Formation of rock geological structure model for drilling process adaptive control system

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Abstract
The study results of the formation methods of ore rocks drilling adaptive control on the basis of generalized information support are presented.
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Improving the quality and efficiency of the automated process control at different stages of production and processing of iron ore can be achieved using the operational information about the process in the management process [1-5]. At the same time, information about the process can be obtained by direct measurement, as well through processing of the process indirect characteristics [1]. Since the characteristics of the drilling process have a random non-stationary character, it is advisable to use the methods of adaptive control in the synthesis of this process control.

In general terms the objective of rock drilling adaptive control as a system with adaptive estimation of parameters, i.e. restoring of unknown characteristics of the object described by the finite parameter vector (restoration of the geological structure model), according to the real-time signals, includes the following steps [6]: geological structure model recovering (the definition of "direct" data describing the object); determination of solvability conditions of the geological structure model reconstructing problem and ensuring the robustness of adaptive control of the contact interaction with nonformalized data; adaptive (global) process control by the specified target function in real time with the "restored" (by object "image") nonformalized data of various mathematical classes about the object.

When building a model of the object it is necessary to determine the parameters on the basis of solving the inverse problem of the geological structure reconstructing model based on indirect data, which are characterized by uncontrolled error δ. Thus, the problem is reduced to the consideration of the interaction of several dynamical systems (fig. 1) [6].

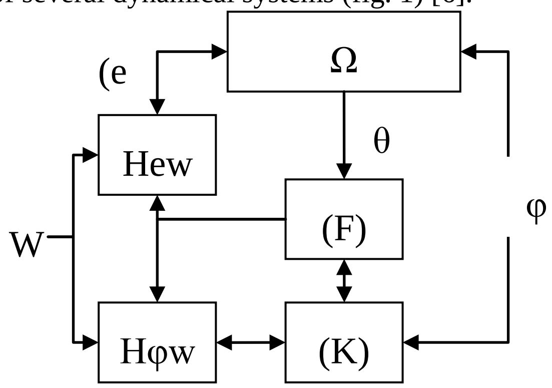

Figure 1. Fuzzy adaptive system

The structure of the system (Fig. 1) includes the following components [6].

Object image restore subsystem, the input of which receives signals $w(t)$ and $\theta(t)$, and on the output signal $\varphi(t)$ is produced. This subsystem is described by the operator depending on parameter:

$$\varphi = H_{\varphi w}(\theta) w . \quad (1)$$

This subsystem typically includes the control object and feedback controller (for adaptive control) or a closed model of the object (for output error identification).

Error subsystem, the input of which receives signals $w(t)$, $\varphi(t)$ and θ(t), and the output error signal *e(t)* for adaptive correction is produced. Considering the parametric dependence of the e to θ and using (1) to exclude dependent on explicitly, as follows

$$e = H_{ew}(\theta) w . \quad (2)$$

Data reconciliation subsystem, in which: reconciliation of data of various mathematical classes and combining them into a single space of generalized fuzzy data are performed. Adaptation subsystem in which e and φ are used to estimate the parameters of θ. Obviously, in this case the parametric dependence on the θ is absent, since θ is a part of the state of this subsystem. Correction algorithm of θ is written as

$$\theta = \Omega(e,\ \varphi) . \quad (3)$$

A parametric dependence of Ω on the value of the step ε and the initial parameter estimation θ can be also include in (3) (Fig. 1). A complete description of the adaptive system has the form (Fig. 1) [6]

$$\begin{bmatrix} e \\ \varphi \\ \phi \end{bmatrix} = \begin{bmatrix} \tilde{F} \\ K \end{bmatrix} \otimes \begin{bmatrix} H_{ew}(\theta) \\ H_{\varphi w}(\theta) \\ F_{\varphi w}(\theta) \end{bmatrix} * \tilde{w} = \begin{bmatrix} \tilde{H}_{ew}(\theta) \\ \tilde{H}_{\varphi w}(\theta) \\ \tilde{F}_{\varphi w}(\theta) \end{bmatrix} * \tilde{w} \equiv H(\theta) * w$$

(4)

where $\theta = \Omega(e,\ \varphi)$, $\tilde{H}_{*}(\theta)$, $\tilde{w}$ – are suggest as a clear and fuzzy classes of data and functions.

Implementation of the rock geological structure recovery subsystem was carried out based on ANFIS - Adaptive neuro-fuzzy system [7, 8]. The used ANFIS implements the fuzzy inference system in the form of a five-layer neural network of direct signal propagation, the first layer of which contains the terms of the two input variables (torque and speed of drilling). Each node of the first layer is a term with a Gaussian membership function, and the network inputs x = {M, v} are connected only with their terms. The node output of the ANFIS first layer is the degree of value membership of the input variable corresponding to fuzzy terms [7, 8]:

$$\mu(x) = 1 \Big/ 1 + \left| \frac{x - c}{a} \right|^{2b} , \quad (5)$$

where a, b and c – are the adjustable parameters of the membership function. The nodes of the second layer correspond to the fuzzy rules and are connected to certain nodes of the first layer, which form the respective rule antecedents [8].

A fuzzy rule is as follows

$R_i : IF\ (x_1\, is\, X_1) \wedge \ldots \wedge x_n\, is\, X_n\ THEN\ y\, is\, B_i, i = \overline{1,k}$

(6)

where A — are the antecedents rules-productions fuzzy sets; y — is the clear value of the rules-productions conclusion; n — is the number of linguistic variables, k — is the number of rules-productions. In the nodes of the third layer the relative degree of fulfillment of the respective fuzzy rules is calculated

$$\vartheta_i^* = \frac{\vartheta_i}{\sum_{j=1}^{k} \vartheta_j}, \quad (7)$$

Each node of the fourth layer is connected to one node of the third layer as well as with all the network inputs. In these nodes the contributions of fuzzy rules in network output is calculated. The results of calculation of the contributions of all the rules adds a single node of the fifth layer. The fragment of graph showing the dynamics of the normalized input variable: torque, is shown in Fig. 2.

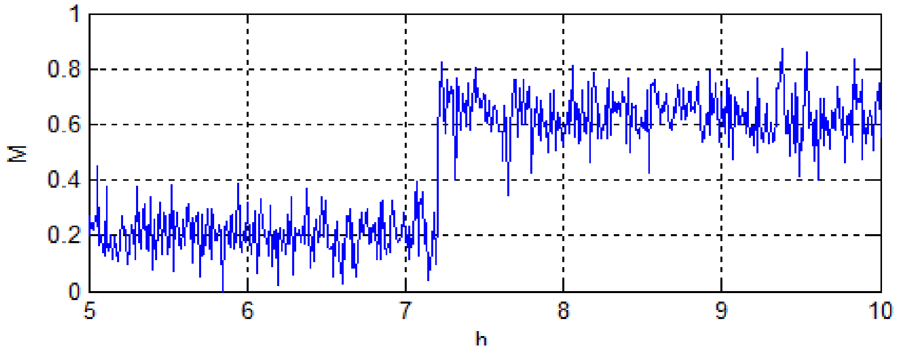

Figure 2. The dynamics of torque in the drilling process

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 [9-12]. The N-number of elements of the statistical sampling, which required for training was determined by the next ratio

$$\frac{2n(n+m)}{(n-2\varepsilon_0)} \le N \le \frac{10n(n+m)}{(n-10\varepsilon_0)}, \quad (6)$$

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

The sample representativeness verification was carried out using the dependence proposed in [9], of the maximum error $\hat{\varepsilon}_m$ on the volume of statistical sampling

$$\hat{\varepsilon}_m = \frac{\arg\Phi\left[\left(P+1\right)/2\right]}{2\sqrt{N}}, \quad (7)$$

where P — is the reliability level; $\Phi(\cdot)$ — 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. The result of this system performance for rock variations recognizing in the process of drilling is shown in Fig. 3.

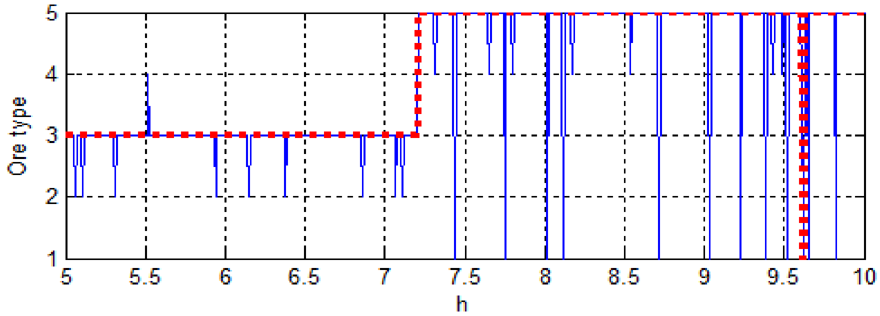

Figure 3. The result of recognition of rock varieties in the drilling process

Rock varieties recognition error in the drilling process using adaptive neuro-fuzzy system was 1.37%. Thus, the formation of the rock geological structure model in the adaptive control system of the drilling process is advisable to carry out using an adaptive-neuro fuzzy system.

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