample of the form (Table 3) it is used for training the feedforward NN. This may also apply to $L$ neural network recognition models, each for its own combination $K_p$ and $K_i$: curve samples are fed to the input $[\{I\}, \{V\}]$, and the recognized step type $A$ is output.

3) The shearer’s operation process under conditions of unpredictable types of steps is recorded or modeled (if steps are unpredictable in time and level, then a complete Markov chain is obtained, as a generalization of the Bernoulli scheme). The PI controller has initial values of coefficients: $K_p^i$ and $K_i^i$. We register the fact of the start of the step and the first $M$ samples of the transition process (Fig. 2).

Figure 2. Formation of a fragment of the first samples of two-dimensional sections (in terms of current and speed) to recognize the jump level $A$. 
In real environmental conditions, the information systems of most technical objects operate in conditions of noise and distortion. Therefore, the input of the recognition model is provided with distorted (consistent low-frequency noise) and noisy (white Gaussian noise) signals $M$ samples of a two-dimensional signal $\{I', \{V'\}$]. The output of the model generates an estimate of the recognized class of the step type $A$. In the general case class $A$ characterizes the levels and sequence of a series of step approximations of changes in the coal resistance to cutting. First $M$ samples of the transition are recorded for a duration of $T_1$. Total duration of the transition process $T_1 + T_2$ (Fig. 3). In parallel, the optimization problem of choosing the ratio of intervals $T_1/T_2$ in which, on the one hand, stable recognition is provided in conditions of interference and noise, on the other hand, there is still a gain of quasioptimal control associated with the proactive correction of the coefficients of the PI controller for the recognized class of the step in the coal resistance to cutting.

4) For the recognized step type $A'$ according to Tables 1, 2, the optimal combination is determined $K_{p \text{opt}}$ and $K_{I \text{opt}}$, for which $S \rightarrow \min$.

5) The correction of the parameters of the PI controller is calculated:

$$
\Delta K_p = \left( K_p^{1} - K_p^{\text{opt}} \right) \left( \frac{S_1}{S_1 + S_2} \right)
$$

$$
\Delta K_I = \left( K_I^{1} - K_I^{\text{opt}} \right) \left( \frac{S_1}{S_1 + S_2} \right)
$$

(1)

where $S_1$ and $S_2$ areas under sections of the observation and prediction curves, respectively, for durations of $T_1$ and $(T_1 + T_2)$ (Fig. 2).

If the controller's computing resources are limited, the calculation of the correction can be simplified:

$$
\Delta K_p = \left( K_p^{1} - K_p^{\text{opt}} \right) \left( \frac{T_1}{T_1 + T_2} \right)
$$

$$
\Delta K_I = \left( K_I^{1} - K_I^{\text{opt}} \right) \left( \frac{T_1}{T_1 + T_2} \right)
$$

(2)

where $T_1$ and $T_2$ the duration of curve registration at the input of the recognition model and the remaining duration of the transition process, respectively.

6) At time $t_0$, more precisely $(t_0 + \Delta t)$, where $\Delta t$ – the time reserved for recognition and correction, new values are assigned to the coefficients of the PI controller:

$$
\begin{align*}
K_p^2 &= K_p^1 + \Delta K_p; \\
K_I^2 &= K_I^1 + \Delta K_I.
\end{align*}
$$

(3)

In this case, the generalized control scheme shown in Fig. 1 is transformed to the form shown in Fig. 3 by adding functional blocks.
Figure 3. Regulation scheme of a shearer with correction of the coefficients of the PI controller of a shearer based on identification of a multidimensional response curve to a disturbing effect.

In general, data sources for identifying the type of disturbing effect on the control object can be used $n$ sections of the multidimensional response curve available for observation (Fig. 4). The curve recognition algorithm must be scalable with respect to $n$, and also meet the speed limits for solving the task of controlling an electromechanical system, since it is necessary to recognize steps when the transient process has not reached the maximum current step (Fig. 1, 2).

Figure 4. Two sections of a two-dimensional curve fragment (current and speed sections based on the UKD300 coal shearer operation model) fed to the input of recognition algorithms.

3. Neural network algorithm for implementing the method

It is possible to implement adjustment of the coefficients of the PI controller using an artificial feedforward neural network, which acts as an operational tool for recognizing a multidimensional response curve in the control loop of the controller parameters.

A control object or data source transients in the observation model, is a functioning model UKD300 coal shearer, implemented in the Simulink [11].

The input of the observation model is supplied with a discrete level of a step in the coal resistance to cutting $A$.

It is accepted that the internal state of the object of observation, with a sufficient degree of approximation for reliable recognition, is described by two scalar values:

7) $K_P$ – proportional component of the PI controller of the cutting induction motor current;
8) $K_I$ – integral component of the PI controller of the cutting induction motor current.

Discrete samples of a two-dimensional curve are taken from the output of the observation model $[[I], \{V\}]$, where $I$ – cutting current cutting induction motor, $V$ – shearer movement speed.

Generating a training sample consists of performing the following steps sequentially:
1) Setting conditions for the initial step level $A = A_1$ and the initial values of the components of the PI controller of the cutting induction motor current $K'_P$ and $K'_I$;
2) Launch of the shearer operating model;
3) Registering and writing to a two-dimensional array of response curve implementations $[[I], \{V\}]_1$ on the step $A_1$;
4) Sequential variation of the operating conditions of the shearer $[A_1, \ldots, A_n]$, $[K_{p1}, \ldots, K_{pm}]$, $[K_{r1}, \ldots, K_{rm}]$ with the launch of the functioning model and registration $M=n \times m \times k$ response curves to a three-dimensional array.

The recognition task is to evaluate the level of the step $A_i, i=1, \ldots, M$ based on a fragment (initial samples) of a two-dimensional curve $[\{I_i\}, \{V_i\}], \text{at given states } K_{p1} \text{ and } K_{r1}$.

The input vector of the training sample contains the first $L$ samples of the recognized curve and, due to different ranges of the curve for current $[1, 10]$ and speed $[1, 100]$ $s_i$, normalized to the interval $s_{i, \text{norm}} \in [0, 1]$: \[
s_{i, \text{norm}} = \frac{s_i - s_{i, \text{min}}}{s_{i, \text{max}} - s_{i, \text{min}}} (b-a) + a \tag{4}
\]

where $a$ and $b$ – limits of the normalized range ($a=0, b=1$).

The output variables of the training sample characterize a scalar value – the level of a step in coal resistance to cutting $A$, and therefore normalization/denormalization of output vectors is impractical.

Thus, it is possible to use a multi-layer feedforward NN of two architectures. The first one, with the so-called scalar output function, has the architecture $\{L, X_1, \ldots, X_N\}$, where $L$ – size of the input layer, $X_1, \ldots, X_N$ – size of hidden layers, number of hidden layers 1. The input signals will be fragments of the cutting current curve section $\{S_{11}, S_{12}\}$ and fragments of a section of the shearer movement speed curve $\{S_{13}, S_{14}\}$, the output $e_i$ consists of one neuron and corresponds to the type of step $A$. The second NN, with the so-called vector output function, has the architecture $\{2L, X_1, \ldots, X_N\}$. The input signals are identical to the first NN, and the number of output neurons corresponds to the number of possible values (variants) $A$. The number of hidden layers is 2.

Calculating weighted output values $w_i(f(s_i))$ the selection of neurons, considering the maximum number of layers, is carried out by using the expression:

\[
c_j = f_j^{[3]} \left( \sum_{m=1}^{n_3} w_{jm}^{[3]} \left( \sum_{h=1}^{n_2} w_{hm}^{[2]} \left( \sum_{l=1}^{n_1} w_{hl}^{[1]} x_l \right) \right) \right)
\tag{5}
\]

where $n_1, n_2$ – the number of neurons in hidden layers.

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

\[
f(x) = \frac{e^{ax} - e^{-ax}}{e^{ax} + e^{-ax}}, j = 1, n_3.
\tag{6}
\]

where $a$ – the steepness parameter of the hyperbolic tangent, $x$ – weighted sum of the neuron's inputs.

The pseudo-Newtonian algorithm, or a second-order procedure, which uses second-order derivatives in addition to the first ones, is chosen as the training algorithm for both NN architectures [16].

In the case of using pseudo-Newtonian simplification without using non-diagonal elements, it is sufficient to use the pseudo-Newtonian Levenberg-Marquardt algorithm [17-19].

In the framework of computational experiments, preference was given to the NN architecture with a vector output function that uses a positional code of the form in the output layer of the NN:

\[
[-1, -1, \ldots, 1, \ldots, -1] \rightarrow c_j, j = 1, M.
\tag{7}
\]

That is, the presence of a single level of the output signal $j$-th neuron in combination with negative levels of other neurons in the target vector indicates that $A_j$-th step of the curve, where the number of the neuron with the maximum output level indicates the number of the desired curve template and, accordingly, the desired step level $A$ (Fig. 5).

In numerical experiments, we used from 10 to 1000 examples of a training sample in which, normalized values coal resistance $A$ changed from 1 to 10 with a uniform step from 1 to 0.01.
With a large sample size, we used an NN with two hidden layers. The number of neurons in the first and second hidden layers is 85 and 35, respectively [20].

![By neural network with vector output function]

Figure 5. Normalized to the range [0,1] result of the NN operation with the vector output function.

4. Conclusion
1) In the framework of this work, it was proposed to use a PI controller to increase the speed of the control system, the coefficients of which adapt to the external operating conditions of the shearer in case of random sudden changes in the load (coal resistance to cutting).

2) As a result of research methods the possibility of using a feedforward NN, which acts as an operational tool for recognizing a multidimensional response curve in the control loop of the shearer controller parameters, is confirmed for adjusting the coefficients of the PI controller. To increase the noise immunity of recognition affecting the shape of input curves, a specialized NN architecture with a vector output function is used. The target training vectors of such an NN are formed by a positional code indicating the type of step being recognized.

3) The approach proposed in the article can also be used for solving other applied tasks in which the control object is nonlinear and the control algorithm needs to adapt to the changing state of the object. The obtained results are planned to be used in the future to improve the load control system of shearer.

5. References
[1] Babokin G I, Shprekher D M, Kolesnikov E B 2019 Mathematical modeling of the electric drive of a shearer with a built-in moving system Bulletin of Tula State University, technical science 3 pp 645-651
[2] Starikov B Ya, Azarh V L, Rabinovich Z M 1981 Asynchronous electric drive of shearers (Moscow) Nedra p 288
[3] Liu C, Qin D, Liao Y 2015 Electromechanical dynamic analysis for the drum driving system of the long-wall shearer Advances in Mechanical Engineering vol. 7 10 pp 1-14
[4] Dubinin S V 1991 Reducing dynamic loads and increasing the efficiency of the external feed system of the shearer PhD (Engineering) dissertation (Donetsk) p 209
[5] Boyko N G 2012 Optimization of parameters of power systems of shearers: monograph State Higher Education Institution “Donetsk National Technical University” p 214
[6] Gorbatov P A, Perinsky M V 2010 Mathematical models for predicting maximum loads in drive subsystems of shearers based on simulation modeling Mechatronic mining equipment-2010 Donetsk National Technical University pp 25-34
[7] Zubarev S G 2014 Improving the movement system of a coal processor by forecasting the load Technological audit and production reserves vol. 6 4(20) pp 17-20
[8] Ivanov A S 2010 Development of a nonlinear load control system for an electric drive cutting a roadheader PhD (Engineering) dissertation (Novokuznetsk) p 160
[9] Kolesnikov E B 1996 Development and research of the mechanism of forward motion with a frequen-cy-controlled electric drive PhD (Engineering) dissertation (Moscow) p 249
[10] Tkachev V V, Bublikov A V 2015 The use of simulation to study the automatic control system for cutter-loader. Monograph (Dnepropetrovsk) National Mining University p 182
[11] Shprekher D M, Babokin G I, Kolesnikov E B, Zelenkov A B 2020 The study of the dynamics of loading an adjustable electric drive of the shearer Bulletin of Tula State University, technical science 2 pp 514-525
[12] Zhao Y 2012 Constant Power Automatic Control System of Electric Haulage Shearer Based on Fuzzy Control Coal mine electromechanical vol. 12 pp 41-43
[13] Zhou Y, Ma H, Wu H, Zhao Y 2013 Constant Cutting-Power Control of Shearer Based on Neural Network Model Predictive Control Trans Tech Publication vol. 823 pp 340-344
[14] Zhou Y, Ma H, Wu H, Zhao Y 2014 The power optimization control of shearer based on ANFIS Trans Tech Publication vol 496-500 pp 1727-1731
[15] Omatu S, Khalid M, Yusof R 1995 Neuro-Control and its applications (London (UK)) Springer p 255
[16] Shepherd A J 1997 Second-Order Methods for Neural Networks (London, Springer-Verlag) p 145
[17] Marquardt D 1963 An algorithm for least squares estimation of nonlinear parameters SIAM pp 431-442
[18] Haykin S 1999 Neural networks: a comprehensive foundation IEEE p 700
[19] Osofsky S 2004 Neural networks for information processing (Moscow) Finance and Statistics p 344
[20] Hecht-Nielsen R 1987 Kolmogorov's Mapping Neural Network Existence Theorem IEEE First Annual Int. Conf. on Neural Networks (San Diego) vol. 3 pp 11-13