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Operative-predictive control of a reactor plant based on fuzzy models

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Abstract – This article discusses an algorithm for fuzzy control of the technological mode of a reactor unit using fuzzy production models of logical inference and fuzzified measurement information from the control object, discusses the methodology of a computational experiment for modeling technological processes of a reactor unit in order to study control algorithms, and conducts a study of algorithms in a computational experiment. Recommendations are given for configuring the developed algorithms as part of an existing automated process control system and retraining the algorithms, if necessary, by the personnel of the engineering research department of an oil refinery, including using a computational experiment on a mathematical model of the technological process of the reactor unit of a catalytic cracking unit.

Keywords – fuzzy control, fuzzy models, membership functions, process variable, control algorithm, operational-predictive control, reactor unit, regulator

I. Introduction

The catalyst regeneration process is carried out with countercurrent movement in the apparatus of the catalyst moving from top to bottom under the action of gravity and atmospheric air passing from bottom to top [1-3]. The regenerator is structurally divided into three regeneration zones. The lower (*NZ*) and upper (*EZ*) zones are intended for regeneration, the intermediate zone is designed to prevent fresh air from coming into contact with flue gases, since this results in intensive additional oxidation of CO to CO2 with a significant release of energy, which can lead to destruction of flue pipelines and sintering of the catalyst .

The shutters at the inlet and outlet of the upper and lower regeneration zones have an automatic drive with remote control.

To stabilize the regeneration mode in the apparatus, it is necessary to stabilize the pressure drops across the zones:$\Delta P_{ez} = P_{in}^{e} - P_{out}^{e}$, $\Delta P_{mz} = P_{in}^{e} - P_{out}^{l}$, $\Delta P_{nz} = P_{in}^{l} - P_{out}^{l}$, which depend on the change in the total air flow, the degree of opening of each of the four dampers. The plant operator stabilizes the pressure differences with these shutters.

The perturbations of the regeneration process include the temperature of the atmospheric air T_a entering the regeneration, the concentration of coke after the cracking reaction *KA*, the temperature of the catalyst at the inlet to the regenerator *XAT*. Controlled variables are: oxygen concentration in flue gases *GHAp*, *GHAy*; flue gas temperature *GTp* and *GTy* for *LZ* and *UZ*, respectively, the temperature of the catalyst in the *LZ*, pressure drops across the regenerator. The controls are: the total air flow for regeneration, the positions of the dampers at the inlet and outlet of the *LZ* and *UZ*.

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II. Materials and Method

The mathematical model of the regeneration unit (RU) does not allow taking into account the aerodynamics and distribution of the gas phase flows inside the regenerator, but takes into account only the air flow into each of the regeneration zones.

Therefore, the control algorithm uses the experience of operating personnel, formalized in the form of a database of fuzzy production models for representing operator actions in possible technological situations [4], [7]. For this, two tasks are solved:

- formation of membership functions of linguistic terms of the measured input and output variables of the technological process;
- formation of fuzzy production models of the type "if ..., then ...".

The solution of the first problem is based on the use of trends in controlled technological parameters, which create an objective image of these modes, taking into account the peculiarities of the technological process by process operators.

The approach is based on the automatic classification of individual variables in the entire spectrum of their actual values by the method of dynamic thickening with a fuzzy classification algorithm for a priori given number of classes, with the allocation of the coordinates of the centers of the classes and the automatic construction of membership functions of the distinct values of these variables to the corresponding classes.

The choice of the number of classes for each variable is determined by the number of linguistic terms intended for use in the fuzzy production model [8-9].

The sequence of assigning (x_{ij})-th observation of each j-th technological parameter to the l-th class and determining the coordinates of the centers of classes ($i = \overline{1,n}; l = \overline{1,k}$, where n is the number of observations, k - the number of classes) is as follows. For fuzzy classification of technological parameters $\bar{x} \epsilon X$ of the catalytic cracking unit, the following algorithm is used [13-16].

A. Algorithm

At the beginning of the training of the algorithm, in the space of technological parameters, the coordinates of the centers of the classes $V_j^l(j = \overline{1,m}; l = \overline{1,k})$ are a priori set. According to the values of the parameters $x_{ij} \epsilon X(i = \overline{1,n}; j = \overline{1,m})$, ranked in ascending order, the values of their membership measures $\mu_{ij}^l(x), (x \equiv x_{ij} \in X;\ i = \overline{1,n}; j = \overline{1,m}; l = \overline{1,k})$ to each of the k classes: $\mu_{ij}^l(x) = 0$ if $\left(l \neq 1 \wedge x_{ij} \leq V_j^1\right) \vee \left(1 < l < k \wedge x_{ij} < V_j^{l-1}\right) \vee (V_j^{l+1} < x_{ij}) \vee (l \neq k \wedge V_j^1 < x_{ij})$;

$\mu_{ij}^l(x) = \frac{1/\left\|x_{ij}-V_j^l\right\|^2}{\sum_{c=1}^{k}\left(1/\left\|x_{ij}-V_j^l\right\|^2\right)}$, if $1 < l < k \wedge V_j^{l-1} < x_{ij} < V_j^{l+1}$;

$\mu_{ij}^l(x) = 1$ if $\left(l = 1 \wedge x_{ij} \leq V_j^1\right) \vee \left(l = k \wedge V_j^l < x_{ij}\right), l = \overline{1,k}); i = \overline{1,n}; j = \overline{1,m}$;

where $\vec{V_j} = \{V_j^1, \dots, V_j^k\}$ is the vector of coordinates of the centers of classes of the j-th technological parameter.

According to the obtained values of the membership functions, the coordinates of the centers of the classes $V_j^l = \frac{\sum_{i=1}^{n}\left(\mu_{ij}^l(x)\right)^2 x_{ij}}{\sum_{j=1}^{n}\left(\mu_{ij}^l(x)\right)^2}, l = \overline{1,k}); j = \overline{1,m}$ and with the found values V_j^l, the values of the membership functions $\mu_{ij}^l, i = \overline{1,n}; j = \overline{1,m};\ l = \overline{1,k})$. The procedure continues until the condition $\delta = \max_l\{\left|\mu_{ijr}^l(x) - \mu_{ij(r-1)}^l(x)\right|\} < \varepsilon, \forall i = \overline{1,n}; \forall j = \overline{1,m};\ \forall l = \overline{1,k}$, where δ and ε are the current and given errors, respectively.

When analyzing the daily trends of technological variables, it was found that their values are mainly grouped into seven classes.

Therefore, five linguistic terms were used, which makes it possible to take into account significant and small deviations of parameters from the norm and to form control actions in a timely manner.

An example of the application of the algorithm is shown in the graph in fig. 1 with a normalized, relative to the range of change over a given period of time, technological parameter.

To form the base of production models for knowledge representation, the results of simulation modeling on the mathematical model of the reactor unit and interviewing experts were used.

The number of possible logical rules is reduced by dividing the process mode indicators into those controlled by the air flow to the upper zone of the regenerator and the air flow to the lower zone. In addition, a specific role (task) is assigned to each air valve. Gate valves at the inlet regulate air flow rates by zones.

Their position is controlled by a fuzzy controller, the task of which is given by a fuzzy control algorithm. The outlet valve positions stabilize the pressure drops in the regenerator.

A database of fuzzy production models of the actions of the operator, who controls the technological process, in possible technological situations has been formed.

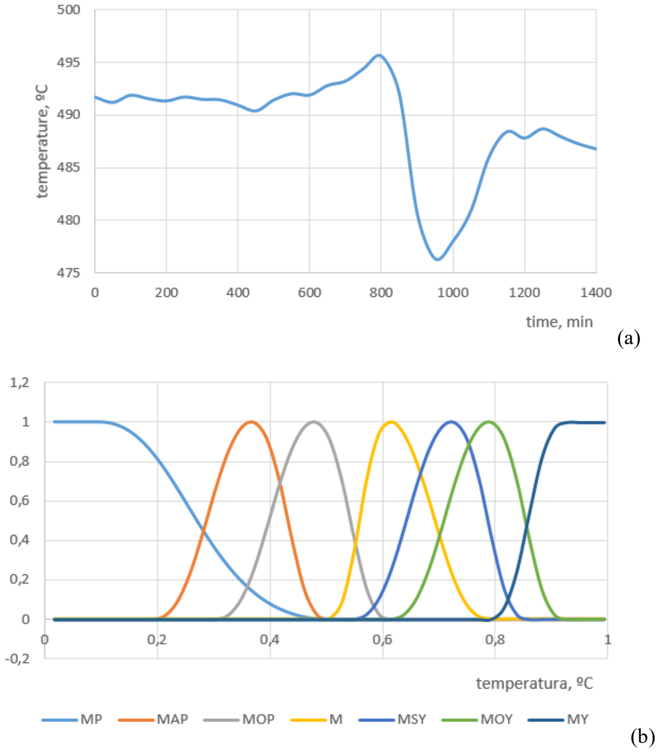

Fig. 1 The air temperature change graph in the lower part of the catalyst regeneration device (a) and the corresponding function corresponding to this parameter (b)

A fragment of the set of rules for controlling the flow to the upper zone is presented below:

If GHAy=MSY and GTy=MSY and XAT=M, then Gbb=MAP,

If GHAy=MY and GTy=MSY and XAT=M, then Gbb =MAP,

If GHAy=MAP and GTy=MAP and XAT=MSY, then Gbb=MY,

where MAP, MP, MOP, M, MOY, MY, MSY are linguistic terms.

The block diagram of the fuzzy air supply control algorithm is shown in Fig. 2.

The fuzzy control algorithm of process control is works as follows:

- a selection of variables used in the algorithm is created in the database;
- according to their indicators, the initial values of the relevance functions are formed;
- parameters change times are recorded;
- each subsequent value of variables is replaced by the previous value;
- the control algorithm determines the time spent by the adjusters to set new values;
- ambiguous decision-making is carried out;
- output values of technological parameters are adjusted to the task value through adjusters;
- the control algorithm is constantly restarted after a technical delay;
- the condition of resetting the values of the membership functions is performed and the membership functions are given new values;

- after a certain time, new values of relevance functions are recorded and fuzzy adjusters are retrained according to these values;
- the range of acceptance of new values of technological parameters indicating the current state Δt is the adjustment parameter of the control algorithm.

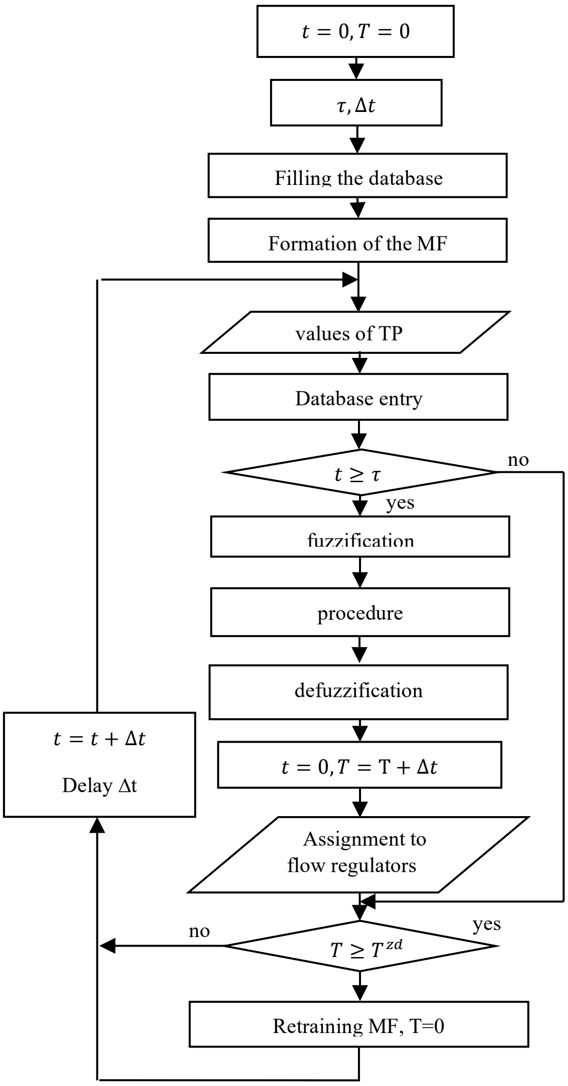

Fig. 2 Block diagram of fuzzy control algorithm

The operation of the algorithm is as follows: in the database (DB), a daily sample of the regenerator variables used in the algorithm is formed, according to the representatives of which the initial values of the membership functions (MF) are formed, the moment of time is fixed. Next, the current values of process variables (TP) are entered, which shift the previous values in the database, and the condition (time τ) of the formation of a task for the flow controllers by the control algorithm is checked. A fuzzy inference (Mamdani's algorithm) is carried out, consisting of fuzzification, inference procedure and defuzzification.

The values of the output variables are transferred to the air flow controllers as references. After a delay of time τ, for example five minutes, the control algorithm is repeated. The condition (time T^{zd}) of MF retraining is checked. At the value of the timer T^{zd}, for example, one hour, the MFs are retrained, T is reset, and the learning cycle time t resumes. The time interval Δt for entering the current values of the TP is the setting parameter of the control algorithm [10-12].

B. Development of computational experiment methods for modeling the technological processes of the reactor block

The study of the operation of the reactor unit in order to clarify the regularities of the flow of the technological process and the degree of influence of its factors on the yield of the target product, as well as to clarify the fuzzy rules and the fuzzy control algorithm, was carried out using a coupled mathematical model adapted to the technological regime of the process of an operating industrial plant, under the influence of various disturbances from the external environment on the regeneration process.

The results and operation of the fuzzy control algorithm are shown in fig. 3 in the form of graphs reflecting the change in process variables with a change in the concentration of coke KA on the catalyst at the inlet to the regenerator air intake.

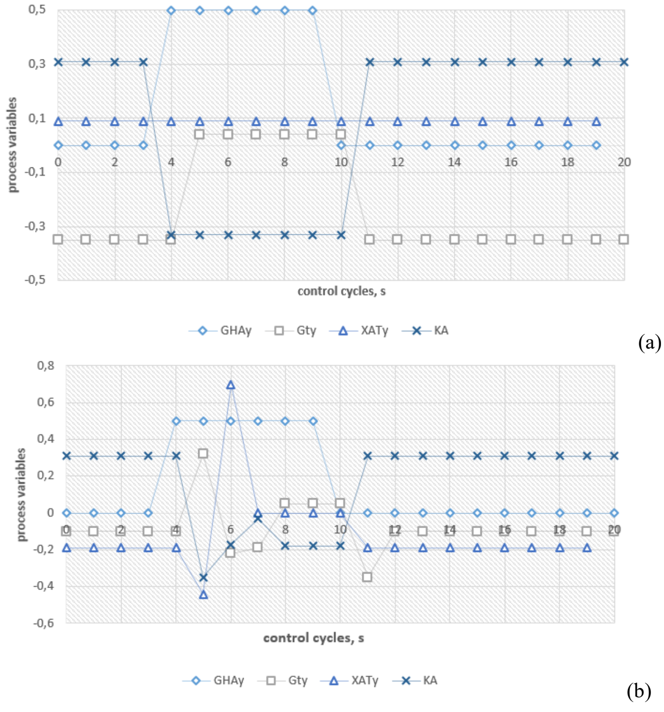

Fig. 3 The process of changing variables a) - without using the fuzzy control algorithm, b) – using the fuzzy control algorithm

On fig. 3a shows the process of changing variables without using the fuzzy control algorithm, in fig. 3b - using. The variables shown in the graphs are normalized relative to the range of change over the same time interval as the membership functions and in the zero control cycle correspond to the center of the term "M". The control actions are the air flow rates in the lower and upper zones (S_{lz}, S_{uz}) of the regenerator.

It has been experimentally established that the duration of transient processes in the regenerator at each control cycle is about five minutes (cycle duration τ is a setting parameter of the fuzzy control algorithm when it is adjusted at the facility). The markers on the graphs indicate the values of process variables at the time of application of the control S_{lz}. The value S_{lz} is a reference for the air flow controller in the air intake and remains constant during the control cycle.

Transient processes are schematically shown by lines connecting adjacent values of variables in steady state. With an increase in KA, GTy increases and GHAy decreases, the control algorithm reduces the setting for the air flow controller in the air intake S_{lz}, reproducing the actions of the operator who controls the technological process .

A maximum of three control cycles (15 min) are required to reach the steady state with a stepwise disturbance in coke concentration; in the case of the second stepwise disturbance in coke concentration (return to the previous value in Fig. 2b), two control cycles are sufficient.

In the computational experiment, the duration of the control cycle was five minutes - the time during which all transient processes in the regenerator in terms of pressure and temperature are completed [17-18].

The fuzzy control algorithm is integrated into any control system, regardless of its type, by organizing two-way communication between the control system and the algorithm implemented in a third-party programming environment, using the OPC DA data exchange protocol. Structural diagram of the control system for the reactor block (RB) is shown in fig. 4.

From the control system, the values of the process variables are fed to the fuzzy controller in the database and to the system; based on the sample from the database, MFs are formed, which are used in fuzzy inference together with fuzzy production models (PM) from the PM database.

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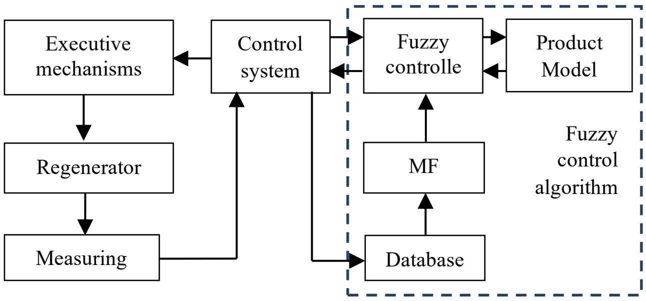


Fig. 4 Structure diagram of the fuzzy control system of the device

C. Computer modeling of the system of operational predictive control of the reactor unit

In order to implement a neuro-fuzzy decision-making and control system at the installation of the reactor block of an oil refinery, individual levels, blocks of the system and imitation of its functioning of the system as a whole were modeled.

Table 1 presents the results of modeling the decision-making process to determine close to optimal modes of the oil catalytic cracking unit. With the same amount of raw materials, the total yields of gasoline and gas at the plant are compared.

Table 1. The results of determining the modes of installation of the reactor unit

Experiment number	**Quantity raw materials**	**The total amount of gasoline and gas produced**		**Total depth of gas and gasoline extraction in % to raw materials**	
		true value on device	based on simulation results	true value on device	based on simulation results
1	*2*	*3a*	*3b*	*4a*	*4b*
1	1637	1090	1109	66,59	67,75
2	1708	1108	1122	64,87	65,69
3	2106	1430	1453	67,90	68,99
4	2012	1329	1343	66,05	66,75
5	2043	1398	1422	68,43	69,60
6	1705	1100	1115	64,52	65,40
:	:	:	:	:	:
50	1720	1130	1148	65,70	66,74

III. Results

Consider the neural identification of the primary oil refining process. The dynamics of the object being identified (reactor-regenerator unit) is significantly variable. To take this into account, experiments on neural identification sets were conducted with significant difference coefficients of the test models of the primary oil refining process.

Let us refer to the neural identification of the model for the reactor temperature. It is assumed that the identified model is characterized by four significant variable parameters: $a_i, i = \overline{1,3}$ (characterizes the temporal dynamics of the model) and f_t (amplification coefficient).

During experiments during computer simulation, these coefficients were subjected to two- and three-fold changes that fully cover the real variability of real process parameters in industrial conditions. The following four cases of the set of process parameters being identified are considered:

Table 2. The results of determining the modes of installation of the reactor unit

	a)	**b)**	**c)**	**d)**
a_0	6,3	12,6	6,3	8
a_1	11,2	11,2	12	6,5
a_2	1	1	3	1
f_t	5,1	8,1	5,1	10

The actual value of the temperature at the output of the reactor and the effect of control If it is clear as a sinusoidal signal Y, then the identifier determines the values at the output of the object. As we can see, for a significant change of object parameters (2-3 times), the neural identifier is quickly trained, the output signal of the object and the signal received from the identifier are compared, and the difference between them is eliminated.

First, we will consider the simulation of an adaptive neural system for operational predictive control of the temperature of the reactor block of the catalytic cracking process.

The results of the operation of the temperature control system when setting and under conditions of significant changes in the parameters of the object are shown in fig. 5(a).

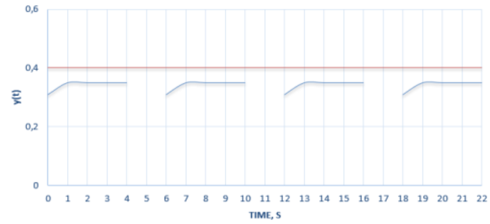
As in the case of identification, the variability of the object parameters was reflected by four sets of parameters: a), b), c) and d). As seen in figure, when moving sequentially from one position to another, the adaptive control system quickly adjusts to the new mode.

It happens in the following way. For case a), the system, quickly adapting, keeps stable and accurate tracking of the task to the system for a long time. When case b) occurs, i.e. change a_0 by 2 times and f_1 by 1,6 times, the neural identifier identifies the reactor model and the neural controller and is configured based on the new adapted object model (trained, i.e. a new weight matrix of the neural network that implements the controller is determined) , and the temperature reaches the target $g_y = 515°C$ and then remains constant. The same can be attributed (Fig. 4(a)) to cases c) and d). On fig. 5, for each case of changing the set of reactor parameters, the weight matrices of the controller are given.

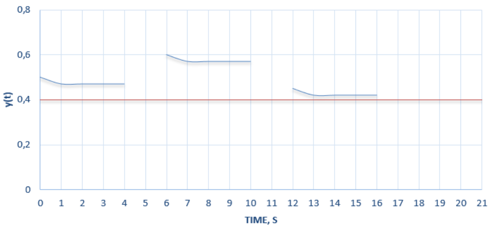
Figure 5(b) illustrates the execution of a simulation of the functioning of the temperature control system discussed above when the neural identifier is disconnected from the system. Since changing the parameters of the controlled object does not identify the reactor, which is a known object, therefore, the controller cannot be adjusted, so the system does not reach the target $g_y = 515°C$ in each of cases a), b), c) and d).

Further, in a computer simulation of the adaptive neural reactor control system being developed to test the effectiveness of the controller adaptation processes, cases are considered when, with the same set of object parameters, random changes are made to the controller weight matrix at random periods of time.

The results of system simulation in the specified mode for case a), as can be seen from this figure, during the period of time when the system test step K changes from 0 to 70, the system has a steady, with acceptable accuracy, transient process (by temperature, when $g_y = 515°C$). The corresponding weight matrix is shown in fig. 5(c) on the first line (below the graph).



(a)



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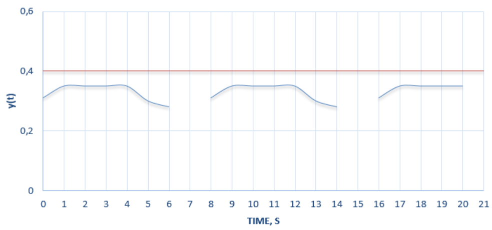
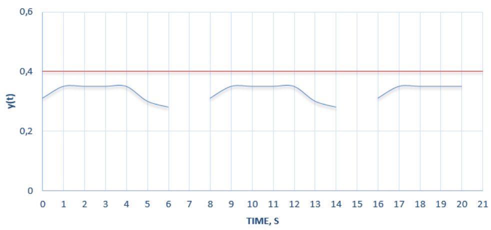
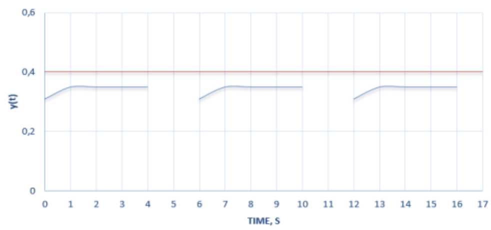


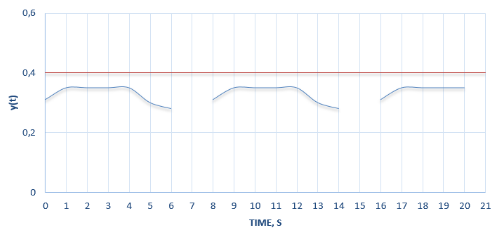
(c)



(d)



(e)



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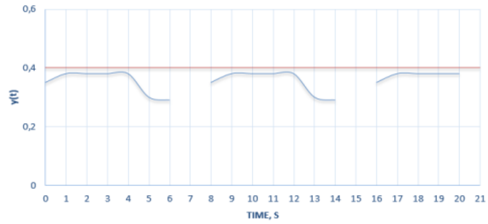
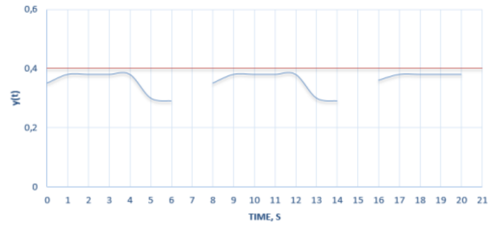


(g)



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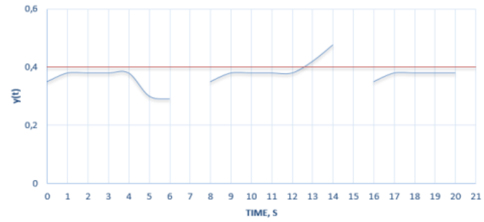

(i)

Fig. 5 Structure diagram of the fuzzy control system of the device

IV. DISCUSSION

Analysis of a comprehensive experimental study of the proposed adaptive neural temperature control system through computer simulation shows the performance of both the neural identifier and neural controller, and the neural control system as a whole.

The results of the system simulation as a whole demonstrate the presence of adaptation, robustness and efficiency of the proposed operative-predictive control system.

V. CONCLUSION

Computer modeling of the proposed system of operational predictive control of the process of catalytic cracking of oil as a whole and its individual levels and blocks was performed, which confirmed the validity of the construction principle, approach, models and algorithms underlying the proposed concept of decision support in operational predictive control of technological processes and productions.

An algorithm for fast predictive control of a complex object has been implemented to make alternative decisions and implement a control system at an oil refinery. To study the fuzzy control algorithm, a methodology for a computational experiment on modeling the processes of a reactor block has been developed. Recommendations are given on the use of the developed tuning algorithms and algorithms for processing existing automated processes as part of the operational control system, including the mathematical model of the reactor block process.

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