

Structural-Parametric Synthesis of an Adaptive Fuzzy-Logical System

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Abstract One of the ways to improve the quality of the process of managing dynamic objects, in the presence of various types of uncertainty of external and internal factors, due to insufficient information about the object and useful signals and noise acting on it, is to develop new and improve existing methods and algorithms for solving problems of structurally parametric synthesis of neuro-fuzzy control systems that can significantly expand the capabilities of dynamic systems. An analysis of existing approaches showed that at present, traditional methods of controlling the absorption process do not meet modern requirements, due to the lack of a system analysis of the entire set of control systems as a whole, the structure of the system and the relationship between its functional elements, etc. The aim of the work is to create an automatic control system dynamic object, allowing to overcome the difficulties associated with the non-stationary process, structural and parametric uncertainty and variability of external influences. A technique for the synthesis of a high-speed control algorithm based on fuzzy-logical inference is proposed, which allows to eliminate empty and zero solutions when determining the architecture and calculating the weights of arcs of a neural network. To correct the parameters and structure of the fuzzy-logical controller, an adaptation block is proposed in the control system loop. The originality of the proposed synthesis method is to ensure high speed of finding control actions due to the possibility of eliminating the redundancy of computational procedures associated with discarding empty and zero solutions in the formation of control devices when choosing the architecture of a neural network and calculating synapse weights. The proposed structural-parametric adaptation algorithm in the process control problems allows to reduce the number of iterations in the process of network training, to reduce the error in the calculation of control values 8 to 1%.

Keywords Adaptive Models, PID-Regulation, Fuzzy Controller, Identification Methods, High-Speed Algorithm

1. Introduction

Currently, control theory pays special attention to the synthesis of mathematical models and control algorithms with insufficient information about the control object and useful signals and noise acting on it. This interest has intensified recently in connection with the study of weakly formalized complex systems and the development of principles and algorithms for controlling these systems.

The most promising direction in solving this problem is the use of universal approximators of a wide class of multidimensional nonlinear functions - adaptive models of fuzzy inference and adaptive fuzzy neural networks. The parameters of adaptive models of both types are tuned by optimizing them in the sense of a certain criterion formed from data from the training sample.

Solving this optimization problem is a difficult task for a number of reasons. Firstly, this is a large dimension of the vector of parameters of the fuzzy model. Secondly, the large dimension of the search space is closely related to the problem of multiextremality of the objective function. In addition, the nature of the function completely depends on the data of the training sample, which change with each new simulated process or object. At present, a large arsenal of tools has been accumulated for solving optimization problems, but the search for new, more effective methods continues. Gradient optimization methods are standard and well-studied. This group of methods uses the value of the gradient of the function to search for the extremum. The disadvantage of these methods is the need to calculate the gradient of the function, the dependence on the initial approximation.

In [13], the use of genetic algorithms in optimization problems for fuzzy inference systems was considered. However, classical genetic algorithms and their varieties are not always effective in solving the problem of multimodal optimization.

In [18], the application of artificial intelligent systems (AIS) in fuzzy classification systems was considered, in particular for generating a base of fuzzy rules. Also considered is the tuning of adaptive models of fuzzy inference implemented in the form of a fuzzy inference system and a fuzzy neural network based on AIS. To overcome the above problems, the principles of fuzzy-logical control are currently widely used, which allow real-time effective control of the process in the presence of random errors. In this case, the speed of fuzzy-logical systems does not exceed several tenths of microseconds, since in order to find the control parameter it is necessary to manipulate only the only value coming from the sensor system at a given time.

To eliminate these shortcomings, it is necessary to complicate the information structure of the system, i.e. to develop cascade, multi-circuit automatic control system (ACS). But in this case, problems arise in the choice of regulators of the internal and external circuits of such systems under conditions of the indefinite nature of disturbing factors. From the position of a systematic approach, almost all conventional systems are systems with incomplete information about the model of an object.

Recently, there has been an extremely high interest in one of the most important applications of the theory of fuzzy sets - the analysis and synthesis of fuzzy regulators and control systems for technological processes and installations. Recently, it has already been more definitely possible to speak of the three types of fuzzy regulators that have formed: logical-linguistic, analytical, and trainees. However, information about them is not systematized and scattered over many publications.

On the other hand, the implementation of traditional fuzzy-logical algorithms used in various intelligent automated control systems has a number of disadvantages, which include a reduction in the output time of the resulting value.

The above is due to the fact that, firstly, the presence of empty solutions, the number of which increases with the increase in the number of fuzzy rules that form the basis of knowledge bases. Empty solutions appear in the conclusions of fuzzy-logical conclusions during the enumeration of terms of input variables depending on specific control rules, while they do not participate in further mathematical calculations, but significantly reduce the speed of the fuzzy-logical control system.

Secondly, the presence of zero sections in terms describing the input and output fuzzy variables that appear during the software implementation of neuro-logical calculation (NLC) algorithms. That is, when it is necessary to perform the operation of taking the maximum

and / or minimum between two terms, the program sequentially iterates over the abscissa through a certain step all the possible values of the fuzzy variable specified on the universal set, and not just those values of the universal set where the value of the membership function (values on the ordinate axis), is different from zero.

Thus, one of the urgent tasks is to eliminate the appearance of empty solutions and zero sections.

2. Research Method

Many technological processes with a number of uncertainties are characterized by the difficulty of maintaining technological parameters and small operating ranges of the process, high energy consumption and other types of uncertainties. Maintaining the specified parameters of the technological process directly affects the volume of production, quality characteristics and, as a consequence, the economic efficiency of production as a whole.

It is known that at present, PID control positional and relay are widely used in industry. About 90% of the regulators in commercial operation use the PID algorithm. The reason for such a high popularity is the simplicity of construction and industrial use, clarity of operation, suitability for solving most practical problems and low cost. The disadvantage of PID control is that when changing operating points due to disturbance, it requires reconfiguration of the controllers. Moreover, with optimal tuning of the PID controller, a detailed knowledge of the dynamics of the object is required. In addition, the tuning methods of the PID controller parameters, used for tuning the Ziegler-Nichols method, involves bringing the object to the oscillation region by switching to the P law and varying the gain, which is not permissible for many real objects, due to the automatic mode not being allowed.

In production conditions, with frequent changes in loads and the influence of uncontrolled disturbances on the control object, the values of its parameters are subject to dynamics, which requires the adjuster of the automatic process control system to manually set new PID controller settings or adapt them (Kim, T., Maruta, I., Sugie T., 2008). However, due to the limited time, the lack of the ability to control disturbances, the complexity of the process of identifying a complex object, it is often impossible to calculate the optimal values of the controller settings, which leads to a decrease in the efficiency of the entire technological process. The need to use active methods of object identification to obtain information about it worsens the situation, as it involves a certain deterioration in the quality of the functioning of the automatic control system and, as a result, production losses. In some technological processes, the use of active methods for identifying an object can lead to its unstable operation. There is a problem of optimizing the process of

adaptation of the regulator, in particular the use of methods with minimal information and time costs. Setting up regulators in traditional automatic control system (ACS) is a very time-consuming task, requiring detailed adjustment of the parameters of the transmission coefficient K_p and constant integration of the T_i object. During commissioning, this operation is performed manually, as a rule, according to the transient response of the system.

Calculation of parameters by formulas cannot give an optimal regulator setting, since analytically obtained results are based on highly simplified object models. In particular, they do not take into account the non-linearity of the "restriction" type, which is always present in the control action. In addition, the parameters K_p and T_i , identified with some error, are used in the model.

The general approach to adjusting the dynamic tuning parameters relative to the calculated values can be qualitative or fuzzy, i.e. in the form of linguistic rules drawn up empirically:

- If the transient process is characterized by weak oscillation or if it is absent for such a long duration, then the controller K_n should be increased, and T_i should be decreased;
- If the transient is highly pronounced oscillatory in nature, then K_n should be reduced.

The following rules are known for tuning dynamic ACS regulators:

- An increase in K_n increases speed; over time, decreases faster;
- Decreasing T_i reduces the stability margin of ACS;
- An increase in K_d increases the stability margin and speed of ACS.

It should be noted that with an increase in the number of controlled parameters, the system performance also decreases.

Fixing the appearance of this characteristic at a certain initial setting and using an idea determined from experience about the nature of the influence of regulator settings on it, they make their corresponding adjustment. Then the experiment is repeated and an analysis of a new characteristic is carried out. If necessary, the settings are changed again until the regulation process is satisfactory. As a result of modern approaches to solving such problems, it is proposed to test the method from the standpoint of the theory of fuzzy logic.

Considering the above-mentioned shortcomings of the traditional PID control system during the absorption process, it is proposed to implement a control system using fuzzy logic methods with the formation of correcting corrections in the operation of the PID controller, where Z - is the task, E - is the error; K_p , T_i , K_d - are the parameters of the PID controller, N - is the disturbance, Y - is the output value. In the

proposed PID controller with fuzzy control methods (Fig. 1), the settings will not be static, their coefficients are planned to be changed depending on the state of the system at the current time. Such a control system will be a non-linear system. This will allow a qualitative change in the control process without resorting to complex descriptions of the mathematical model of the absorption process and implicit dependencies of the system parameters, as well as make the control process more adaptive.

A controller with fuzzy control methods based on a traditional controller will adjust the coefficients in the PID controller settings depending on the current value of the control parameter. The algorithm of the fuzzy controller will be based on a set of rules that are formed in the knowledge base block in accordance with the expert knowledge of the process.

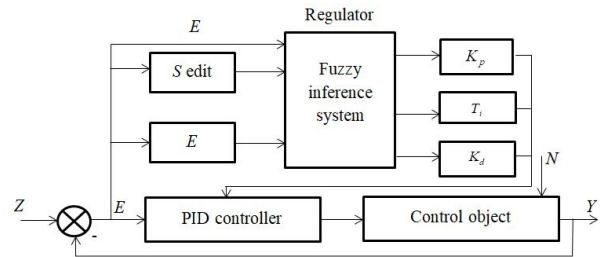


Figure 1. Controller with fuzzy logic methods

Based on the above, this fuzzy-logic inference algorithm consists of the following steps:

1. Creation of membership function for input and output variables.
2. Compilation of fuzzy control rules (FCR) that describe the relationship between input and output parameters.
3. The calculation of the values of the degree of truth for each FCR.
4. Creating a knowledge base, the relationship between the input and output variables of the system parameters.
5. Entering information from sensors.
6. Determination of cutoff coefficients for conclusions.
7. Calculation of cut-off levels to determine the NLC mechanism.
8. Determination of the truncated membership functions of the conclusions of the NLC mechanism.
9. The union of truncated AF.
10. Defuzzification.
11. Output parameter output.

Let the following data be received from the active control system of the equipment of the facility: $a = 15$, $b = 26$. The degrees of membership for each premise will be:

$$\alpha_{11} = 1; \alpha_{12} = 0,04; \alpha_{13} = 0,76;$$

$$\alpha_{21} = 1; \alpha_{22} = 0,15; \alpha_{23} = 0,94.$$

The cut-off levels for each premise of the FCR are

found:

$$\begin{aligned} \alpha_1 &= \min(1, 0,04, 0,76) = 0,04; \\ \alpha_2 &= \min(1, 0,04, 0,94) = 0,04; \\ \alpha_3 &= \min(1, 0,15, 0,76) = 0,15; \\ \alpha_4 &= \min(1, 0,15, 0,94) = 0,15; \\ \alpha_5 &= \min(1, 0,04, 0,76) = 0,04; \\ \alpha_6 &= \min(1, 0,04, 0,94) = 0,04; \\ \alpha_7 &= \min(1, 0,15, 0,76) = 0,15; \\ \alpha_8 &= \min(1, 0,15, 0,94) = 0,15. \end{aligned}$$

The clipping levels are calculated:

$$\begin{aligned} y'_1 &= 0,04; \\ y'_2 &= \min(0,04, 0,15, 0,04) = 0,04; \\ y'_3 &= \min(0,15, 0,04, 0,15) = 0,04; \\ y'_4 &= 0,15. \end{aligned}$$

Next, truncated membership functions are found and, based on the center of gravity method, control decisions are determined:

$$y'' = 32,25;$$

$$p' = 86,98 + 0,13v - 15,6s$$

Let the set value be $y_{adj} = 38$, the output value of the neuro-fuzzy network is calculated: $y''_1 = 39,83$. It can be seen that after the first iteration of training, the error between the two values is already $39,83-38=1,83$.

The resulting value is $y''_{10} = 36,98$.

The results showed that after 10 iterations, the accuracy of training is about 5 %, therefore, it is necessary to carry out the correction of one parameter. In this case, it is advisable to change the fuzzy-logical operations in the third or fourth layer of the neuro-fuzzy network - use the max operation instead of min, then to obtain the desired result $y_{adj} = 38$ 15 iterations will be required, which is one more than in the considered example.

To adjust the adaptive fuzzy controller parameters, it is proposed to use the error back propagation algorithm to adjust the weight coefficients of neural networks.

In this case, the output signal $\wp(\tau)$ neuron in τ -st moment of time ($\tau = 1,2,\dots$) defined as

$$\wp(\tau) = f(\sigma(\tau)) = \frac{1}{1 + e^{-\alpha\sigma(\tau)}}, \quad (1)$$

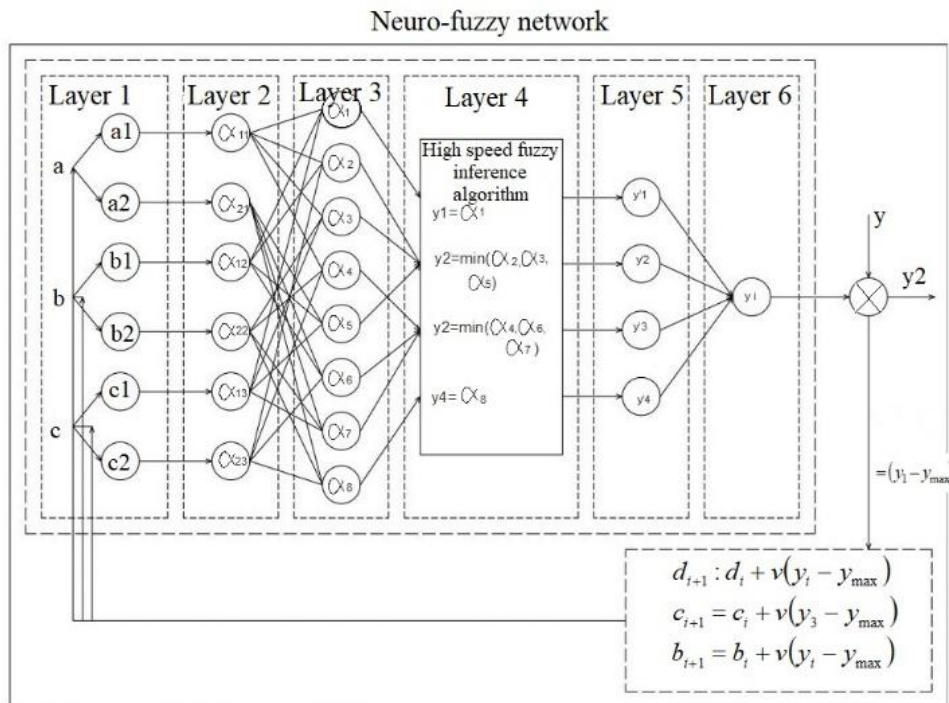


Figure 2. The scheme of a neuro-fuzzy network based on a high-speed algorithm of fuzzy inference

Moreover

$$\sigma(\tau) = w_0 + w(\tau) \cdot e(\tau). \quad (2)$$

As a result, we get a lot of output signals

$$\wp_1(\tau_1), \dots, \wp_i(\tau_i), \dots, \wp_n(\tau_n), \quad (3)$$

which corresponds to the reference value of the output signal a $\wp_0 = \text{const}$,

$$\lim_{n \rightarrow \infty} \wp_n(\tau_n) = \wp_0 = \text{const}.$$

To determine the error based on a comparison of signals (1) and (3), we use the expression presented in the form of a half-sum of squares of differences

$$E(\tau) = \frac{1}{2} [\varepsilon(\tau)]^2 = \frac{1}{2} [\wp_0 + \wp(\tau)]^2. \quad (4)$$

For weight correction w you can use the rule of steepest descent, which takes the form

$$w(\tau + 1) = w(\tau) + \gamma \frac{dE(\tau)}{dw(\tau)}, \quad (5)$$

where, $\gamma > 0$ determines the value of the correction step. Note that

$$\frac{dE(\tau)}{dw(\tau)} = \frac{dE(\tau)}{d\sigma(\tau)} \frac{d\sigma(\tau)}{dw(\tau)} = \frac{dE(\tau)}{d\sigma(\tau)} e(\tau). \quad (6)$$

We introduce the notation

$$\delta(\tau) = \frac{dE(\tau)}{d\sigma(\tau)} \quad (7)$$

then algorithm (5) takes the form

$$w(\tau + 1) = w(\tau) + \gamma \delta(\tau) e(\tau). \quad (8)$$

Calculation Method $\delta(\tau)$ carried out as follows

$$\begin{aligned} \delta(\tau) \frac{dE(\tau)}{d\sigma(\tau)} &= \frac{1}{2} \frac{d}{d\sigma(\tau)} ([\varepsilon(\tau)]^2) = \frac{1}{2} \frac{d}{d\sigma(\tau)} ([\wp_0 - \wp(\tau)]^2) = \\ &= -(\wp_0 - \wp(\tau)) f'_\sigma(\sigma(\tau)) = -(\wp_0 - \wp(\tau))(1 - \wp(\tau)) \wp(\tau). \end{aligned} \quad (9)$$

Given (9), the algorithm for setting the weight coefficient w of the neuron

$$w(\tau + 1) = w(\tau) - \gamma (\wp_0 - \wp(\tau))(1 - \wp(\tau)) \wp(\tau) e(\tau) \quad (10)$$

and the weight coefficient w_0 of the neuron

$$w_0(\tau + 1) = w_0(\tau) - \gamma (\wp_0 - \wp(\tau))(1 - \wp(\tau)) \wp(\tau). \quad (11)$$

Finally get

$$w(\tau + 1) = w(\tau) - \gamma \left(\frac{T_{AM}}{K_2 \cdot K \cdot m_{ChKT}} - \wp(\tau) \right) (1 - \wp(\tau)) \wp(\tau) e(\tau), \quad (12)$$

$$w_0(\tau + 1) = w_0(\tau) - \gamma \left(\frac{T_{AM}}{K_2 \cdot K \cdot m_{ChKT}} - \wp(\tau) \right) (1 - \wp(\tau)) \wp(\tau). \quad (13)$$

where $m_{ChKT} = \text{const}$ - time constant and static coefficient of the chromel-kopel thermocouple, $T_{AM} = \text{const}$ - actuator time constant.

The use of an adaptive fuzzy-logical controller allows you to provide a fairly good quality control. The error back propagation algorithm for setting the weight coefficient of one neuron or the set of weight coefficients of an artificial neural network can be used as an algorithm for adapting a control system under conditions of significant a priori uncertainty or partial change in the parameters of the control object.

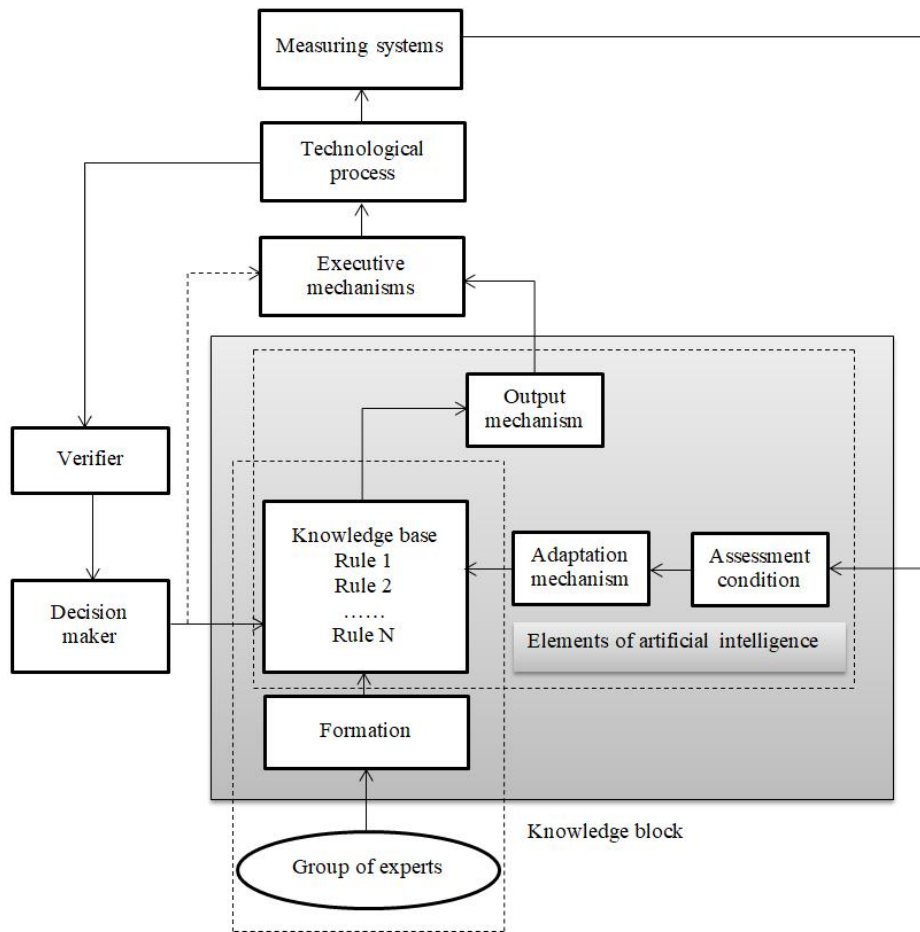


Figure 3. Structural diagram of ACS by actuators

In view of the above, a structural diagram of an automated control system for actuators is proposed (Fig. 3), which includes an adaptation block that is presented to correct not only the parameters, but also the structure of the control stages.

In the “adaptation block”, not only the parameters are corrected, but also the structure of the control stages, that is, the entire control system as a whole. The adaptation block consists of the following blocks “Output mechanism”; “Assessment of the condition of the OS”; “Knowledge Base”; “The adaptation mechanism”.

The disadvantage of the scheme is the large error of the learning results of the neuro-fuzzy network, which is 8 %. This means that if the output of the control system should be a result of 100, then an 8% error will form a result equal to 92 (Takagi-Sugeno model).

In order to reduce the learning outcomes, the following neuro-fuzzy network was developed based on the proposed high-speed algorithm of fuzzy logical inference.

Its advantage is that layer 4 has fewer conclusions, which increases the efficiency of decision-making. At the same time, in the fourth layer there is a reduction in operations in an adaptive neuro-fuzzy inference system, operating on the basis of the mechanism of a high-speed

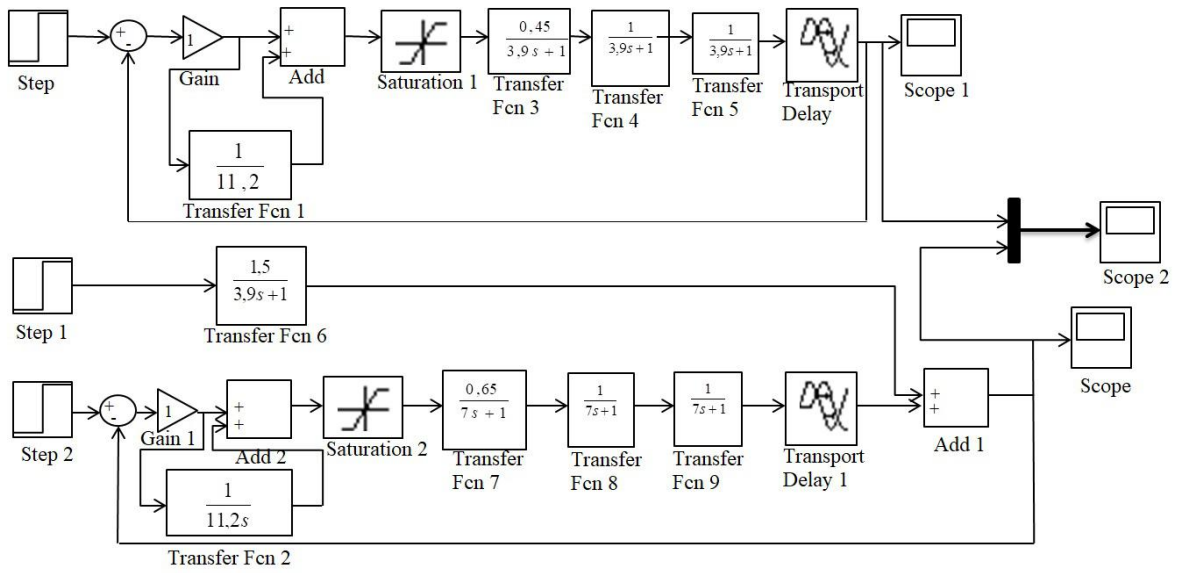
algorithm of fuzzy-logical inference (M_{HSAFLI}), by 2 times compared to traditional ANFIS.

This network works as follows.

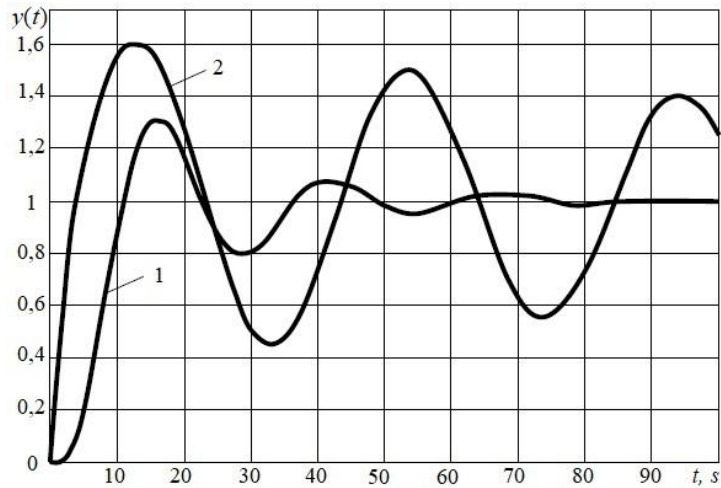
In the control process, information from the sensors enters the output unit and the state assessment unit. After that, from the output unit and the state evaluation unit, the obtained values of the control parameter are sent to the “adaptation” block, in which, in turn, the reference value of the control parameter is set. The adaptation unit calculates the control parameter in real time and compares the calculated and reference values. And if they do not match, it adapts the results to reference values, after which it generates control signals. A neuro-fuzzy network based on a high-speed algorithm of fuzzy logical inference is presented in Fig. 2.

3. Discussion

Let the transfer function of the regulatory object on the job channel $Z - Y$ $W(s)^{Z-Y} = [0,45/(3,9s + 1)^3]e^{-0,52s}$, where a computer model of the ACS was assembled (Fig. 4, a) and its transient response 1 was obtained (Fig. 4, b).



a



b

Figure 4. The structural diagram of a fuzzy adaptive ACS with a third-order object (a) and transients along a task channel $Z = 1$ (b): 1 - a deterministic ACS, 2 - an undefined ACS

To check the stability (robustness) of the system, an uncertainty factor is introduced into the model - adding an external disturbance channel $N - Y$ with transfer function $W^{N-Y}(s) = 1,5 / 3,9s + 1$ and increase the values of the object parameters K_p and T_i by 60 %. As a result $W(s)^{Z-Y} = [0,65 / (7s + 1)^3] e^{-0,52s}$. Requirements for the regulatory process $A1 < 1,5$, $T_p < 60s$. The analysis shows that the quality indicators of the object have deteriorated, the object is located on the border of

the stability region, and the regulator must be adapted to the new operating conditions of object 2 (see Fig. 4, b).

As a result of the analysis of the results of the fuzzy adapter with input values $A1 = 1,6$ and $T_p = 100s$, defined by the transient identifier (Fig. 4, b, 2), settings are recommended $K_p = 1,58$, $T_i = 19,4$. The adapter's performance has been proven with acceptable quality indicators $A1 = 1,3$, $T_p = 55,2s$, identified by the process (Fig. 4, b, 1).

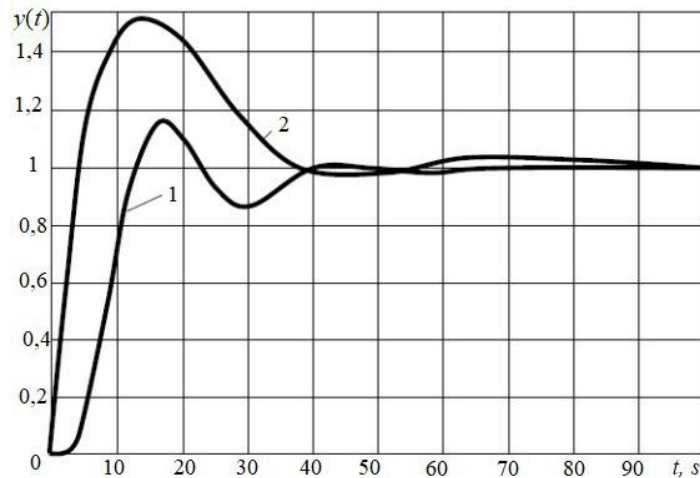


Figure 5. Transients during settings using a fuzzy adapter: 1 - with a deterministic object, 2 - with an undefined object

4. Conclusions

The proposed method for the synthesis of a high-speed algorithm of fuzzy-logical inference based on a neural-fuzzy network allows us to eliminate empty and zero solutions in the problems of determining the architecture and calculating the weights of the arcs of the neural network of the process. To correct the parameters and structure of the fuzzy-logical PID controller, the inclusion of an adaptation block in the control system loop is proposed. Adaptation is carried out taking into account the state of the object and external influences. Using the method of fuzzy-logical PID control law in the operation of the controller of the control system allows you to get a better transition process, which eliminates the use of computational procedures specific to the classical method of regulation, thereby improving the quality indicators of the target product.

The proposed approach may be useful in the modernization of control systems for a wide class of dynamic objects where linear PID controllers are used.

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