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Engineering Calculation And Algorithm Of Adaptation Of Parameters Of A Neuro-Fuzzy Controller

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ABSTRACT

As part of the study, a control scheme with the adaptation of the coefficients of the neuron-fuzzy regulator implemented. The area difference method used as a training method for the network. It improved by adding a rule base, which allows choosing the optimal learning rate for individual neurons of the neural network. The neural network controller applied as a superstructure of the PID controller in the process control scheme. The dynamic object can function in different modes. This technological process operates in different modes in terms of loading and temperature setpoints. Because of experiments, the power consumption and the amount of time required maintaining the same absorption process, using a conventional PID controller and a neural-network controller evaluated. It concluded that the neuro-fuzzy controller with a superstructure reduced the transient time by 19%.

KEYWORDS

Neural network, PID controller, neural network optimizer, area difference method, nonlinear systems.

INTRODUCTION

To date, scientific research on the improvement of process control systems i. With the application of methods of intellectual technologies, this problem is very relevant, because the majority of real control objects have non-linear characteristics, which change during operation, while they are controlling, in most cases, by linear PID controllers. Coefficients of such controllers often selected for a particular state of the object, but when the transition to other states occurs, values of these coefficients do not provide transition processes of the required quality. This leads to a decrease in the quality of regulation and to an increase in energy consumption for controlling technological processes.

One of the possible ways of this problem is to build adaptive process control systems [2], which automatically select PID coefficients. The methods for constructing such systems can be divided into two groups. The first group consists of the classical methods, such as the Ziegler-Nichols method [10], the frequency method of A.G. Alexandrov [1], the method underlying Siemens adaptive PID controllers [5], and methods based on modeling of the control object [6]. The second group is the methods based on artificial intelligence methodology. The methodology of neural networks (NS) and fuzzy logic used to solve the problem. This is because NS have nonlinear properties and the ability to learn, which gives adaptive properties to neural network control systems [11, 12].

In this case, the most realizable from a practical point of view is the application of the control scheme of dynamic objects based on autotuning of coefficients of PID regulator. KP, KI, KD with the help of NS (self-adjusting PID-neurocontroller scheme), which allows taking into account the non-linear properties of the object, without making significant changes in the existing control systems.

SOLUTION METHOD

Currently, a microcontroller based on SCADA system used to control the variable states of the control object; in this case, the dynamics of the control object (CA) described by the difference-differential equation "input-output", defined in implicit form:

$$\varphi(y^{(n)}, y^{(n-1)}, ..., y; u^{(m)}, u^{(m-1)}, ..., u) = 0, \quad (1.1)$$

Where $u = u(t)$ and $y = y(t)$ - input and output of the object under study, respectively; m and n - maximum orders of derivatives $u(i), y(j)$ for input and output variables $u(t)$ and $y(t)$, $(m \le n); \varphi(\cdot)$ - some nonlinear function.

To synthesize an adaptive fuzzy controller, write the discrete transfer function of the linearized object, $W_{OC}(z)$ which, taking into account expression (1.1), will be of the form:

$$W_{OY}(z) = \frac{\Delta Y(z)}{\Delta U(z)} = \frac{a_0 z^{-m} + ... + a_{m-1} z^{-1} + a_m}{b_0 z^{-n} + ... b_{n-1} z^{-1} + b_n}, \quad (1.2)$$

Where $\Delta Y(z)$ and $\Delta U(z)$ - discrete Laplace images for deviations $\Delta y(k)$ and $\Delta u(k)$, and the coefficients $a_p, (\rho = 0,1,2,..., m)$ and $b_\gamma, (\gamma = 0,1,2,..., n)$ depend on the type of nonlinear function $\varphi(\cdot)$, the base mode coordinates u_0, y_0 and the sampling period chosen $.T_0$.

The discrete transfer function of the linearized neural network looks like this:

$$W_{HC}(z) = \frac{\Delta U\ (z)}{\Delta V\ (z)} = \frac{c_0 z^{-p} + ... + c_{p-1} z^{-1} + c_p}{d_0 z^{-q} + ... + d_{q-1} z^{-1} + d_q}, \quad (1.3)$$

Where $\Delta V\ (z)-$ discrete Laplace image for the deviation $\Delta v\ (k)$, and the coefficients of $c_s, (s = 0,1,2,..., p)$ and $d_t, (t = 0,1,2,..., q)$

depend on several factors at once: the number of neurons σ the type of activation function of neurons; weights of synaptic connections $W_{\alpha\beta}, W_{\beta}, (\alpha = 1,2,..., p+q+1; \beta = 1,2,..., \sigma)$, from the value of the network input. v_0.

To give the property of the system astatism, i.e. to increase the accuracy of the control system, integrators N – one in each of the N channels of the control system, in this case the equation of the control system has the form:

Where $V_i(z)$ and $E_i(z)$ - discrete Laplace images for coordinates $v_i(k)$ and $e_i(k)$.

Then the dynamics of the control object in a stationary mode is described by a transfer matrix of $W_{OC}(z)$ size, $N \times N$, and the structure under consideration is an – NN transfer matrix $W_{NN}(z)$ of the same size as the characteristic equation of a closed linearized control system will have the form:

$$V_i(z) = \frac{T_0}{1-z^{-1}} E_i(z), (i = 1,2,..., N),$$

(1.4)

$$\det\left[I + \frac{T_0}{1-z^{-1}} W_{OC}(z) W_{NN}(z) \right] = 0. \qquad (1.5)$$

We represent the transfer matrices $W_{OC}(z)$ and $W_{NN}(z)$:

$$W_{OC}(z) = \left\| \frac{a_{ij}(z)}{b\ \ (z)} \right\|_{N\times N}; W_{HN}(z) = \left\| \frac{c_{ij}(z)}{d\ \ (z)} \right\|_{N\times N}, \qquad (1.6)$$

Where $a_{ij}(z)$ and $b\ \ (z)$ - polynomials z^{-1}, with respect to m_{ij} having orders and n , respectively; $c_{ij}(z)$ and $d\ \ (z)$ - polynomials with respect to z^{-1}, whose orders are equal to p_j and $\sum_{i=1}^{N} q_i$.

To synthesize the control system, we determine the number of nonlinear algebraic equations by the formula

$$RL = R\max\left\{ N + n + \sum_{i=1}^{N} q_i; N - 1 + m_{ij} + p_j \right\}. \qquad (1.7)$$

The total number of unknown controller parameters (i.e. the number of adjustable weights NN) is calculate by the formula:

$$(KP) = \left[2N + \sum_{i=1}^{N} (p_i + q_i) \right] \cdot \sigma. \qquad (1.8)$$

Then the conditions for the mathematical closure of the system of equations (KP) (RL), takes the form:

$$\left[2N+\sum_{i=1}^{N}(p_i+q_i)\right]\sigma \geq R\max_{i,j}\left\{N+n+\sum_{i=1}^{N}q_i;N-1+m_{ij}+p_j\right\}.$$

Letting go of the expression on the right-hand side of this inequality, we arrive at the following system of inequalities:

$$\left[2N+\sum_{i=1}^{N}(p_i+q_i)\right]\sigma \geq R\cdot\max_{i,j}(N+n+\sum_{i=1}^{N}q_i);$$

$$\left[2N+\sum_{i=1}^{N}(p_i+q_i)\right]\sigma - Rp_j \geq R(N-1+m_{ij}+p_j),(i,j=1,2,...N).$$

or in final form:

$$(2N+\sum_{i=1}^{N}p_i)\sigma+(\sigma-R)\sum_{i=1}^{N}q_i \geq R(N+n);$$

$$\left[2N+\sum_{i=1}^{N}(p_i+q_i)\right]\sigma - Rp_j \geq R(N-1+m_{ij}),(i,j=1,2,...N). \qquad (1.9)$$

The desired solution to the problem of structural synthesis of a control system based on the criterion of minimum complexity is a neural-network controller described by a set of integers minimizing the value (1.7) when constraints (1.8) are satisfied. The tuning of the parameters of the multidimensional neural network controller carried out according to a high-speed fuzzy-logical inference algorithm.

The accuracy of training fuzzy models. This is because traditional fuzzy inference algorithms use hard arithmetic operations for finding the minimum and maximum. In addition, the accuracy of fuzzy models influenced by the architecture of fuzzy rules, together with the chosen method of defuzzification operation.

To eliminate these shortcomings, it was propose to use soft arithmetic operations in fuzzy models to determine the minimum and maximum. It possible to calculate the control action taking into account any changes in the input parameters. At the same time, for training a neuro-fuzzy system, it was propose to use the area difference method [3].

When using soft arithmetic operations of fuzzy-logical inference [4], the soft minimum and soft maximum defined as follows:

Soft minimum:

$$\min_{\delta}(x_1,x_2)_I=\frac{x_1+x_2+\delta^2+\sqrt{(x_1-x_2)^2+\delta^2}}{2}.$$

Soft maximum:

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$$soft-\max(x_1,x_2)=\left|\gamma\cdot\max(x_1,x_2)+0{,}5(1-\gamma)(x_1+x_2)\right|, где\ \ \gamma=0{,}7.$$

In defuzzification, the calculation of variables carried out by the area difference method.

The learning algorithm of the neuro-fuzzy system consists of the following stages, while the terms of the membership function are triangular or trapezoidal membership functions [7-8], described by the expression of the trapezoidal membership function:

$$f(x;a,b,c,d)=\begin{cases}0, & x\le a;\\ \dfrac{x-a}{b-a}, & a\le x\le b;\\ 1, & b\le x\le c;\\ \dfrac{d-x}{d-c}, & c\le x\le d;\\ 0, & d\le x.\end{cases}$$

Where a,b,c,d – membership function parameters; x – quantitative value of the input parameter, having a triangular shape for a fuzzy system.

The system has two input variables each with three terms $X_1=\{x_{11}\}+\{x_{12}\}+\{x_{13}\}$ and $X_2=\{x_{21}\}+\{x_{22}\}+\{x_{23}\}$ and an output variable having five terms, $y\in Y\{y_1\}+\{y_2\}+\{y_3\}+\{y_4\}+\{y_5\}$.

Stage 1. Operation fuzzification of input variables.

Stage 2. Determination of the degree of membership for each input information.

Stage 3. A fuzzy knowledge base containing fuzzy rules synthesized (Table 1.)

Table 1

Fuzzy knowledge base

FR	IF		THEN	FR	IF		THEN	FR	IF		THEN
FR_1	x_{11}	x_{21}	y_5	FR_4	x_{11}	x_{21}	y_4	FR_4	x_{11}	x_{21}	y_3
FR_2	x_{11}	x_{22}	y_4	FR_5	x_{11}	x_{22}	y_3	FR_5	x_{11}	x_{22}	y_2
FR_3	x_{11}	x_{23}	y_3	FR_6	x_{11}	x_{23}	y_2	FR_6	x_{11}	x_{23}	y_1

Stage 5. Operation defuzzification carried out by the area difference method. In this case, the areas of the trapezoidal terms of the FP calculated by the formula:

$$S = \frac{h}{6}(b_1 + 4b_2 + b_3),$$

Where h – height of a geometric figure; b_1, b_2, b_3 – the length of the lower, middle and upper base of the geometric figure.

Stage 6. Network training. When training the network, you can use the standard ANFIS backward error propagation method. However, in our case, the correction of the truncated areas of the terms of the output variable carried out until y_{defuz} is as close as possible to the reference value in accordance with the ratio:

$$y_{output} = (w)_i + \delta(y_{defuz} - y_{ref}),$$

(1.15)

Where δ - training step of the neuro-fuzzy inference system (by default δ = 0.02).

The neural network weights, w, calculated based on the ANFIS standard error propagation method.

Should note that the use of the method of soft arithmetic operations in the learning process has shown an advantage over traditional teaching methods. Should note that that the proposed method for training fuzzy systems has a response to the resulting variable in the entire range of definition of input and output parameters.

The adaptation of the neural network parameters carried out according to the following procedure.

Layer 1. It is a process of fuzzification of input variables; each of them has a pair of terms with a membership function. The network inputs connected exclusively to their terms.

Layer 2. The outputs of the neurons of the first layer are the values of the degree of membership for each of the prerequisites of the input variables.

Layer 3. Each node of this layer corresponds to a specific fuzzy control rule of the FCR. The outputs of the nodes of this layer are the values of the degrees of truth.

Layer 4. In this layer, the membership functions of the output parameter formed.

Layer 2- 4 represent the mechanism of fuzzy inference.

Layer 5. The process of defuzzification of the output parameter is in progress.

In the process of learning the neural network, new terms of the membership function of the output parameter formed until the value obtained in the neural fuzzy network is equal to a given number. $y = y_p$.

RESULTS OF THE STUDY

Based on these considerations, a simulation model of a fuzzy absorber temperature control system in the Matlab environment was built (Fig. 1) and a number of computational experiments were carried out in the presence of external and parametric disturbing influences.

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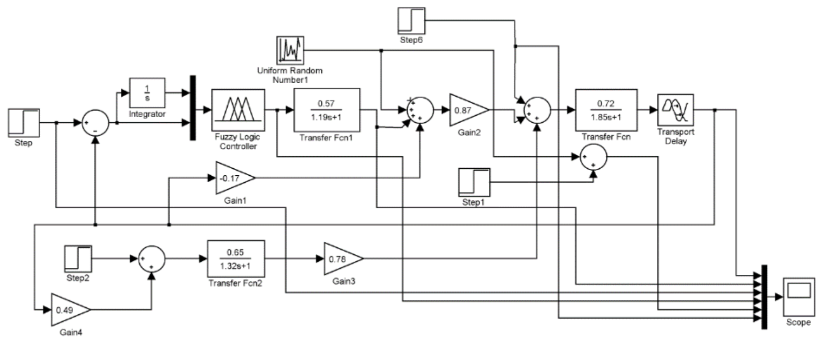

Fig. 1. Simulation model of an adaptively fuzzy absorption column temperature control system

As a reference model, we will use the transfer function corresponding to the real state of the process:

$$W(p)=\begin{bmatrix}\dfrac{5}{(p+10{,}96)(p+0{,}46)} & \dfrac{2{,}5}{(p+10{,}96)(p+0{,}46)}\\ \dfrac{0{,}28(p+12.50)}{(p+10)(p+0{,}5)} & \dfrac{10}{(p+10)(p+0{,}5)}\end{bmatrix}.$$

In a computational experiment in the Simulink MatLab environment, an abrupt change in the temperature of the external environment (load) considered (Fig. 2).

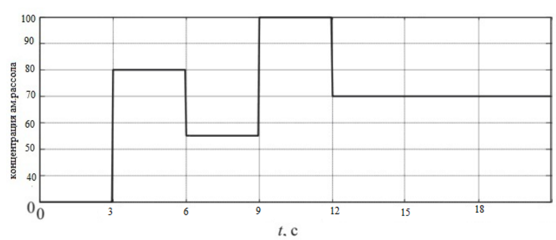

Fig. 2. Temperature change relative to nominal mode

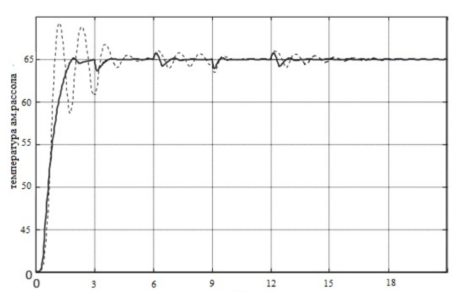

Fig. 3 Transient plots in an adaptive control system with a reference model with a constant and variable adaptation coefficient

The experiment showed that the best adaptation coefficient is $\gamma = 0{,}65$.

In fig. 3 shows a comparison of the operation of an adaptive-fuzzy system with a reference model with an adaptation coefficient (dashed line) and an adaptive system with a reference model with a variable controlled by a trained ANN. Figure 3 shows a graph of the change during a transient. It could see from the graphs that the proposed system gives a better result than the classic one.

CONCLUSION

The paper proposes an algorithm for adaptive adjustment of the parameters of a neuro-fuzzy controller using the area difference method, which ensures the speed and accuracy of generating control actions. It shows that the use of soft arithmetic operations for the development of control actions makes it possible to take into account any changes in the properties of the control object and external influences. In addition, an algorithm for training neural networks based on the area difference method presented, which makes it possible to reduce the time for calculating controls. The developed algorithm implemented in the Matlab environment and a simulation experiment carried out to determine the possibility of the method.

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