METHODS OF SHIP HANDLING IN AVOIDANCE BY THE FUZZY LOGIC CONTROL

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ABSTRACT

In this paper, the author presents the methods of ship handling in avoidance by the fuzzy logic control. The goal of the presented system is to support the navigator in decision making, with possible full replacement of his work in the future. Introduced system has to assure safe trip of ship in each navigational conditions with regard of weather conditions and met navigational objects of static or dynamic nature. The paper devotes the regulators for ship control as: Logic-linguistic regulators, Analytical regulators, Trained Fuzzy Regulators, Comparative Analysis of Fuzzy Controllers, Synthesized by the Methods of Fuzzy Logic and Probability Theory.

Keywords: Logic-linguistic regulators, Analytical regulators, Trained Fuzzy Regulators, Comparative Analysis of Fuzzy Controllers.

INTRODUCTION

The ship is kept on the assumed passing trajectory using the rules of fuzzy inference. The fuzzy controllers are characterized by lower sensibility to disturbances than that revealed by conventional controllers widely used in naval autopilots. Another quality which 66 makes fuzzy controllers more effective than their conventional counterparts is possibility to incorporate expert's elements and basis of knowledge into the controller's basis of knowledge. As mentioned above, the fuzzy controller of ship's motion is divided into two parts: the course controller and the speed controller, working simultaneously. These two parts are structurally identical. The input signals for the both controllers are: the deviation of the output value from that assumed, and speed of the deviation changes in time. For the course controller the assumed value is the course, while for the speed controller – speed. In order to research the method of ship handling in avoidance by the fuzzy logic control, the author studies the regulators as: Logic-linguistic regulators, Analytical regulators, Trained Fuzzy Regulators and Comparative Analysis of Fuzzy Controllers then synthesized them by the Methods of Fuzzy Logic and Probability Theory. The fuzzy controllers comprise fuzzy sets, union of Boolean and intersection operations, and composition with the linguistic values of the variables, fuzzy relation, formed by one or more logical operations and fuzzy inference rule output for a known input. First-linguistic logic regulators (LLR) have a very strong influence on subsequent research in the field of fuzzy control systems, and deserve to present the basic principles of their construction, and then show how these principles are implemented in one of the regulators.

The subjectivity of the selection of intervals and linguistic variables and the associated decline in the quality of governance can be largely eliminated in the so-called analysis of fuzzy controllers and control systems, functionality that is provided by known analytical and numerical methods of parametric identification, analysis and synthesis of linear and nonlinear systems involving fuzzy dynamic models. Such control must be able to acquire knowledge about the behavior and the system and on their basis to develop the control, in which the control error does not exceed the permissible value. In the learning process, in addition to the

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controller, part of the object model, which should also acquire knowledge and adjust to the changing conditions of operation of the facility. Specified requirements and description of the controller and the control object in a fairly fully satisfies the TS-fuzzy model of the structure of the five-layer neural network of direct action, known as the ANFIS (Adaptive - Network - based Fuzzy Inference Systems).

LITERATURE REVIEW

In this subject, there are researches of authors such as A. Lebkowski, R. Smierzchalski, W. Gierusz and K. Dziedzicki (2008). Their works are based on the system joins work of three computer techniques, evolutionary algorithms to marking of optimum path of passages, fuzzy logic to control ship after set path of passage and multivariable robust control to precise movement of the vessel with very small velocity and any drift angle. . In this paper, the author suggests the regulators for ship control as: Logic-linguistic regulators, Analytical regulators, Trained Fuzzy Regulators, Comparative Analysis of Fuzzy Controllers, Synthesized by the Methods of Fuzzy Logic and Probability Theory.

METHODOLOGY

Logic-Linguistic Regulators

The principle of constructing LLR is considered as the example of a simple generalization of the controller with one input x (usually control error) and one output y (regulating or controlling action) associated with the fuzzy rules [1, 2, 3, 4 - 14]:

$$\left.\begin{array}{c} R^1\text{: if } x \text{ is the } X^1,\ y \text{ is } Y^1\text{, otherwise:} \\ R^2\text{: if } x \text{ is } X^2 \text{ then there } Y^2\text{, otherwise:} \\ \dots\ \dots\ \dots \\ R^n\text{: if } x \text{ is } X^n \text{ then there } Y^n, \end{array}\right\} \quad (1)$$

Containing of fuzzy sets $X^{\theta} \in T_x$ and $Y^{\theta} \in T_y$.

The algorithm of functioning of LLR in one form or another form have the conversion routines (variable Fuzz) for the measured value x^0 of x in the linguistic meaning of X', fuzzy inference (fuzzy inference *FI*) of the linguistic output Y' of a known input X' and set of rules $R = \{R^1, \dots, R^n\}$ and transformation (De-fuzzy *Def*) linguistic output values Y' in real y^0 (Figure 1)

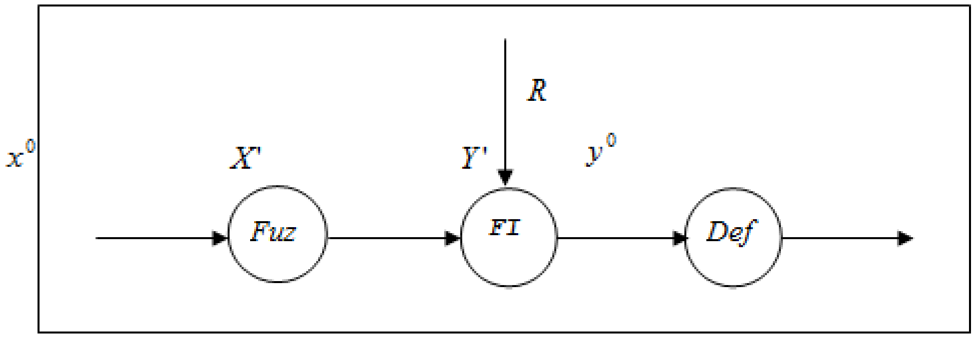

Fig.1. Converting the entrance to the fuzzy controller

The measured variable input x with the value x^0 corresponds to the so-called "degenerate" fuzzy set X' with the membership function:

$$X'(x) = \begin{cases} 1, & if\ \ x = x^0 \\ 0, if & x \neq x^0, \end{cases}$$

Where x^0 - the point called the singleton set. It is written the expression for the fuzzy inference for the given LLR by a set of rules (1):

$$\left.\begin{array}{c} R^1\text{: if } x \text{ is the } X^1\text{, then } y \text{ is the } Y^1\text{, otherwise} \\ R^2\text{: if } x \text{ is the } X^2\text{, then y is the } Y^2\text{, otherwise} \\ \ldots \\ R^n\text{: if } x \text{ is the } X^n \text{ then } y \text{ is the } Y^n, \\ x \text{ have } X' \\ y \text{ have } Y' \end{array}\right\} \quad (2)$$

The values are true statements "x is X^0", "y has an Y^0", and "x has X'" in the rules (1) and in the premise of corollary expression (2) are defined by the respective membership functions:

$$X^{\theta}(x), Y^{\theta}(y) \text{ and } X' \text{ for } x \in X, y \in Y.$$

Each rule R^0 - fuzzy implication is:

$$R^0 = \text{if } x \text{ is } X^{\theta}\text{, then } y \text{ is } Y^{\theta} = X^{\theta} \rightarrow Y^{\theta}.$$

The LLR as the procedures used by the maximum output composition Zadeh [1]:

$$Y'(y) = (X' \circ R)(y) = \bigvee_{x \in X} (X'(x) \wedge R(x, y)) \quad (3)$$

Where: $R(x, y) = \bigvee_{\theta=1}^{n} R^{\theta}(x, y) = \bigvee_{\theta=1}^{n} X^{\theta}(x) \wedge Y^{\theta}(y)$

At the point x^0, the expression (3) after the substitution takes $X'(x^0) = 1$ has the form

$$Y'(y) = \bigvee_{\theta=1}^{n} R(x^0, y) = \bigvee_{\theta=1}^{n} X(x^0) \wedge Y(y). \quad (4)$$

The output value can be determined by maximizing

$$y^0 = \max_{y \in Y} Y'(y) \quad (5)$$

Or computing "center of gravity" of the membership function:

$$\int_{y_{\min}}^{y^0} Y'(y)dy = \int_{y^0}^{y_{\max}} Y'(y)dy \quad (6)$$

The most well-known and often-quoted LRR is designed to control the engine [14], has four inputs (x_1 - the error of pressure equal to the deviation of the actual value from the set value; x_2 - the error rate; x_3 - the variation rate of x_1; x_4 - the variation rate of x_2) and two outputs variables (y_1 - heat variation; y_2 – variation of vapor pressure). The variable ranges of the input X_1, ..., X_4 and the output Y_1 of the variables x_1, ..., x_4, y_1 are divided into seven intervals with the following linguistic values: *PB* – big positive number; PS – average positive number; *PM* - small positive number; *ZE* - zero; NS- small negative number; *NM* - average negative number; *NB* - big negative number. The variable range Y_2 of y_2 has five slots to them with certain linguistic values *NB, NS, ZE, PS, and PB*. These values form the two linguistic term – sets:

$$T_1 = \{NB, NM, NS, ZE, PS, PM, PB\}$$

And

$$T_2 = \{NB, NS, ZE, PS, PB\}$$

Fuzzy controller consists of two sets of rules j = 1, 2, determining the heat and pressure variable y_1 and y_2;

$$\begin{array}{l} R_j^1: if \;\; x_1 \; is \; X_{1j}^1 \; and \; x_2 \; is \; X_{2j}^1 \; and ... \\ ... and \; x_4 \; is \; X_{4j}^1, \; then \; y_j \; is \; Y_j^1, otherwise: \\ R_j^2: if \; x_1 \; is \; X_{1j}^2 \; and \; x_2 \; is \; X_{2j}^2 \; and ... \\ ... and \; x_4 \; is \; X_{4j}^2, \; then \; y_j \; is \; Y_j^2, otherwise: \\ \bullet\bullet\bullet \\ R_j^{n_j}: if \;\; x_1 \; is \; X_{1j}^{n_j} \; and \; x_2 \; is \; X_{2j}^{n_j} \; and ... \\ ... and \; x_4 \; is \; X_{4j}^{n_j}, \; then \; y_j \; is \; Y_j^{n_j}, \\ \underline{x_1 \;\; is \; X_{1j}^{'} \; and \; x_2 \; is \; X_{2j}^{'} \; and ... and \; x_4 \; is \; X_{4j}^{'},} \\ \qquad\qquad y_j \; is \; Y_j^1. \end{array}$$

Statements "$x_i \;\; is \; X_{ij}^{\theta_j}$" and "$x_i \;\; is \; X_{ij}^{'}$" in the premise of the corollary expression (5) with the values of truth, given by the respective membership functions $X_{ij}^{\theta_j}(x)$ and $X_{ij}^{'}\left(x_j\right), i=\overline{1,4}, j=1,2 \theta_j=\overline{1,n}$, integrated by the logical connective "and", is realizing the intersection operation. Then the left part of the truth of rule θ_j is defined as:

$$X_{1j}^{\theta_j}(x_1) \wedge X_{2j}^{\theta_j}(x_2) \wedge ... \wedge X_{4j}^{\theta_j}(x_4),$$

And the true premise will be:

$$X_{1j}^{'}(x_1) \wedge X_{2j}^{'}(x_2) \wedge ... \wedge X_{4j}^{'}(x_4), j=1,2.$$

The maximum expression of the composition (3) takes the form:

$$Y_j^{'}(y_j) = \bigvee_{\substack{x_1 \in X_1 \\ ... \\ x_4 \in X_4}} \left(\left[X_1^{'}(x_1) \wedge X_2^{'}(x_2) \wedge ... \wedge X_4^{'}(x_4)\right] \wedge R_j(x_1,..., x_4, y_j)\right), \tag{7}$$

Where

$$R_j(x_1,..., x_4, y_j) = \bigvee_{\theta_j=1}^{n_j} (X_{1j}^{\theta_j}(x_1) \wedge X_{2j}^{\theta_j}(x_2) \wedge ... \wedge X_{4j}^{\theta_j}(x_4) \wedge Y_j^{\theta_j}(y_j)).$$

As $x_1^0,..., x_4^0$ is singleton of set $X_i^{'}$, therefore after substituting $X_i^{'}(x_i^0)=1, \;\; i=\overline{1,4},$ into the expression (7), it's obtained the implication Mamdani as following:

$$Y_j^{'}(y_j) = R_j(x_1^0,..., x_4^0, y_j) = \bigvee_{\theta_j=1}^{n_j} (X_{1j}^{\theta_j}(x_1^0) \wedge X_{2j}^{\theta_j}(x_2^0) \wedge X_{4j}^{\theta_j}(x_4^0) \wedge Y_j^{\theta_j}(y_j)), j=1,2. \tag{8}$$

Actual output values y_1^0 and y_2^0 are determined based on the membership functions $Y_1^{'}(y_1)$ and $Y_2^{'}(y_2)$ by using the relations (5) and (6).

This LLR with the implication (8) is called the Mamdani controller. If in the expression (4) it's taken *R(x, y)* = 1, the controller Mamdani will be a static characteristic of the multi position (Fig. 2a), which disrupts the linear and continuous of the output *y* with respect to the input *x*.

There have been the attempts to eliminate these deficiencies in [7, 8 and 9] and concluded that it is necessarily used the implication of Lukasiewicz as a fuzzy relation *R(x, y)* in equation (3):

$$R_L(x, y) = 1 \wedge \left[1 - X(x) + Y(y)\right]. \tag{9}$$

Indeed, if $R_L(x, y) = 1$ it is assumed that the implication (9) in the expression (4) with one output:

$$Y'(y) = \bigvee_{\theta=1}^{n} R_L^0(x, y)$$

It allows getting a better LLR with a static characteristic of a saturated linear function (Fig. 2b).

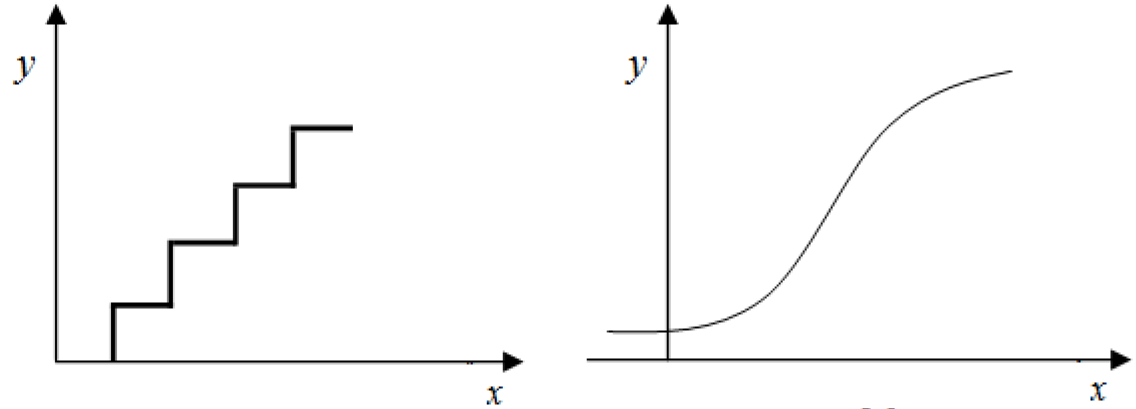

Fig 2. The static characteristic of the fuzzy controller

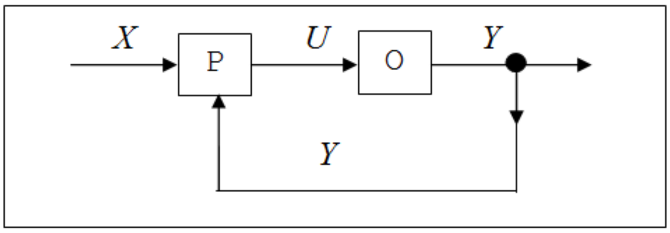

Fig 3. The diagram of closed-loop control system

However, the regulators and fuzzy control system using Zadeh implication are practically applied prevailingly. They were the subject of many studies in which the regulators and control systems are presented by the fuzzy differential:

$$\dot{X}(t) = X(t) \circ R \tag{10}$$

And difference equations:

$$X_{t+1} = X_t \circ R. \tag{11}$$

In the research [3], it has been analyzed the stability and controllability of fuzzy dynamic systems of the type (10) and (11). For these purposes, it's attracted Lyapunov function [3] and methods of assessment of stability based on such specific concepts of fuzzy sets, the energy of fuzzy sets and fuzzy relation *R*, the peak characteristics of fuzzy sets and measure their proximity [7, 8 and 9].

The main disadvantage of the proposed approach is the absence of specific recommendations on the selection and synthesis of fuzzy controllers and control systems with certain dynamic properties (controllability, stability and quality control processes). The first attempt synthesizing of the minimum optimal error of the regulation LLR was made in a closed control system (Figure 3) on the basis of defined tables 1 and 2: F_{OU} and F^* of the object and the optimal closed-loop system, respectively [23]. The compactness of the presentation to be represented in the analytical form tabular operator control object *O*:

$$\dot{Y} = F_{OU}(Y,U), \tag{12}$$

The optimum closed-loop system:

$$\dot{Y} = F^{\bullet}(Y,X), \tag{13}$$

And synthesized operator *P*:

$$\dot{Y} = F_{PX}(X, Y), \tag{14}$$

in which the linguistic variables is typified for the control job *X*, the output *Y*, its speed $\dot{Y}$ and the control *U* take values $T = \{NB, NM, NS, ZE, PS, PM, PB\}$ in term. The operator of the object (12) is based on the results of its study of static and dynamic characteristics. For a table of the operator of the object (12), it is easy to get the contrary operator F_{OU}^{-1} on the control *U*:

$$U = F_{OU}^{-1}(\dot{Y}, X) \tag{15}$$

And the operator $F^{\bullet}$ of the optimal closed-loop system can be obtained based on the schedule of the linguistic dynamics (Figure 4) and the following heuristic considerations.
Points 1, 2,..., 7 on the schedule is characterized by equality of the linguistic values *X* and the output *Y*, as well as the maximum rate of the output $\dot{Y} = ZE$ that prevents overshoot.

Table 1. Fuzzy operator of the object

Control *U*	Output *Y*						
	NB	*NM*	*NS*	*ZE*	*PS*	*PM*	*PB*
NB	*ZE*	*NS*	*NS*	*NM*	*NB*	*NM*	*NS*
NM	*PB*	*ZE*	*NB*	*NB*	*NB*	*NM*	*NB*
NS	*NS*	*NS*	*ZE*	*NM*	*NM*	*NB*	*NB*
ZE	*PB*	*PB*	*PB*	*ZE*	*PS*	*PS*	*PS*
PS	*NM*	*ZE*	*PS*	*NB*	*PB*	*PM*	*PB*
PM	*NM*	*NS*	*ZE*	*PS*	*ZE*	*NS*	*NB*
PB	*NB*	*NB*	*NB*	*ZE*	*PB*	*PB*	*PB*

Table 2. Fuzzy operator of a closed system

Control *U*	Output *Y*						
	NB	*NM*	*NS*	*ZE*	*PS*	*PM*	*PB*
NB	*ZE*	*NS*	*NS*	*NM*	*NB*	*NB*	*NB*
NM	*PS*	*ZE*	*NS*	*NS*	*NM*	*NB*	*NB*
NS	*PS*	*PS*	*ZE*	*NS*	*NS*	*NM*	*NB*
ZE	*PB*	*PM*	*PS*	*ZE*	*NS*	*NM*	*NB*
PS	*PB*	*PM*	*PS*	*PS*	*ZE*	*NS*	*NM*
PM	*PB*	*PB*	*PM*	*PS*	*PS*	*ZE*	*NS*
PB	*PB*	*PB*	*PB*	*PM*	*PS*	*PS*	*ZE*

As the mismatch between *X* and *Y*, i.e. the regulation error should increase the rate of the output $\dot{Y}$, directed towards one of these points. The direction and size of the arrows $\dot{Y}$ correspond to the accepted linguistic meaning. For example, at the point "○" in the schedule of the linguistic dynamics of the optimal closed-loop system, it is identified one set of operator data as table $F^{\bullet}$: *X* = *PS*, *Y* = *PM*, $\dot{Y}$ = *NS* and corresponding rule: if *X* = *PS*, *Y* = *PM*, then $\dot{Y}$ = *NS*. Now it's formulated the problem of synthesis of the optimal fuzzy controller. For all the linguistic values of the job *X* and the output *Y* via the operator of the optimal closed-loop system (13) and the inverse operator of the object (15) it is determined the control *U*, i.e. three <*U*, *X*, *Y*>, which form the operator of the regulator (14).

Subsequently, it's considered the procedure to determine the control U^* in a three <U^*, X^*, Y^*> when X^* = *NS*, Y^* = *PM*. Substituting of X^* = *NS* and Y^* = *PM* in Table 2 (the operator F^* of the control object) will give $Y^\bullet$ = *NM*. For Y^* = *PM* and $Y^\bullet$ = *NM* from Table 1 (the operator F_{OU} of the control object) it's obtained U^* = *NM*, i.e. to implement the inverse operator of the object and the required three <*NS*, *PM*, *NM*>.

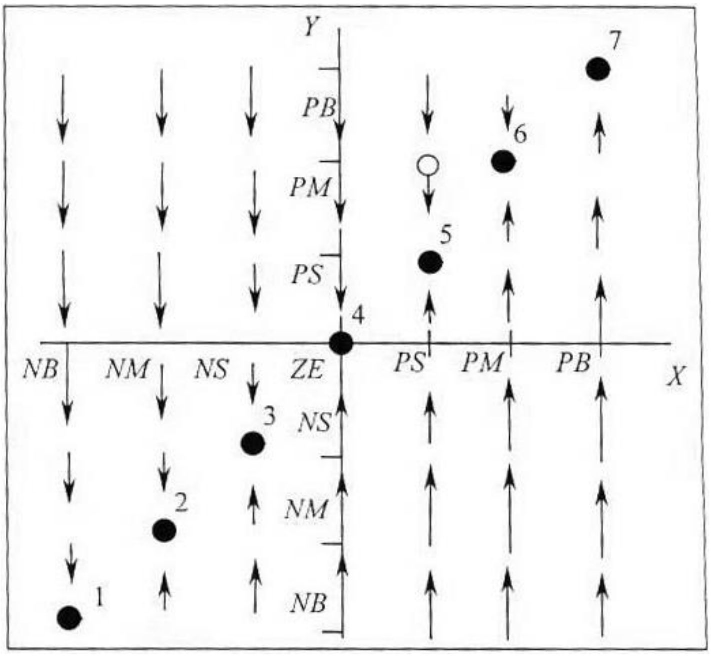

Fig. 4 Schedule of linguistic dynamics

In general, the inverse operator F_{OU}^{-1} is not unique. The optimal operator control becomes multivalent, which greatly reduces the practical value of this approach to the synthesis of LLR. Further development of the methodology for the synthesis of the operator control in the table form is obtained in [6]. On the basis of static characteristics and transition functions of the first order aperiodic link, it's created the object operator as the channels F_{OU} and the disturbance F_{OW} (Figure 5), as well as a qualitative description of the regulatory process succeeded in synthesizing the fuzzy controller that efficiently operated in varying of the job parameter *X*,

$$F_P' = F_X \cup F_Y \cup F_E$$

And the compensator, which eliminates the effect of disturbances *W* in the output,

$$F_K = F_W \cup F_Y \cup F_E$$

Here $\cup$ - a union operation component that can be realized three-phase control. In the first phase of control $U_X = F_X(X, E)$ of the regulator with a significant change of *X*, in the value U_X is firstly determined limitation. As soon as the output quantity *Y* reaches a neighborhood of *X*, the static characteristics of channel *U-Y* will select the control action in which the steady output will be close to the assignment value. The control U_W or output component U_W = F_W (*W*) of the compensator F_K are formed in the basis of the two principles of fuzzy invariance. In static characteristics of channel *W-Y*, the possible reaction of output Y_W to the disturbance *W* will be evaluated. Also, the control U_W, causing a variation of the output *Y* is determined equal in magnitude and opposite in sign to the value Y_W. This makes it possible to provide partial compensation for disturbance or independent (invariant) of the output *Y* for the disturbance *W*.

It may be achieved more fully compensation if selecting of the control U_W, where the variable rate of Y_U will be equal in magnitude and opposite in direction speed Y_W.

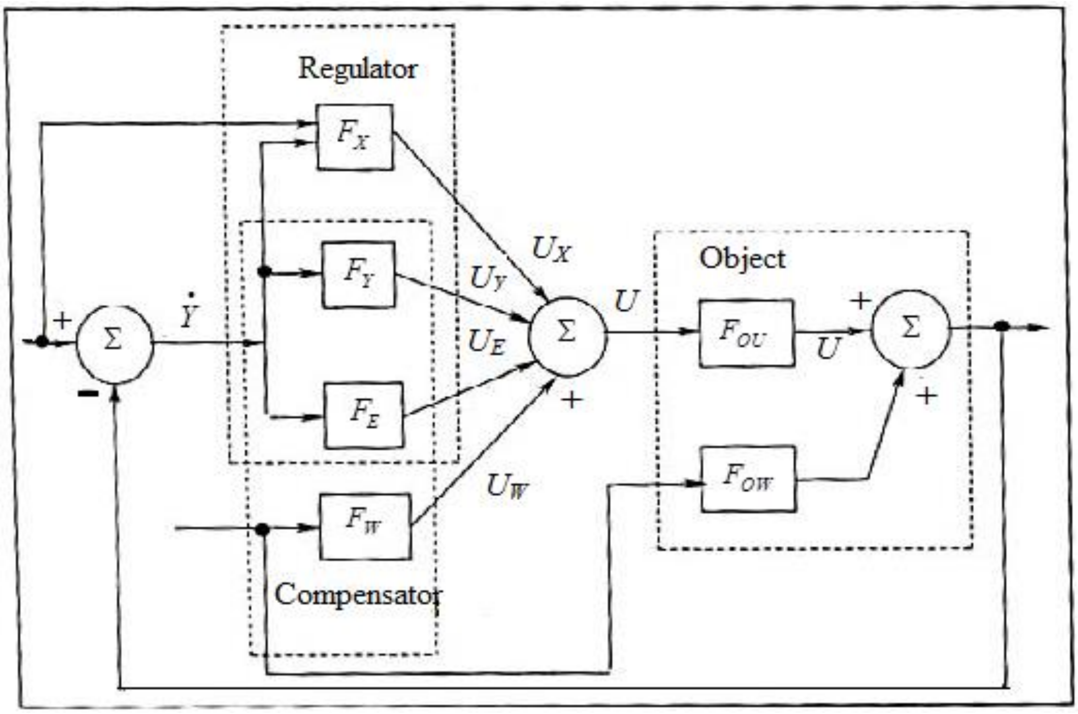

Fig. 5 The control circuit fuzzy controller and compensator

The component F_Y serves to eliminate overshoot, and the component F_E - static error. Based on the proposed principles of formation of the components of the regulator and compensator, it's developed the methods for the synthesis table operators F_X, F_W, F_Y and F_E, allowed providing the required quality of the temperature control at the outlet of the furnace acetone. The same methods for the synthesis table of fuzzy control have been proposed to control the distillation plant and other chemical objects [1, 23]. The main disadvantages of LLR table type include their limited dimension (the total number of variables must not exceed three and a subjective choice of intervals and the corresponding values of linguistic variables). It's noted that the important advantage of LLR. As previously mentioned, LLR is similar to the multi-position switch, which trigger levels are selected based on the properties of the control object. This makes it possible to largely compensate for the effect of non-linearity of the object that significantly degrade the performance of control systems with linear P, PI and PID controllers

Analytical Regulators

A special place is occupied by the so-called fuzzy model Tanaka and Sudzhenko or TS-model [14]. First, analytical way, and then to the specific problems of modeling and control were demonstrated its high approximation ability. Fuzzy TS-model consists of a set of production rules containing the right side of the linear differential equation:

$$\begin{gathered} If\ \ y(t-1)\ is\ Y_1^\theta,\dots,y(t-r)\ is\ Y_r^\theta, \\ x(t)\ is\ X_0^\theta,\dots,x(t-s)\ is\ X_s^\theta, \\ then\ \ y_0(t)=a_0^\theta+\sum_{k=1}^{r}a_k^\theta y(t-k)+\sum_{l=1}^{s}b_l^\theta x(t-l), \\ \theta=\overline{1,n} \end{gathered} \tag{16}$$

Where:
$\mathbf{a}^\theta = (a_0^\theta, a_1^\theta, ..., a_r^\theta), \mathbf{b}^\theta = (b_0^\theta, b_1^\theta, ..., b_s^\theta)$ - The vectors of the customizable parameters;
$\mathbf{y}(t-r) = (1, y(t-1), ..., y(t-r))$ - The state vector;
$\mathbf{x}(t-s) = (x(t), x(t-1), ..., x(t-s))$ - The input vector;
$Y_1^\theta, ..., Y_r^\theta; X_0^\theta, ..., X_r^\theta$ - The fuzzy sets

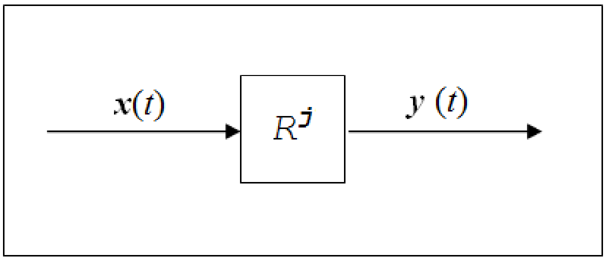

Fig. 6 - Fuzzy block

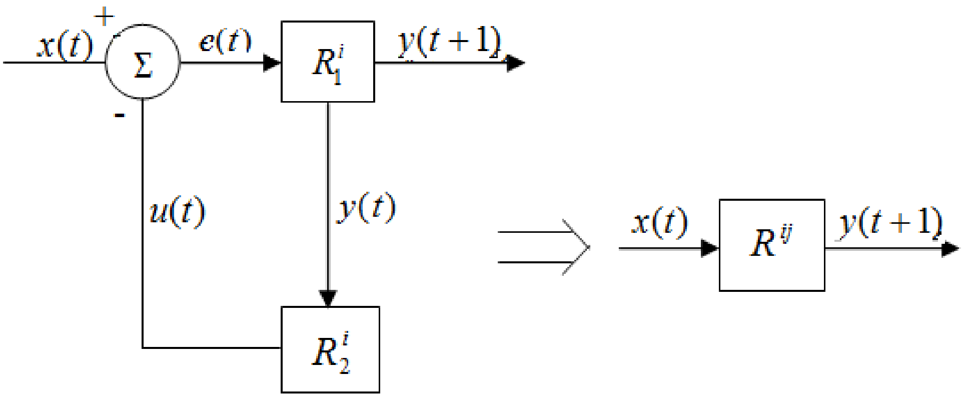

Fig. 7 - Connection diagram with feedback and its mathematical model

Expression (16) can be greatly simplified if it's reassigned:
- The input variables:

$$(u_0(t), (u_1(t), ..., u_m(t)) = (1, y(t-1), ..., y(t-r), x(t), ..., x(t-s))$$

- The coefficients of the difference equation:

$$(c_0^\theta, c_1^\theta, ..., c_m^\theta) = (a_0^\theta, a_1^\theta, ..., a_r^\theta, b_1^\theta, ..., b_s^\theta)$$

- The facilities and features:

$$(U_1^\theta(u_1(t)), ..., U_m^\theta(u_m(t))) = (Y_1^\theta(y(t-1)), ..., Y_r^\theta(y(t-r)), X_0^\theta(x(t)), ..., X_s^\theta(x(t-s)))$$

Where:

$$m = r + s + 1.$$

Analytic form of fuzzy model (16) is designed to calculate the output $\hat{y}(t)$ looks like:

$$\hat{y}(t) = \mathbf{c}^T \tilde{\mathbf{u}}(t)$$

Where:
$\mathbf{c} = (c_0^1, ..., c_0^n, ..., c_m^1, ..., c_m^n)^T$ - The vector of specifies parameters;
$\tilde{\mathbf{u}}^T(t) = (u_0(t)\beta^1(t), ..., u_0(t)\beta^\theta(t), ..., u_m(t)\beta^1(t), ..., u_m(t)\beta^n(t)))$ - The advanced input vector;
$\beta^\theta(t) = \dfrac{U_1^\theta(u_1(t)) \otimes ... \otimes U_m^\theta(u_m(t))}{\sum_{\theta=1}^{N}(U_1^\theta(u_1(t)) \otimes ... \otimes U_m^\theta(u_m(t)))}$ - Fuzzy function, where $\otimes$ - the operation to minimize or work.

With the given data at the initial moment *t = 0*, the vector *c(0) = 0* will correct the matrix *Q(0)*, size $nm \times mn$ and value *u(t)* at $t = \overline{1,N}$, the parameter vector *c(t)* is calculated by using a known multi-stage least squares method [4]:

$$\mathbf{c}(t) = \mathbf{c}(t-1) + Q(t)\tilde{\mathbf{u}}(t)\left[y(t) - \mathbf{c}^T(t-1)\tilde{\mathbf{u}}(t)\right], \tag{17}$$

$$Q(t) = Q(t-1) - \frac{Q(t-1)\tilde{\mathbf{u}}(t)\tilde{\mathbf{u}}^T(t)Q(t-1)}{1+)\tilde{\mathbf{u}}^T(t)Q(t-1)\tilde{\mathbf{u}}(t)}, \tag{18}$$

$$Q(0) = \gamma I, \quad \gamma >> 1,$$

Where *I* - the unit diagonal matrix.

Full identification algorithm, in addition to the algorithm (17), (18), also comprises the identification number of rules algorithms *n*, the order *r*, *s* of the differential equations and parameters of membership functions [1, 3, and 24].

For closed loop control with fuzzy controller based on the model (16) is also relevant stability problem and its quantification. In the spirit of the classic representation of linear systems and Tanaka - Sudzhenko [14] proposed a fuzzy control unit (Figure 6) - a dynamic object described by a fuzzy model of a difference (16) in vector form:

$$\begin{aligned} &R^i : if \;\; \mathbf{y}(t) \;\; is \;\; \mathbf{Y}^i \;\; and \;\; \mathbf{x} \;\; is \;\; \mathbf{X}^i, \\ &then \; y^i(t+1) = a_0^i + \sum_{k=1}^{r} a_k^i y(t-k+1) + \sum_{l=1}^{s} b_l x(t-l+1), \end{aligned} \tag{19}$$

Where:

$\mathbf{y}(t) = [y(t), y(t-1),..., y(t-r+1)]^T$, $\mathbf{x}(t) = [x(t), x(t-1),..., x(t-s+1)]^T$, $\mathbf{Y}^i = [\mathbf{Y}_1^i,..., \mathbf{Y}_r^i]$
$\mathbf{X}^i = [\mathbf{X}_1^i,..., \mathbf{X}_s^i]$; r, s - the order of the difference equation;

$\mathbf{y}(t)$ is $\mathbf{Y}^I \Rightarrow y(t)$ is Y_1^i and ... and $y(t-r+1)$ is Y_r^i.

Of these units, various compounds are formed (parallel with feedback) and displays their mathematical model.

For example, a compound with feedback (Figure 7) contains object units:

$$\begin{aligned} &R_1^i : if \;\; \mathbf{y}(t) \;\; is \;\; Y_1^i \;\; and \;\; \mathbf{e}(t) \;\; is \;\; E_1^i, \\ &then \;\; y^i(t+1) = a_{10}^i + \sum_{k=1}^{r} a_{1k}^i y(t-k+1) + \sum_{l=1}^{s} b_{1l} e(t-l+1) \end{aligned}$$

And controller:

$$\begin{aligned} &R_2^i : if \;\; \mathbf{y}(t) \;\; is \;\; Y_2^j \;\; and \;\; \mathbf{e}(t) \;\; is \;\; E_2^j, \\ &then \;\; u^j(t) = a_{20}^j + \sum_{k=1}^{r} a_{2k}^j y(t-k+1) \end{aligned} \tag{20}$$

Equivalent unit:

$$\begin{aligned} &R^{ij} : if \;\; \mathbf{y}(t) \;\; is \;\; \mathbf{Y}^{ij} \;\; and \;\; \mathbf{e}(t) \;\; is \;\; E^{ij}, \\ &then \;\; y^{ij}(t+1) = a_{10}^i - b_1^i a_{20}^j + b_1 x(t) + \sum_{k=1}^{r} (a_{1k} - b_1^i a_{2k}^j) y(t-k+1), \end{aligned}$$

Where:

$$i = 1,2,..., n_1, \; j = 1,2,..., n_2;$$

$$\mathbf{e}(t) = [x(t) - u(t), x(t-1) - u(t-1),..., x(t-m+1) - u(t-m+1)]^T;$$

$$Y^{ij} = (Y_1^i \cap Y_2^j), E^{ij} = (E_1^i \cap E_2^j).$$

Conclusion of the analytical estimates of stability of fuzzy systems (19) and (20) by means of Lyapunov method based on the equation of free movement:

$$R^i : if \;\; \mathbf{y}(t) \;\; is \;\; Y_1^i \;\; and \;\; \mathbf{y}(t-r+1) \;\; is \;\; Y_r^i,$$

Then:

$$y^i(t+1) = a_1^i y(t) + ... + a_r^i y(t-r+1), i = \overline{1,n},$$

The right-hand part of which can be written in matrix form $A_i \mathbf{y}(t)$,

Wherein: $\mathbf{y}(t) = [y(t), y(t-1),..., y(t-r+1)]^T$,

$$A_i = \begin{bmatrix} a_1^i & a_2^i & ... & a_{r-1}^i & a_r^i \\ 1 & 0 & ... & 0 & 0 \\ 0 & 1 & ... & 0 & 0 \\ 0 & 0 & ... & 0 & 0 \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ 0 & 0 & ... & 0 & 0 \\ 0 & 0 & ... & 1 & 0 \end{bmatrix} \quad (21)$$

In [3, 4-10], the fuzzy system (21) provided the calculated dependence:

$$y(t+1) = \sum_{i=1}^{n} w^i A_i \mathbf{y}(t) / \sum_{i=1}^{n} w^i,$$

Generally, It is asymptotically stable, if all the subsystems exist the positive definite matrix B such that:

$$A_i^T B A_i - B < 0, \forall i \in \{1,2,..., n\}.$$

The validity of this assessment was confirmed only for the simplest proportional controller.

A similar approach to the analysis of sustainability based on the method of Lyapunov was developed in [4] for the fuzzy system in state space:

$$R^i : if \ \ \mathbf{y}(t) \ \ is \ \ \mathbf{Y}_1^i, ..., \mathbf{y}(t) \ \ is \ \ Y_r^i,$$

$$\text{i.e.,}\ x(t) \ \text{is} \ X^i \ \text{then:}$$

$$y_1(t+1) = a_{11}^i y_1(t) + a_{12}^i y_2(t) + ... + a_{1r}^i y_r(t) + b_1^i x(t),$$

$$...$$

$$y_1(t+1) = a_{r1}^i y_1(t) + a_{r2}^i y_2(t) + ... + a_{rr}^i y_r(t) + b_r^i x(t)$$

And an analytical assessment of the stability of a closed system with a proportional controller. In order to achieve stability, it's offered by gradients to refine the parameters a_{jl}^i and the control gain.

Trained Fuzzy Regulators

Neuro-fuzzy generalized TS-structure model having n inputs and m rules implementing mechanism output y, is shown in Figure 8 [17, 18].

In the first layer with $x_i = x_0^i, i = \overline{1,m}$, the degree of membership functions are calculated, and the second layer are T-handled operator of minimizing or product. In the third layer (N), normalized weights are determined $\overline{w}^\theta = w^\theta / (w^\theta + w^\theta), \theta = \overline{1,n},$ in the fourth layer, they are multiplied by appropriate values y^θ derived from the linear equations:

$$y^1 = b_0^1 + b_1^1 x_1 + b_2^1 x_2 + ... + b_m^1 x_m,$$
$$y^2 = b_0^2 + b_1^2 x_1 + b_2^2 x_2 + ... + b_m^2 x_m,$$
$$...$$
$$y^n = b_0^n + b_1^n x_1 + b_2^n x_2 + ... + b_m^n x_m.$$

The fifth layer - addition and obtaining final values $\hat{y}$.

The received procedure of TS-knowledge model of the object is to determine the coefficients of $b_i^\theta, i = \overline{0,m}, \theta = \overline{1,n},$ the parameters of membership functions $\mathbf{d}_0^\theta, i = \overline{1,m}$ and rules of *n*, for which the outputs of the model $\hat{y}$ and the object *y* are same or gets close.

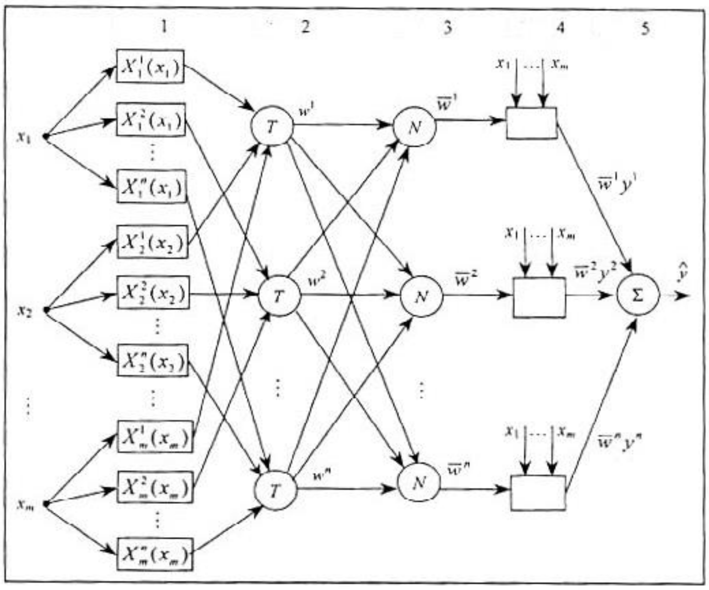

Fig. 8 Neuro-fuzzy structure TS-model

If the number of rules *n* is fixed, the membership function $\mathbf{X}_i^\theta(x_i, \mathbf{d})$ is continuous with respect to parameters **d** and the product is processed by T-operator $(w^\theta = \prod_{i=1}^{m} \mathbf{X}_i^\theta(x_i), \theta = \overline{1,n})$, the TS-models can be trained by back propagation BP (Back Propagation), proposed in [20, 21]. It is to minimize the square error $I = 0,5(y - \hat{y}(\mathbf{c}))^2$ by gradient method:

$$\mathbf{c}^{\lambda+1} = \mathbf{c}^\lambda - h\frac{\partial I}{\partial \mathbf{c}} \tag{22}$$

Where: **c = (b, d)** - the parameter vector; *h* - Working step.

Based on the definition of the chain rule for partial derivatives by $\mathbf{d}_l^\theta$:

$$\frac{\partial I}{\partial \mathbf{d}_l^\theta} = \frac{\partial I}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w^\theta} \cdot \frac{\partial w^\theta}{\partial \mathbf{X}_l^\theta} \cdot \frac{\partial \mathbf{X}_l^\theta}{\partial \mathbf{d}_l^\theta}$$

And by $\mathbf{b}_l^\theta$:

$$\frac{\partial I}{\partial b_l^\theta} = \frac{\partial I}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial b_l^\theta}$$

Without intermediate calculations, it’s written them analytical expressions:

$$\frac{\partial I}{\partial \mathbf{d}_l^\theta} = (y-\hat{y}) - \frac{y\theta - w^\theta \hat{y}}{\sum_{j=1}^{2} w^j}\left(\prod_{\substack{i=1\\ i\neq l}}^{m} \mathbf{X}_i^\theta(x_i)\right)\frac{\partial \mathbf{X}_l^\theta}{\partial \mathbf{d}_l^\theta}, l=\overline{1,m},$$

$$\frac{\partial I}{\partial b_l^\theta} = (y-\hat{y})x_l, l=\overline{1,m}, \theta=\overline{1,n}, x_0 = 1.$$

As the membership functions, it's usually chosen sigmoid $X(x) = (1+\exp(dx))^{-1}, d>0,$ or radial $X(x) = \exp(d_1(x-d_2))$ - basis functions, d, d_1 *and* d_2 differentiable.

It's presently posed the training problem of fuzzy-neuro directed action regulator *P*, i.e., connected in series with the object *O* (Figure 9).

The object of control with one output is supposedly described by a discrete equation of order *r*, *s*:

$$y(t+1) = f_0(y(t),...,y(t-r),u(t),...,u(t-s)) \tag{23}$$

Suggested that the object of control is reversible, i.e. there exists the function f_0^{-1} in inverse to the equation (23):

$$u(t) = f_0^{-1}(y(t+1), y(t)...,y(t-r),u(t-1),...,u(t-r)).$$

It's considered the neuro TS-model (see. Fig. 8) with *m*-dimensional input vector:

$$\mathbf{x}_p(t) = (y(t+1), y(t),...,y(t-r),u(t-1),...,u(t-r)) : \hat{u}(t) = f_p(x_p(t),c_p),$$

Which provides the required proximity $\hat{u}(t)$ to $u(t)$ at respective inputs and which serves as a regulator. In order to control, the regulator is educated by *AOP* algorithm with a minimum square error:

$$I_p = 0{,}5(x(t+1) - y(t+1))^2 = 0{,}5e_p^2(t+1)$$

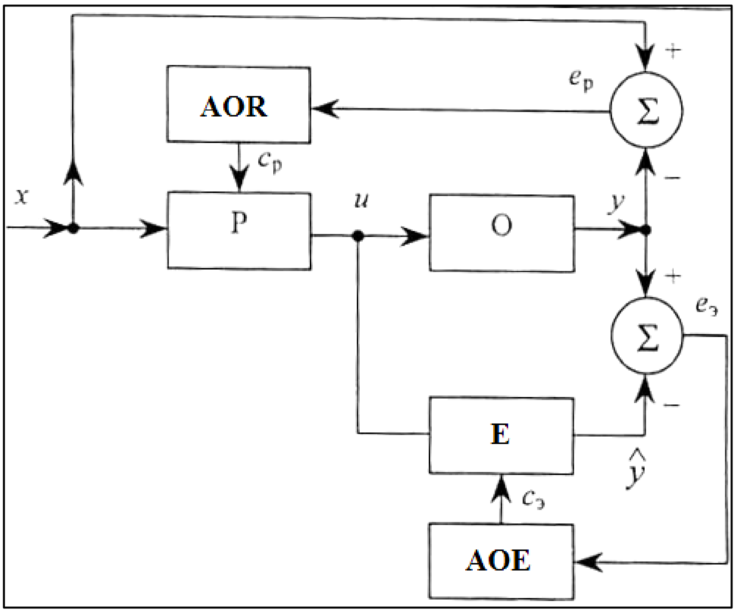

Fig. 9 - Serial control circuit

In a sequential scheme (see Figure 9), it'd be calculated the expression:

$$\frac{\partial I_p}{\partial \mathbf{c}_p} = \frac{\partial I_p}{\partial y}\cdot\frac{\partial y}{\partial u}\cdot\frac{\partial u}{\partial c_p}$$

Wherein, the undefined value of the derivative $\partial y / \partial u$. It can be easily found by using neuro-fuzzy model of the object, called an emulator:

$$\hat{y}(t+1) = f_E(\hat{y}(t),...,\hat{y}(t-r),u(t),...,u(t-r)c_E),$$

It's computed $\partial\hat{y}/\partial u$ instead of $\partial y/\partial u$. The education of emulator *E* by *AOE* algorithm, providing a minimum square error:

$$I_E = 0,5(y(t+1) - \hat{y}(t+1)^2 = 0,5e_E^2(t+1),$$

As well as a regulator, carried out by BP-method [14].
All of the major shortcomings of the first training control systems are associated with BP method, particularly as the local search nature and one part of the gradient method; demand continuous and differentiable functions belonging; not determined by the order (*r, s*) and the number of rules *n*.

In order to eliminate the "loop", there are the researches used the genetic algorithm (shake) to change the size of the working step gradients of *h* in formula (22) and the components of the vector *c* [10, 11 and 12]. Other researchers [22] believe that for the purpose of training is enough to use only the genetic algorithms to overcome the first two drawbacks BP method.
The greatest effect was achieved with a hybrid training to carry out a genetic algorithm to refine the parameters of the membership functions ***d***, together with the multi-stage least squares method (17), (18) to find the vector ***b***, and other algorithms that determine the order of *r, s* and the number of procedures *n* in TS -model [14]. This approach failed to appreciably eliminate all the drawbacks BP method.

RESULTS

The integrating actuator generates a control action according to the formula $u_k = u_{k-1} + \Delta u_k$. The normalized value of control deviation and its increment is $y = 0{,}2; \Delta y = 0{,}9$. These values correspond to the four input linguistic variables:

$$Y = ZE; Y_2 = PS; \Delta Y_1 = PM; \Delta Y_2 = PB \tag{24}$$

With the following values of the membership functions:

$$\mu_1(\varepsilon) = 0{,}4; \mu_2(\varepsilon) = 0{,}6; \mu_1(\Delta\varepsilon) = 0{,}3; \mu_2(\Delta\varepsilon) = 0{,}7.$$

This allows getting a ratings control interventions:

$$\Delta U_1 = PS; C_1(\Delta u_1) = \min[\mu_1(\varepsilon), \mu_1(\Delta\varepsilon)] = 0{,}3;$$
$$\Delta U_2 = PM; C_2(\Delta u_2) = \min[\mu_1(\varepsilon), \mu_2(\Delta\varepsilon)] = 0{,}4$$
$$\Delta U_3 = PM; C_3(\Delta u_3) = \min[\mu_2(\varepsilon), \mu_1(\Delta\varepsilon)] = 0{,}3;$$
$$\Delta U_4 = PM; C_4(\Delta u_4) = \min[\mu_2(\varepsilon), \mu_2(\Delta\varepsilon)] = 0{,}6.$$

Thus, the regulating effect is determined by two linguistic variables *PS* and *PM*, with a rating of 0.3 and 1.3, respectively. The increment values of regulatory impact is the abscissa x_0 of the center of cube that consists of two triangles, based on ranges of linguistic variables *PS* and *PM*, with a height of 0.3 and 1.3, respectively, where: $x_0 = 0{,}603$. In general, the resulting number should be multiplied by the increment of the measuring range of regulatory impact.

The synthesis of fuzzy controller based on probabilistic methods is carried out in [1, 2 and 3]. For accepted above values $y = 0{,}2; \Delta y = 0{,}9$, the linguistic variables are also defined by (24). But instead of the membership functions, they correspond to the following values of the density distribution:

$$p_1(\varepsilon) = 1{,}2; p_2(\varepsilon) = 1{,}8; p_1(\Delta\varepsilon) = 0{,}9; p_2(\Delta\varepsilon) = 2{,}1.$$

Table 3. The Operator of Fuzzy Linear PI – Regulator

$y/\Delta y$	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NM	NM	NS	NS	ZE
NM	NB	NM	NM	NS	NS	ZE	PS
NS	NM	NM	NS	NS	ZE	PS	PS
ZE	NM	NS	NS	ZE	PS	PS	PM
PS	NS	NS	ZE	PS	PS	PM	PM
PM	NS	ZE	PS	PS	PM	PM	PB
PB	ZE	PS	PS	PM	PM	PB	PB

The linguistic variables of the regulatory impact increment are formed according to the table 3. The density values of the distribution of linguistic variables increment regulatory impact in this case are:

$$\Delta U_1 = PS;\ p_1(\Delta u) = 1{,}08;$$
$$\Delta U_2 = PM;\ p_2(\Delta u) = 2{,}52;$$
$$\Delta U_3 = PM;\ p_3(\Delta u) = 1{,}62;$$
$$\Delta U_4 = PM;\ p_4(\Delta u) = 3{,}78.$$

The regulatory impact increment in this case is equal to the mean (center of gravity) of the found linguistic variables $\Delta u = 0{,}627$.

In [1, 23] explores questions of construction of fuzzy PI and PID controllers and comparison with the classical probabilistic methods of synthesis of regulators. Consider the construction of fuzzy linear PI controller with two entrances. Table, which is implemented by PI - the algorithm looks Table 3.

DISCUSSION

The appearance of TS-model had an enormous influence on the subsequent development of the theory of fuzzy control systems:

- Among the fuzzy models for the first time it was a legitimate use of the traditional parametric identification;
- Despite the presence in the right part of the rules of linear differential equations to TS-model, by specifying the parameters *c*, of the order of *r*, *s* and increase in the number of rules *n* can be described with very high accuracy nonlinear dynamic processes;
- Averaging properties of the output mechanism and a specific kind of membership functions make it possible to model TS-little sensitive to noise and measurement errors;
- Being a non-linear and continuous function of the input variables and parameters, TS-model provides the opportunities of the analytical study of stability of nonlinear systems with its presence and subsequent training to achieve the desired quality of transients.

Despite the achievements in the theory and application of fuzzy controllers, there are still many questions that need to be resolved. This applies to the justification and the choice of the method of synthesis of control and evaluation of the advantages of the synthesis of fuzzy controllers in comparison with classical synthetic methods, such as probabilistic methods. The basis of the synthesis of fuzzy controllers is judgment and experience of the expert.

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Meanwhile, in the theory of probability to assess the quantitative measure of certainty experts use subjective probabilities [22, 23]. Naturally, the probabilistic methods of synthesis are now more solid mathematical foundation than the methods of fuzzy logic, based on the choice of membership functions and determining the basic linguistic variable [22].

CONCLUSIONS

The similar approaches to stability analysis of fuzzy systems using the Lyapunov method, followed by a synthesis of the regulators are set out in [10, 11]. The limitations of the Lyapunov method is obvious: it allows for the stability control system is only the most simple proportional regulators and gives recommendations for the achievement of the required quality of transients. Maintaining the quality of transients in fuzzy control systems can provide a trained fuzzy controllers and control systems.

Trained fuzzy controllers and control systems are classified as the most promising. They maintain high efficiency in terms of interference and measurement error and quickly adjusted to changing production conditions, thereby reducing losses from uncontrolled. However, in some cases, LLR show high performance. For example, in the control systems rather simple objects LLR can successfully compete with the trained controllers.

Thus, for example, the results of the synthesis of fuzzy control methods of fuzzy sets and probabilistic methods are virtually identical. However, it must be admitted that in the test example of the methods of probability theory more logically justified and do not require special heuristics.

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