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IDENTIFICATION OF NEURO-FUZZY STRUCTURES FOR ADAPTIVE CONTROL SYSTEM OF DRILLING WITH OBJECT MODEL IDENTIFIER

The quality of automated control over technological processes on various stages of iron ore processing can be increased by using the latest information on a technological process. The data can be obtained by both direct measurements and applying a mathematical model. As drilling characteristics are of random and non-stationary, it is reasonable to apply methods of adaptive control with an object model identifier while synthesizing this process control. The research is aimed at investigating methods of forming a model for the system of adaptive control for drilling with a control object identifier. Under rapidly changing conditions of borehole drilling it is expedient to apply a strategy of the two-level adaptive control, 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 does not influence much the prediction result. While processing and analyzing the current information on the latest characteristics of drilling and forming the adaptive control it is reasonable to apply neuro-fuzzy structures with two Gaussian functions of term membership for each variable and three or four deferred inputs.
Keywords: drilling automation, neuro-fuzzy model, adaptive control**.**

The problem and its connection with scientific and practical tasks. The formation of control for an object with uncertain parameters is an important problem of the automated control theory. Non-stationary 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 main objective of the adaptive system with an identifier is to form a model-identifier of a control object on the basis of fuzzy and incomplete information [1].

Analysis of research and publications. The quality of automated control over technological processes on various stages of iron ore mining and processing can be improved by using the latest information on the technological process while controlling it [2-6]. In this case, the information on the technological process development can be obtained by both its direct measurements and 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 [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 designed indices of drilling quality under all admissible values of the unknown parameters ξ.

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

Material presentation and results. Under rapidly changing conditions of borehole drilling it is necessary to use a two-level adaptive control strategy, which implies simultaneous drilling investigation and control [7, 8].

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

The information on the technological process development can be obtained not only by its direct measurement but also by interpreting some indirect factors [9-10]. In the course of the research, the following parameters are under control: drilling speed, rotation speed, traction and torque. In addition to 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 the Adaptive Neuro-Fuzzy Inference System (ANFIS) [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.

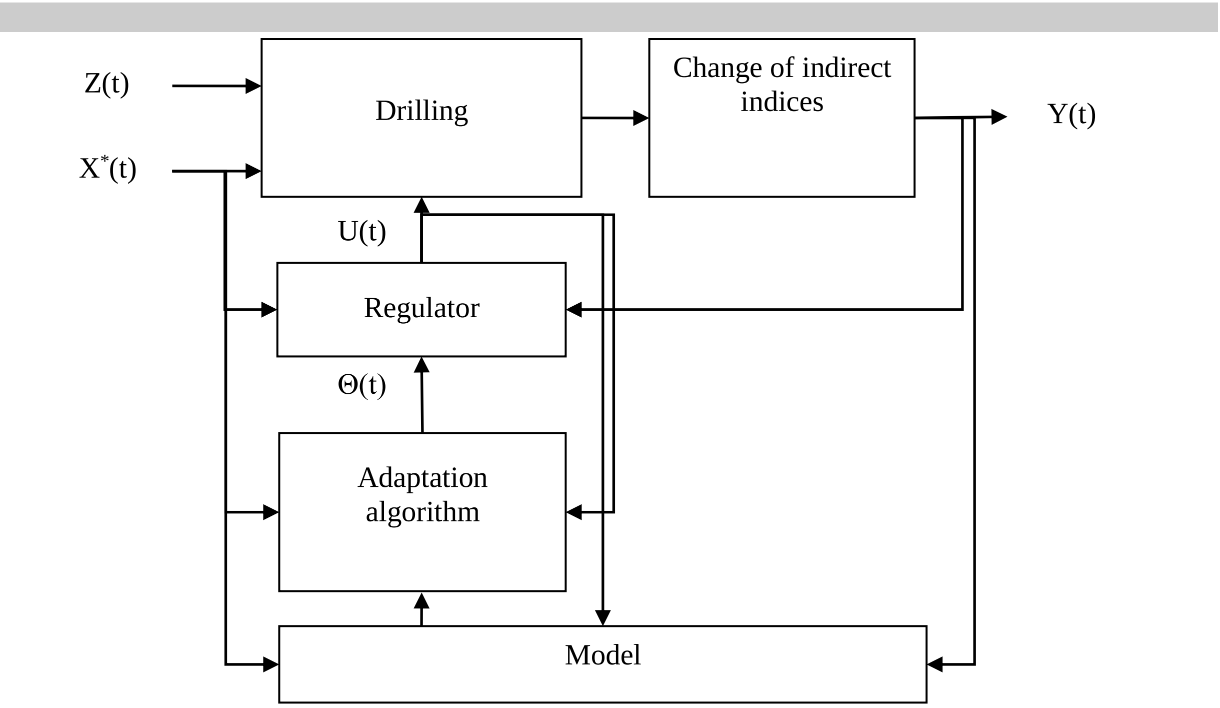

Fig. 1. Adaptive system of drilling control

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

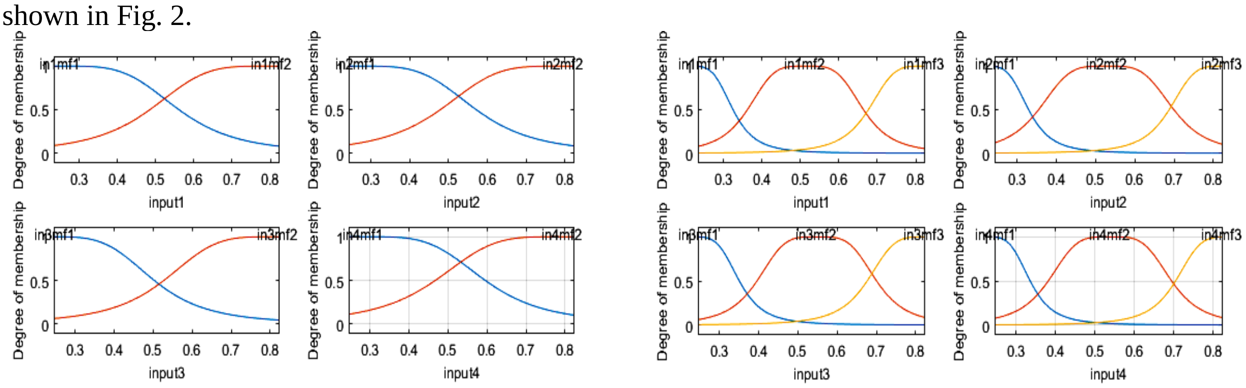

Fig.2. Membership functions of input variable terms

The results of assessing the influence of the membership function number on identification efficiency indices of are presented in Table 1.

Table 1

Influence of 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

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 identification efficiency indices is shown in Table 2.

Table 2

Influence of membership function type on identification efficiency indices

Convention	pimf	gaussmf	gbellmf	psigmf	trapmf	trimf
Training time, sec, c	5.1406	5.1125	5.2969	5.2344	5.0625	5.1094
RMSE	0.0205	0.0204	0.0215	0.0206	0.0207	0.0214

The best results (Table 2) are achieved when trapezoid membership functions (the minimum training 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 training time is applied.

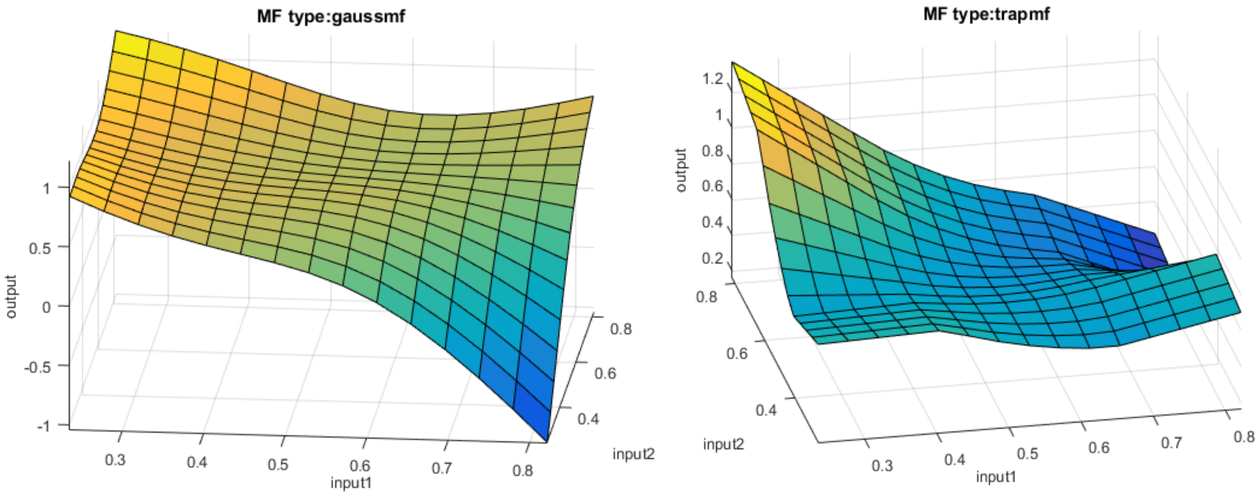

Fig. 3. View of fuzzy inference surfaces with various membership function types

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

Table 3

Influence of deferred input number on identification efficiency indices

Input number	2	3	4	5	6
Training time, sec	2. 5469	3.0938	6.5313	24.1563	169.9531
RMSE	0. 0554	0.0209	0.0214	0.0324	0.0326

The dependency of the standard training error on the number of the epochs for the training and checking selections is presented in Fig. 4.

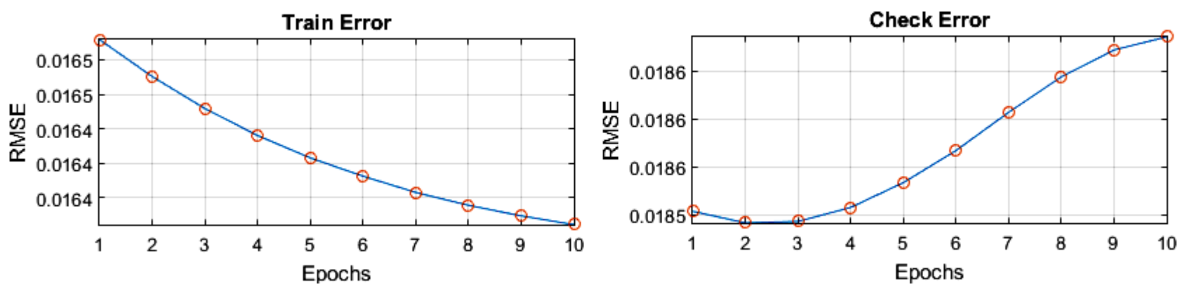

Fig. 4. Error change in training process

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

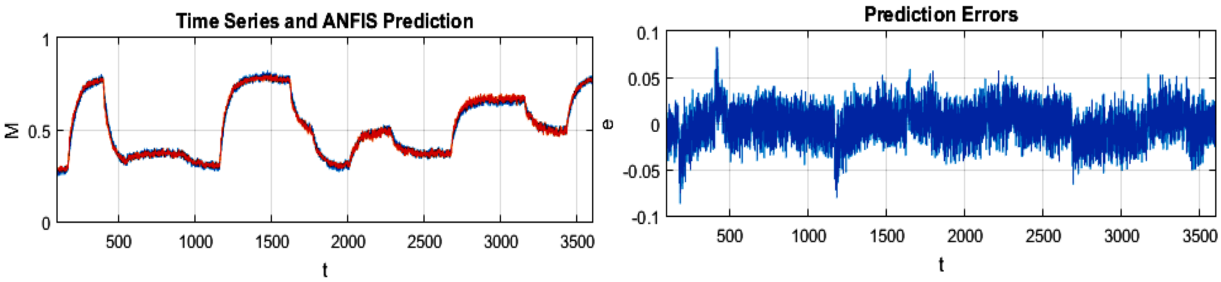

Fig. 5. Comparison of prediction results with initial data

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

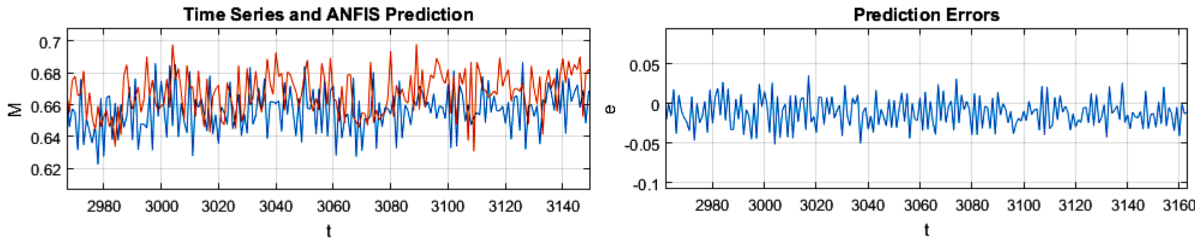

Fig. 6. Results of model check on test data

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

Conclusions and further research directions. 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 three or four deferred inputs.

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