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ADAPTIVE CONTROL AND IDENTIFICATION OF DRILLING SYSTEM WITH CONSIDERING THE TYPE OF DRILLED ORE MATERIAL

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Abstract: *The object* is to investigate methods for forming a model for the system of adaptive control over drilling with the control object identifier.

The following *methods* have been used in the course of the research: analysis of domestic and foreign experience, systematization of available approaches and methods, methods of numerical simulation for synthesis and analysis of mathematical model, methods of mathematical statistics and probability theory for processing the results of experiments, methods of analytical design and computer simulation in the synthesis and analysis of control system, methods of system analysis in the development of control algorithms.

The scientific novelty consists in determining optimal parameters – number of membership functions, membership function type, inputs number - for neuro-fuzzy subsystem of drilling control system with considering the type of drilled ore material.

The practical significance of the studies is a structure of adaptive control and identification of drilling system with considering the type of drilled ore material including model of geological structure.

The results of the research investigate a strategy of the two-level adaptive control of borehole drilling under rapidly changing conditions which implies simultaneous drilling investigation and control. The subsystem of prediction is implemented on the basis of an adaptive neuro-fuzzy system. The applied neuro-fuzzy system realizes the Sugeno fuzzy inference in the form of a five-layer neural network of signal feedforward, the first layer of which contains the terms of input variables (the current signal value and its delayed values). It should be noted that the membership function type did not influence much on the prediction result. While processing and analyzing the current information about the latest characteristics of drilling and while forming the adaptive control it is reasonable to apply neurofuzzy structures with Gaussian membership functions.

Key words: drilling automation, neuro-fuzzy model, adaptive control.

Introduction. The creation of control for an object with uncertain parameters is an important problem of the automatic control theory. Nonstationary and uncertain parameters of control objects cause the necessity to create regulators with adaptable parameters ensuring the unchanged accuracy and quality of a system. The creation of the adaptive system with an identifier is aimed at forming a model-identifier of a control object on the basis of fuzzy and incomplete information [1].

Materials and methods

1. Analysis of research and publications

The quality of automatic control over technological processes on various stages of iron ore mining and processing can be improved by using the latest information about the technological process while controlling it [2-6, 12-15]. In this case, the information on the technological process development can be obtained both by its direct measurement and by using a mathematical model [2].

As drilling characteristics are random and non-stationary it is reasonable to apply the methods of adaptive control with an identifier of an object model while synthesizing this process control. The research is aimed at investigating the methods of forming a model for the system of adaptive control over drilling with the control object identifier [7]. In general, when forming the adaptive control of drilling rocks one should consider the fact that the control object is under the influence of the following input impacts: driving $X^{*}(t)$, controlling $U(t)$ and disturbing $Z(t)$. The object's behaviour characterized by the output variables $Y(t)$ depends on a set of unknown parameters ξ with the given set of admissible values Ξ among which one should distinguish physical and mechanical characteristics of rock types. In this case, it is necessary to form the control that would ensure the given indices of drilling quality under all admissible values of the unknown parameters ξ.

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The research is aimed at investigating the methods of forming a model for the system of adaptive control over drilling with the control object identifier.

2. Research results

Under rapidly changing conditions of borehole drilling one should use a strategy of the twolevel adaptive control which implies simultaneous drilling investigation and control [7, 8].

When applied to drilling prospecting boreholes containing several rock types, one should include an extra block of the model formation into the control system structure (Fig.1).

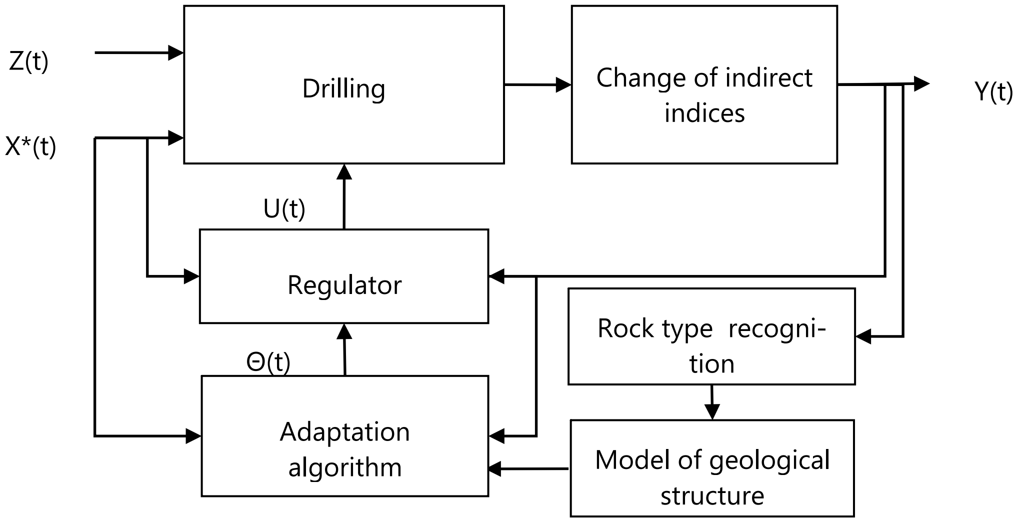

Figure 1. Adaptive system of drilling control

The information on the technological process development can be obtained not only by its direct measurement but also on the basis of interpretation of indirect factors [9-10]. In the course of the research, the following parameters are under control: drilling speed, rotation speed and torque. Besides the mentioned parameters, the research work [10] investigates the possibility of using the axis load while identifying the rock geological structure in drilling.

The predicting subsystem is realized on the basis of ANFIS – the adaptive neuro-fuzzy inference system [11]. The applied ANFIS realizes the Sugeno fuzzy inference in the form of a five-layer neural network of signal feedforward the first layer of which contains the terms of input variables (the current signal value and its delayed values). While forming the model the initial data selection is divided into two parts: training and checking.

The result of the adjustment of the membership functions in case of two or three terms of input variables is shown in Fig. 2.

The results of assessing the influence of the membership function number on the efficiency indices of the identification are presented in Table 1. The best results (the shortest time and the smallest standard error of prediction) are obtained in case of two membership functions with RMSE=0.0215 and the execution time of 5.2188 sec.

The result of investigating the influence of the membership function type on the identification efficiency indices is shown in Table 2.

The best results (tab. 2) are obtained when trapezoid membership functions (the minimum learning time) and the Gaussian membership functions (the minimum error) are used. However, it should be noted that the membership function type does not have any significant influence on the prediction result. Later, the Gaussian membership function ensuring the minimum learning time is applied (Fig. 3).

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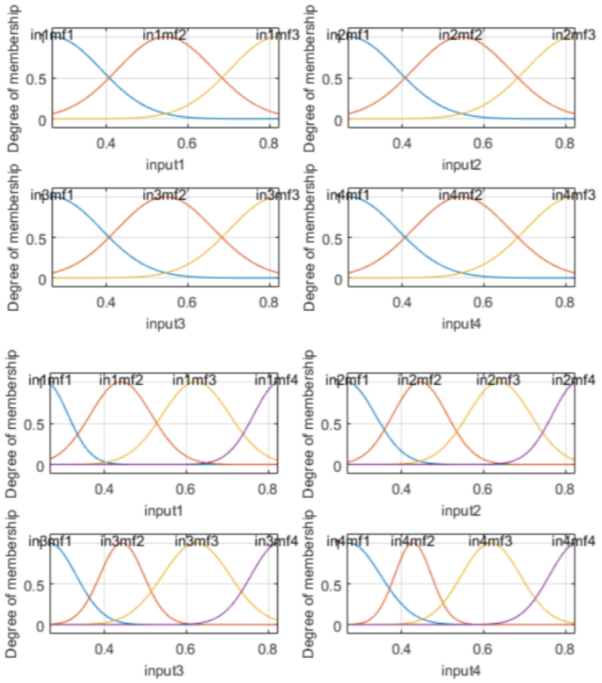

Figure 2. Membership functions of input variable terms

Table 1. Influence of the membership function number on identification efficiency indices

Membership function number	RMSE	Execution time, sec
2	0.0215	5.2188
3	0.0223	129.4844
4	0.0226	1805.2000

Table 2. Influence of membership function type on identification efficiency indices

Convention	Gaussmf	Gbellmf	Psigmf	Trimf
Learning time, sec	5.1125	5.2969	5.2344	5.1094
RMSE	0.0204	0.0215	0.0206	0.0214

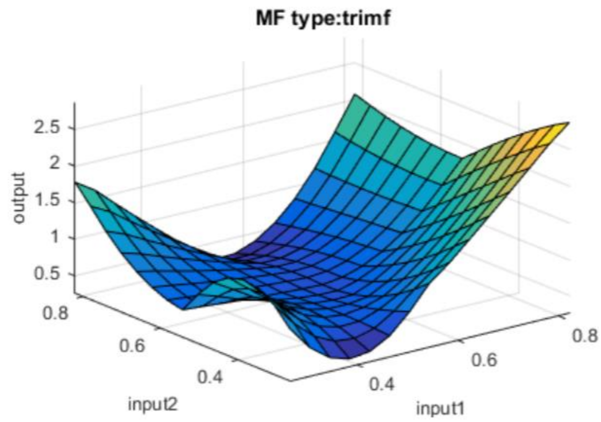

Figure 3. View of fuzzy inference surfaces with various types of membership functions

The investigation of the influence of the deferred input number on the identification efficiency indices reveals (tab. 3) that the best results are achieved with three or four deferred inputs.

Table 3. Influence of deferred input number on identification efficiency indices

Input number	2	3	4	5	6
Learning time, sec	2.5469	3.0938	6.5313	24.1563	169.9531
RMSE	0.0554	0.0209	0.0214	0.0324	0.0326

The joint graph of the prediction initial data and results as well as the prediction error is shown in Fig. 5.

The fragment of the joint graph of the prediction results and the check data as well as the prediction error is shown in Fig. 6.

The dependency of the standard learning error on the number of the epochs for the training and checking selections are presented in Fig. 4-6.

Training of ANFIS was carried out by the method of back error propagation with the error level of 0 and the cycles number of 25. The volumes of statistical sampling and the parameters of neuro-structures were identified on the basis of recommendations [7-8]. The N-number of elements of the statistical sampling, which required for training was determined by the next ratio

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$$\frac{2n(n+m)}{(n\quad 2\varepsilon_0)} \le N \le \frac{10n(n+m)}{(n\quad 10\varepsilon_0)} \qquad (1)$$

where *n* – is the number of input signals; *m* – is the number of outputs; ε_0 – is a relative error of neural network model.

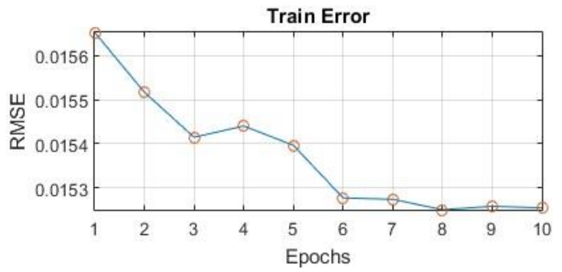

Figure 4. Train error change in the training process

Figure 5. Check error change in the training process

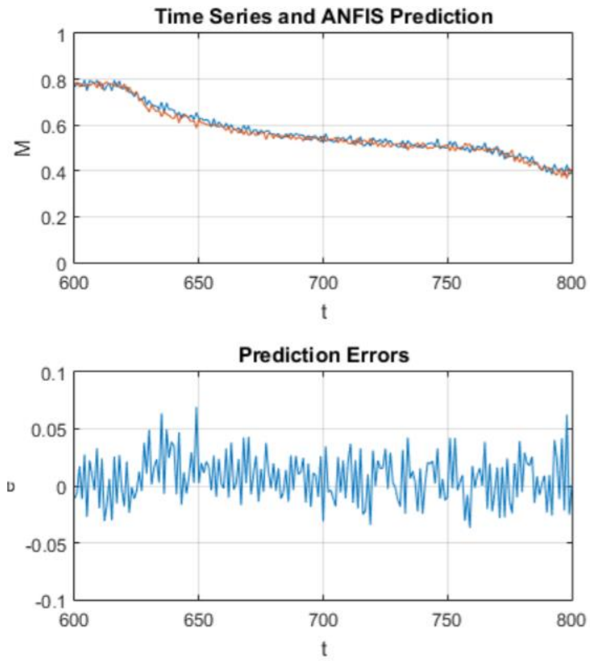

Figure 6. Prediction results

The sample representativeness verification was carried out using the dependence proposed $\widehat{\varepsilon}_m$ on the volume of in [7], of the maximum error statistical sampling

$$\widehat{\varepsilon} = \frac{\arg\Phi rg\Phi{-}1)/2)}{2\sqrt{N}} \qquad (2)$$

where *P* – is the reliability level; Φ(·) – is the Laplace function; *N* – is the elements number of statistical sampling. With a value of reliability level of *P*=0,9 (90%) the appropriate level of significance is (1-*P*)=0,1.

Thus, the prediction error of the neurofuzzy model with four deferred inputs and two terms of input variables and ten training epochs is within 5-7%.

Conclusion. While processing and analyzing the current information about the latest drilling characteristics and forming the adaptive control it is reasonable to apply neuro-fuzzy structures with two Gaussian functions of term membership for each variable and 3-4 deferred inputs.

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