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# Adaptive Identification of the Neural System of Controlling Nonlinear Dynamic Objects

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**ABSTRACT*:***An adaptive identifier is proposed for a neural-fuzzy control system of a nonlinear dynamic object that operates under conditions of uncertainty of internal properties and the external environment. Algorithms of structural and parametric identification in real time, which is a combination of the algorithm for identifying the coefficients of linear controls and the method of the theory of interactive adaptation, are developed. Adaptive neuron-non-linear control system for a nonlinear dynamic object, contain an identifier and a regulator built on the basis of the fuzzy Sugeno model. Such a regulator structure in combination with the optimal choice of fuzzy controller parameters allows, with a minimum of settings, to implement adaptive control systems of undefined and non-stationary mechanisms regardless of their structure. To impart adaptive properties to the fuzzy identifier, it is suggested to estimate the rate of change of the control error. The developed hybrid model built on the basis of neural networks and fuzzy models, it makes it possible to improve the efficiency of the task of managing complex dynamic objects under uncertainty.

**KEYWORDS:** nonlinear dynamic object, neuron-fuzzy identification, interactive adaptation, training, fuzzy logic, neural network, model.

## I.INTRODUCTION

Most of the dynamic objects that operate under uncertainty are characterized by complex and poorly understood connections between technological variables, the presence of perturbing and random jamming, measured with a large error. In addition, the presence of nonlinear elements makes it difficult to apply linear algorithms for adaptive control of dynamic objects under conditions of uncertainty [1].

At present, neural and fuzzy regulators based on the theory of fuzzy logic and neural networks are widely used to manage such objects. Hybrid application of a neural network and fuzzy logic in neuron-fuzzy systems, realizing their positive properties, gives high efficiency of the control process [3.4].

The development of control systems for many technological processes capable of supporting the basic operating parameters within specified limits is a complex multicriteria optimization problem under conditions of uncertainty in the operating characteristics of the control object and the parameters of the external environment. To solve such a difficult task, it is promising to introduce the technology of developing intelligent control systems based on a fuzzy controller that has adaptive properties.

In connection with this, the most relevant in the field of building control systems is the development of universal methods and algorithms for the automated synthesis of system parameters, based on neural networks and fuzzy logic.

In such systems, the control object and the regulator are described by fuzzy adaptive models, the structure of which is formed on the basis of analysis of technological variables and the nature of the relationships between them with the ability to adjust to the changing conditions of the object's operation.

In this paper, a highly effective method is proposed for constructing and teaching a neuron-sensitive control system that has a high adaptive capacity.

Let the dynamics of the control object be represented in the form of non-linear difference control:

$$y(i+1) = f\,(y(i),\dots,y(i-r),\vec{x}(i),\dots,\vec{x}(i-s),u(i),\dots,u(i-q)), \quad (1)$$

where is the current discrete time; y (i) is the output signal:

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$$f(y(i),...,y(i-r),\vec{x}(i),...,\vec{x}(i-s),u(i),...,u(i-q))$$

is some nonlinear function with known orders r, s, q.
The input coordinates of the object are limited at any time, i.e.

$$u^{\min} \le u(i) \le u^{\max} \quad (2)$$
$$\bar{x}^{\min} \le \bar{x}(i) \le \bar{x}^{\max}, i = \overline{1,N}$$

It is required to construct a control system for a dynamic object (1), which provides a minimum of root-mean-square errors when conditions (2) are fulfilled.
To solve the problem, we will use a combined control principle with adaptation.
In this system, the application of the identifier is proposed to adjust the parameters of the controller. The identifier is based on the fuzzy Sugeno model [5]. To create the value of input and output variables with delay, elements with delay are added.
The dynamic model of the identifier is represented as:

$$\hat{y}(i+1) = f_э(u(i),...,u(i-q),\vec{x}(i),...,\vec{x}(i-s),y(i),...,y(i-r),\vec{c}_э). \quad (3)$$

having orders q, s, r, which, after the formalization of the variables

$$\vec{x}_э(i) = (x_{э1}(i),..., x_{эм}(i)) = (u(i),..., x(i),..., y(i-r)) \qquad (4)$$

represent in the form of a fuzzy Sugeno model

$$R_э^{\theta}: \text{if } x_{э1}(i) \ x_{э1}^{\theta}, x_{э2}^{\theta}(i); x_{э2}^{\theta},...,x_{эм}(i); x_{эм}^{\theta},$$
$$y^{\theta}(i+1) = b_{э0}^{\theta} + b_{э1}^{\theta} x_{э1}(i) + ... + b_{эм}^{\theta} x_{эм}(i), \theta = 1, n' \qquad (5)$$

Here c is the vector of the ID settings. The analytical expression for fuzzy identification is:

$$\hat{y}(i+1) = \sum_{\theta=1}^{n'} \beta_э^{\theta} \cdot y^{\theta}(i+1) \qquad (6)$$

$$\text{Where } \beta_э^{\theta} = \omega_э^{\theta}(i) / \sum_{\theta=1}^{n'} \omega_э^{\theta}(i); \ \omega_э^{\theta}(i) \prod_{i-1}^{m'} x_{э1}^{\theta}(x_{э1}(i)),$$

its vector representation "

$$\hat{y}(i+1) = \vec{b}_э^{T} \cdot \bar{\bar{x}}_э(i), \qquad (7)$$

as well as an algorithm for identifying coefficients

$$H_э(i) = H_э(i-1) - \frac{H_э(i-1) \cdot \bar{\bar{x}}(i) \cdot \bar{\bar{x}}_э^{T}(i) \cdot H_э(i-1)}{H \cdot \bar{\bar{x}}_э^{T}(i) \cdot H_э(i-1) \cdot \bar{\bar{x}}_э(i)}$$

$$\vec{b}_э(i) = \vec{b}_э(i-1) + H_э(i) \cdot \bar{\bar{x}}_э(i) \cdot (y(i) - \bar{b}_э^{T}(i-1) \cdot \bar{\bar{x}}_э(i)), \qquad i = \overline{1,N}, \ (8)$$

where $\bar{\bar{x}}_э(i) = (\beta_э'(i),..., \beta_э^{n}(i), \beta_э'(i) \cdot x_{э1}(i),..., \beta_{эm'}^{n'}(i))^{T}$ is the extended modified input vector;

$$(\beta_{э0}^{1}(i),..., \beta_{э0}^{n'}(i), \beta_{э1}'(i),..., \beta_{эm'}'(i),..., \beta_{эm'}^{n'}(i))^{T}$$

- vector of customizable parameters for the identifier. T is the sign of transposition.
The main characteristic defining the fuzzy set x is the membership function $X_э$, ($x_э$), which has the form of a sigmoid

$$X_э(x_э) = (1 + \exp(d_{э1}(x_э + d_{э2})))^{-1}$$

Parameters of identifier membership

$$d_э = (d_{э1,l}^{\theta}, d_{э2,l}^{\theta}), l = \overline{1,m'}, \qquad \theta = \overline{1,n'},$$

are determined by the method of back propagation of the error by minimizing the quadratic discrepancy

$$E_э(i+1) = 0{,}5 e_э^{2}(i+1) = 0{,}5(y(i+1) - y(\vec{d}_э, \vec{x}_э(i)))^{2}$$

gradient descent

$$d_э(\lambda+1) = d(\lambda) - h_э\left(\frac{\partial E_э}{\partial d_э}\right),$$

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where is the working step parameter.
Using the method of least squares, we define the required values of the parameters of the membership function, we will formulate a system of equations:

$$\frac{\partial E_э}{\partial \mathrm{d}_{э11}} = (y-\hat{y})\frac{(y^{\theta}-\omega_э{}^{\theta}\hat{y})}{\left(\sum_{j=1}^{n'}\omega_э{}^{1}\right)^2}\cdot\left(\prod_{\substack{j=1\\ j\neq 1}}^{m'} x_{э1}{}^{\theta}(x_{э1})\right)\left(1-X_{э1}{}^{\theta}(x_{э1})\right)\left(x_{э1}+d_{э2,l}{}^{\theta}\right),$$

$$\frac{\partial E_э}{\partial \mathrm{d}_{э11}} = (y-\hat{y})\frac{(y^{\theta}-\omega_э{}^{\theta}\hat{y})}{\left(\sum_{j=1}^{n'}\omega_э{}^{1}\right)^2}\cdot\left(\prod_{\substack{j=1\\ j\neq 1}}^{m'} x_{э1}{}^{\theta}(x_{э1})\right)\left(1-X_{э1}{}^{\theta}(x_{э1})\right)\cdot d_{э2,l}{}^{\theta}, l=\overline{1,m'}, \theta=\overline{1,n'}$$

For structural identification, a criterion is used that characterizes the average relative errors:

$$J_э = \frac{1}{\mathrm{N}+1}\sum_{i=0}^{N}\left(\left|y(i+1)-\hat{y}(i+1)\right|/y(i+1)\right)\leq J_э{}^{H}$$

Where $J_э{}^{H}$ is the average relative error of the identifier with a valid value
Structural and parametric identification is completed when condition

$$J_э = \frac{1}{N}\sum_{i=0}^{N}\left(\left|y(i+1)-\hat{y}(i+1)\right|/y(i+1)\right)\leq J_э^{н},$$

where $J_p{}^{H}$ is the nominal value of the learning error.

The parameters of the identifier membership functions $d_{p1,l}{}^{\theta}, d_{p2,l}{}^{\theta}, \theta=1,n'', l=1,m''$ are determined by learning to control it with a minimum quadratic error

$$E = 0{,}5e^2(i+1) = 0{,}5(y^H-\hat{y}(i+1))^2$$

Using the gradient method

$$d_p(\lambda+1) = d_p(\lambda)+\Delta d_p(\lambda),$$

Where $\Delta d_p = (h_p\cdot\partial E\cdot\partial d_p)$ is the working step, hp is the working step parameter.

This regulator structure in combination with the optimal choice of fuzzy regulator parameters allows, with a minimum of settings, to implement adaptive control systems of undefined and non-stationary mechanisms, regardless of their structure.
To make the adaptive properties of the fuzzy identifier, in order to ensure the stability of the dynamic system to disturbances (changes in the parameters of the control object and external influences), an estimation of the rate of change of the control error E.
Such a control object is not a neural network, so there is a certain difficulty in learning a fuzzy identifier with a functional converter.
An important method of using a fuzzy identifier is to learn it.
To train the identifier, an algorithm based on the theory of interactive adaptation is proposed [1].
The essence of this algorithm is that the error that is required for learning is calculated implicitly.
When using the algorithm of interactive adaptation, the system is divided into N-subsystems, each of which has an integrable output signal yn and an integrable input signal xn, the relation between them is represented as a functional dependence

$$F_n : X_n \longrightarrow Y_n, n=1,2,..., N$$

The ratio of the i-th element of the system has the form:

$$y_i(t) = F_i[x_n(t)], i=1,2,..., N \qquad (1)$$

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Let the interaction between the elements and the external signal be linear and described $u_i(t)$ by the equation:

$$x_i(t) = u_i(t) + \sum_{K \in J_i} \alpha_K \cdot y_i(t), i \in N$$

where $J_i = \{K : y_K = i\}$ are the sets of connected inputs of the i-th element; - weight of bonds. In this case, the ratio of the input and output of the i-th element is described by the following equation:

$$y_i(t) = F_i[u_i(t) + \sum_{K \in J_i} \alpha_K \cdot y_i(t), i \in N$$

The training of neural networks is to minimize the error of the control system. This is done by adjusting the weights of neural network connections.
If the system is described by equation (1), then the weights of the links are adjusted according to the following rule:

$$\alpha_K = F'_{\textit{вхK}}[x_{\textit{вхK}}] \cdot \left( \frac{y_{\text{выхK}}}{y_{\textit{вхK}}} \right) \cdot \sum_{S \in Q_{\textit{выхJ1}}} \alpha_S \cdot \alpha_S - \gamma \cdot F'_{\textit{вхK}}[x_{\textit{вхK}}] \cdot y_{\textit{выхK}} \cdot \frac{\delta E}{\delta y_{\textit{вхK}}}, (2)$$

where> 0 is the coefficient determining the learning rate; $F'_{\textit{вхK}}[x_{\textit{вхK}}]$ is the Frechet derivative [1]; E - loss function (error); to K.
Provided that equation (1) has a unique solution for k, where the loss function
E (y1, ..., yk; u1, ..., un) will decrease monotonically in time and the following equality will be satisfied:

$$\alpha_K = -\gamma \frac{\delta E}{\delta \alpha_K}, k \in K$$

Mathematically, the neural network learning algorithm is represented as:

$$Pn = \sum_{S \in Dn} \omega_S \cdot r_{pres}$$
$$r_n = \tau(Pn),$$

where n is the neuron index, S is the synapse index, Pn is the set of input synapses of the neuron n; pres and post - presynaptic and postsynaptic neuron corresponding to the synapse S; $\omega_S$ - the weight of the synapse S; Pn is the membrane potential of the neuron n; rn is the excitation frequency of the neuron n; activation function of the sigmoid type, which is represented as:

$$\tau(x) = \frac{1}{1 + e^{-x}}$$

The weight of synapses is determined by the formula:

$$\dot{\omega}_s = r_{pres}(\varphi_{posts} \tau(-P_{posts}) + \gamma \cdot f_{posts}),$$

Where $$\varphi_n = \sum_{S \in A_n} \omega_s \cdot \dot{\omega}_s$$

To reduce the time of regulation and overshoot the system, it is necessary to change the initial weights of the system, taking their values equal to the steady ones.
The next most important stage for the implementation of various mathematical operations on input and output information is the choice of the membership function (FP). Currently, dozens of different types of FP exist. The most common are triangular, trapezoidal and Gaussian forms of membership functions. The choice of one or another type of OP depends on the particular case.
We offer a trapezoidal membership function:

$$\mu\left(\frac{dE}{dt}\right) = \begin{cases} 1 - \frac{b - x}{b - a}, & a \le x \le b \\ 1, & b < x < c \\ 1 - \frac{x - c}{d - c}, & c \le x \le d \end{cases}$$

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The choice is due to the fact that this membership function is described with the help of 4 bytes of parameters (binary words) that unambiguously define it on the considered space of variation of the output variable.
In the course of mathematical modeling of the control process, it was found that when using a fuzzy controller, there is an occurrence of insensitivity to the change in the duration of the transient process, and in addition, its application allows improving the quality parameters of the transient process.
The proposed approach to creating a fuzzy regulator allows significantly reducing the duration of the cycle of generation and implementation of control actions under conditions of uncertainty in the nature of the transient processes. This approach can be recommended when creating a management system for technological objects that functioned in conditions of incompleteness or unreliability of information about the parameters of the control object.

## II. CONCLUSION

The paper proposes an adaptive neural control system for a nonlinear dynamic object containing an identifier and a regulator based on the fuzzy Sugeno model. Algorithms of structural and parametric identification are developed, based on the method of interactive adaptation of models. A combination of positive properties of neural networks and fuzzy models is suggested, which allows to effectively solve the problems of managing complex dynamic objects in conditions of uncertainty

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