INFORMATICA, 2002, Vol. 13, No. 3, 287–298

Adaptive Fuzzy Control of Nonlinear Plant with Changing Dynamics

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Received: June 2002

Abstract. This paper analyses the control of nonlinear plant with the changing dynamics. Adaptive controllers, based on fuzzy logics, are synthesized for the control of air pressure and water level. Their satisfactory efficiency is experimentally demonstrated under different working conditions. Fuzzy controllers are compared to conventional PI and PID controllers.

Key words: nonlinear plant, fuzzy logic control, rule base, PI control, PID control, level, pressure control.

1. Introduction

Water level and air pressure control is a classical problem in control engineering. These problems are usually analyzed in literature in separate cases, mathematical models are defined for water level or air pressure systems, and digital control methods are investigated (Ogata, 1997; Driankov, 1998). In most cases simple control system conditions are assumed, such as natural water/air flow, not affected by additional forces.

The control problem becomes more complex if water level and air pressure control are considered in one system. In such case the change of water level or air pressure set point, changes the dynamics of the whole system and this requires the adaptation of controller parameters. When water flows through pipes, the silt gathers on inner side decreasing its diameter and herewith the amount of flowing water. This feature changes the dynamics of the flow system and stipulates an adaptation of controller parameters. In this paper the effect of such phenomenon on control system is also analyzed.

In this paper adaptive fuzzy controllers are introduced as an alternative for the water level and air pressure control. In the absence of sufficiently precise process mathematical model and in the presence of non-linearity, fuzzy logic based control usually have an advantage over conventional PI or PID control (Ogata, 1997; Chen, 2001). The primary control problem, considered with this control system, is regulating both water level and air pressure at the specified set points. The secondary problem is that of decreasing variations of manipulated variables, as these affect the useful life – time of physical devices, in this case water and air pumps.

2. Control Plant

The plant's scheme is shown in Fig. 1. Its central part is a close tank with adjustable water level and air pressure. The variables of the process "pressure" and "level" can be varied using the inlet water flow and/or the inlet airflow. These are varied with separate pumps (1, 2). The pumps are the actuators and have an electrical input-range of 0 to 10 V. The tank has two outlets for water flow and two outlets for airflow. The manual valve (5) and/or the combination of the magnetic valve (4) and manual valve (4a) control the exit water flow. These valves and the control of the water pump manipulate the stationary condition of water flow. The manipulating of pressure is performed through control of the valves (6, 6a, 7) and the air pump (2). Air chamber (3) increases the time constant of the pressure loop and equalizes pulses in the airflow. The water flows in and out of the tank through rubber hoses, what are circled in rings. This water flow peculiarity increases plant's nonlinear characteristics. The water flow in this case depends on the water temperature and its softness. These characteristics influence the water flow resistance. The change of level and pressure set points itself changes the dynamics of the plant. This is because water level and air pressure are dependent on each other, so the change in air pressure affects the water level, whereas the change in water level affects the air pressure. This is obvious as the decrease in air pressure means that less force acts on water and less power is needed to keep the water at the desired level. The change of water level changes the size of tank area, left for air, and the less the area the less the power is needed to keep the pressure at a given set point.

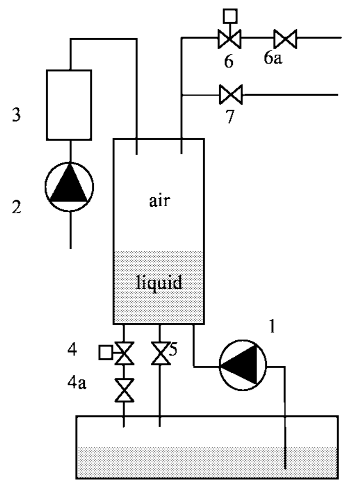


Fig. 1. Plant scheme.

3. Plant's Linear Model

The physical processes in the plant can be approximately described by a linear mathematical model (Fig. 2).

Here $\dot{m}_{eL}$ is inlet air mass flow, $\dot{m}_{eW}$ – inlet water mass flow, h – water level, p – air pressure. $U_{Pi},\ U_{Li}$ are manipulated variables, and $U_{Po},\ U_{Lo}$ are controlled variables of pressure and level, respectively.

$$G_{SL}\left(s\right)=\frac{K_{SL}}{\left(1+sT_{1L}\right)\left(1+sT_{2L}\right)},\quad G_{SW}\left(s\right)=\frac{K_{SW}}{\left(1+sT_{1W}\right)} \tag{1}$$

– actuators' transfer functions,

$$G_{11}=\frac{p(s)}{\dot{m}_{eL}(s)}=\frac{K_{11}}{l+sT_L},\qquad G_{21}=\frac{h(s)}{\dot{m}_{eL}(s)}=\frac{K_{21}}{(1+sT_L)(1+sT_W)} \tag{2}$$

– sub-model pressure transfer functions,

$$G_{22}=\frac{h(s)}{\dot{m}_{eW}(s)}=\frac{K_{22}}{l+sT_W},\qquad G_{12}=\frac{p(s)}{\dot{m}_{eW}(s)}=\frac{s\cdot K_{12}}{(1+sT_L)(1+sT_W)} \tag{3}$$

– sub-model level transfer functions.

The model is implemented with the Concept 2.1 programming unit and compared with the actual plant (Fig. 3). The gains $K_{SL},\ K_{SW}, K_{11}, K_{12}, K_{21}, K_{22}$ and time components T_W and T_L are calculated at the working point: level $h_o\ =\ 10\,\mathrm{cm}$, pressure $p_o = 20\,\mathrm{mbar}$, temperature $Q = 295\,\mathrm{K}$.

From Fig. 3 it is seen that the plant model corresponds to the actual situation only at the working point for which it was linearized. The change of set points makes the model inadequate. This means that the process is nonlinear, because for every other set point it is necessary to recalculate the model parameters. Besides, this model is simplified by ignoring saturation effects, water flow friction non-linearities, and other characteristics, that make noticeable influence to the actual process. The nonlinear characteristics of the plant and not accurate enough its mathematical model induced to use fuzzy logic for the control of the plant.

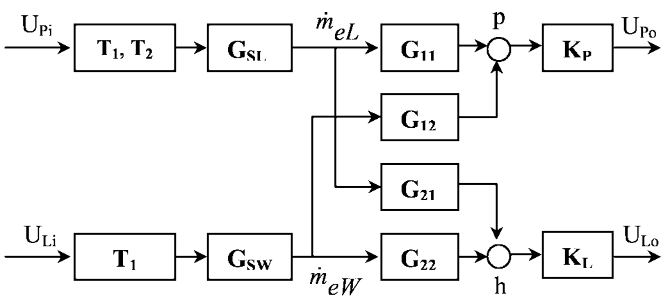


Fig. 2. Plant model's structural scheme.

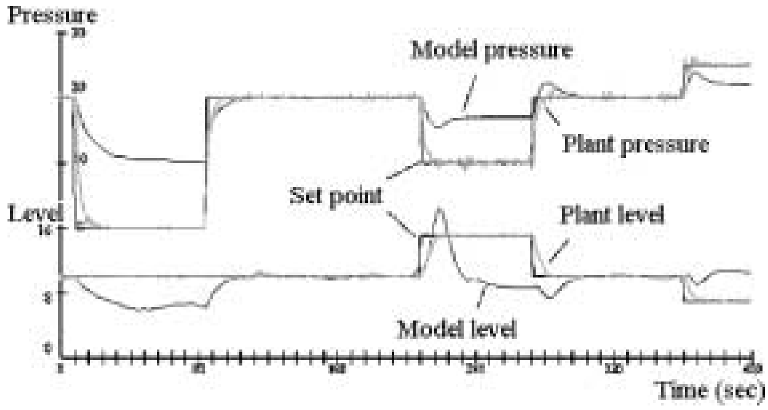


Fig. 3. Comparison of plant ouput and the output of its model.

4. Adaptive Fuzzy Controller

Two uncoupled adaptive fuzzy controllers are used for the control of water level and air pressure in the plant. Both controllers have the same structure; different are only the gains and knowledge bases (Fig. 4). The structural scheme consists of four main parts: the plant, the fuzzy controller to be tuned, the rule-base initializer and the learning mechanism (an adaptation mechanism). The fuzzy controller uses the learning mechanism to observe numerical data from fuzzy control system. Using this data, it characterizes the fuzzy control system's current performance and automatically adjusts the fuzzy controller so that given performance objectives are met. The learning mechanism consists of two parts: a "fuzzy inverse model" and a "knowledge-base modifier". The fuzzy inverse model performs the function of mapping the deviation from the desired behavior to changes k in the process input, that are necessary to force process error e to zero. The knowledge-base modifier adjusts the fuzzy controller's rule-base to affect the changes needed in the process inputs.

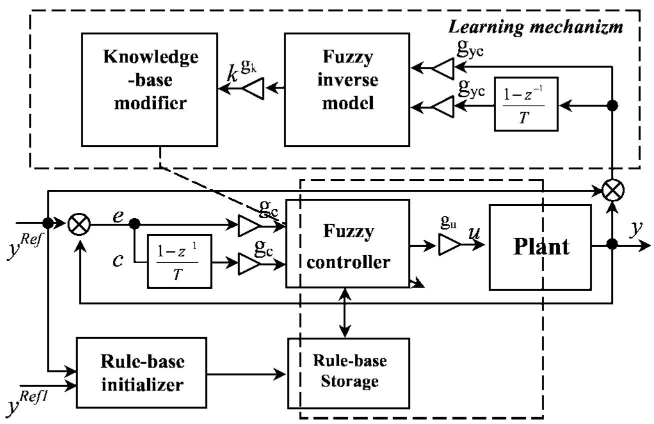


Fig. 4. Adaptive fuzzy controller.

Plant's water level and air pressure fuzzy controllers each have two input signals and one output – control action. The input signals for water level control are the water level error e_l and the change in error c_l. The input signals for air pressure control are the pressure error e_s and the change in error c_s. The controllers control actions are water pump control signal u_l, and air pressure pump control signal u_s. Nine triangular symmetric membership functions are used on all the input universes of discourse. The membership functions are normalized and uniformly distributed across the universes of discourse (Fig. 5).

For the evaluation of rules the minimum operator (Cox, 1994; Passino, 1998) is used to represent the premise and the implication, and COG (center of gravity) method for the process of deffuzification (Passino, 1998; Chen, 2001). The input and output universes of discourse are normalized to intervals $[-1; 1]$. The scaling controllers' gains for the level error, the change in level error, the pressure error, and the change in pressure error are chosen via the design procedure to be $g_{el} = 1/2.22,\ g_{cl} = 1/0.33,\ g_{es} = 1/5$, and $g_{cs} = 1/1.01$. The gains g_{cl} and g_{cs} were chosen by the experiment, analyzing the values that inputs c_l and c_s get during the system performance under different reference inputs. According to the gain values, the inputs universes of discourse are the following: $[-2.2, 2.2]$ for input e_l, $[-0.33, 0.33]$ for input c_l, $[-5.0, 5.0]$ for input e_s, and $[-1.01, 1.01]$ for input c_s. The output gains are used to extend the output from interval [0, 1] to [0, 10] as 10 is the maximum voltage, the pumps can obtain. The controllers' output universes of discourse are covered with seventeen symmetric, triangular membership functions, with the base widths equal to 0.25.

The adaptive fuzzy controller has two rule-bases. The first one stores the knowledge about how to control the system at given water level and air pressure set points and is used by rule-base initializer to form the second rule-base which is directly used by the controller. The second rule-base describes how to control the process at particular actuating error and its change in time. The rule-bases consist of rules that have an *If–Then* form. At the start up of the controllers, the assumption is made that the controllers know nothing about how to control the process. The learning mechanism modifies the rule-bases and remembers the modifications thus providing the controller with the information about the process. The learning mechanism is a two input one output fuzzy system, whose outputs are the fuzzy controller's rule-base correction values. The learning mechanism has its own rule-base of how to define the necessary changes. The *If–Then* rules are arranged so that the output membership function centers are equal to a scaled sum of the rules' premise linguistic-numeric indices. All the membership functions are labeled

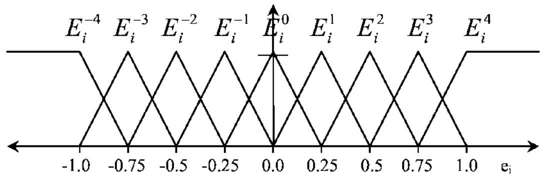


Fig. 5. Set of normalized membership functions used for all four inputs "Level error"(e_l), "Level derivative error" (c_l), "Pressure error" (e_s), and "Pressure derivative error" (c_s).

with linguistic-numeric indices that are integers with zero at the middle. As each learning mechanism input is defined with nine membership functions, the linguistic-numeric indices are set as follows: "-4", "-3", "-2", "-1", "0", "1", "2", "3", "4". Then the center of learning mechanism output fuzzy set Y^s membership function is located at

$$(i+j)\frac{1}{8}, \tag{4}$$

where $s = i + j$ is the index of the output fuzzy set Y^s, i and j are the linguistic-numeric indices of the input fuzzy sets (i – for error, j – for change in error), 1/8 is the base width of output membership function (Passino, 1998). The evaluation of equation (4) for all linguistic-numeric indices results in the rule base of the form of matrix, where each element represents the centers of seventeen distinct output membership function centers.

The normalizing gains, associated with water level learning mechanism inputs ye_l and yc_l, are chosen to be $gy_{el} = 1/2$ and $gy_{cl} = 1/0.33$, and normalizing gains, associated with air pressure learning mechanism inputs ye_s and yc_s, are chosen to be $gy_{es} = 1/2.5$, and $gy_{cs} = 1/1.01$, respectively. The output gains, gk_l and gk_s are chosen to be 0.128, and 0.012, respectively. These gains are also named as learning ratio. The learning mechanism also utilizes symmetric triangular-shape membership functions for the input and output universes of discourse, minimum to represent the premise and implication, and COG (center of gravity) defuzzification (Chen, 2001). This method calculates a crisp output according to equation (5)

$$u^{crisp} = \frac{\sum\limits_i b_i \cdot \int \mu_{(i)}}{\sum\limits_i \int \mu_{(i)}}, \tag{5}$$

where b_i is the center of the membership function of the consequent of rule (i), $\int \mu_{(i)}$ – the area under the membership function $\mu_{(i)}$. (5) is the classical formula for computing the center of gravity. $\int \mu_{(i)}$ is easy to calculate if membership functions are symmetric, triangular-shape, peak at one and have a base width of w. Then the area under the triangle "chopped off" at height h is equal to

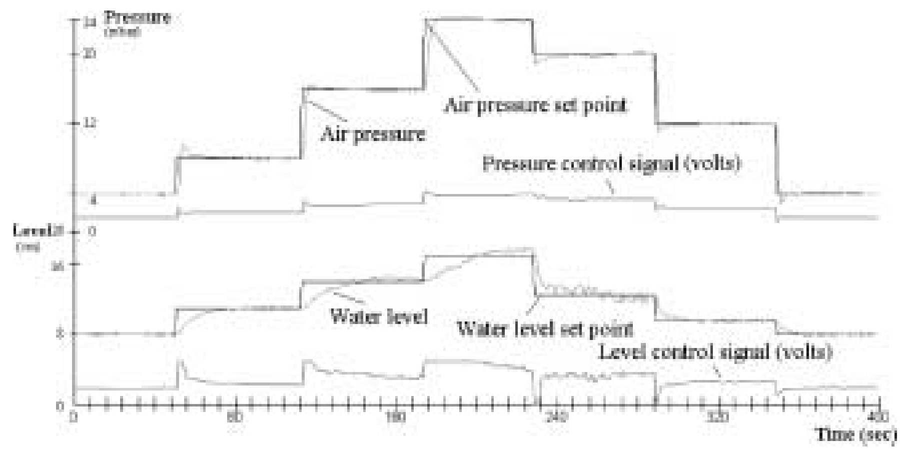
$$w\left(h - \frac{h^2}{2}\right). \tag{6}$$

Given this, the computations needed to compute the crisp output are not too significant (Passino, 1998).

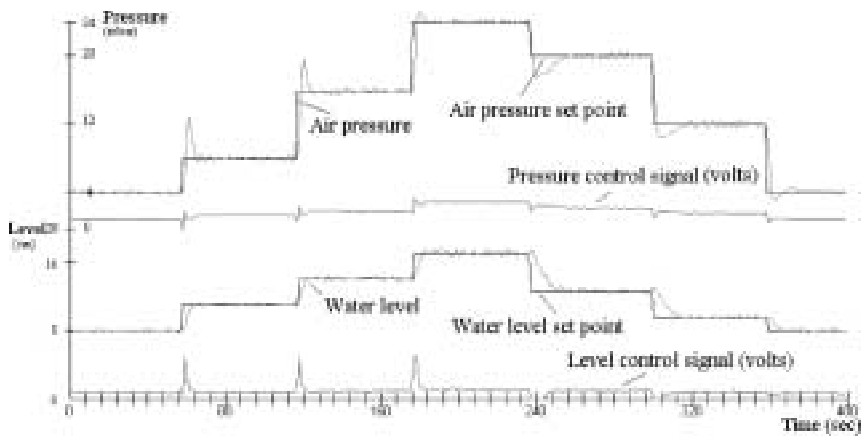
5. Experiment Results

The purpose of experiments was to evaluate the efficiency of adaptive fuzzy controllers under different working conditions. i.e. changing reference signals, changing plant dynamics, when the throughput of output water and air is decreased twice. The reference signals have step form and are chosen for water level to be 8, 11, 14, 17, 12.5, 9.5, and 8 cm, and for air pressure – 4, 8, 16, 24, 20, 12, and 4 mbar. Level and pressure reference signals change their values in approximately 57 sec. The experiment results, controlling the plant with adaptive fuzzy, PI, and PID controllers, are given in Figs. 6, 7, 8 and Table 1.

Each graph is split into two parts: the upper part shows the plant's air pressure response to the step form air pressure reference signal, gray signal is the pressure control

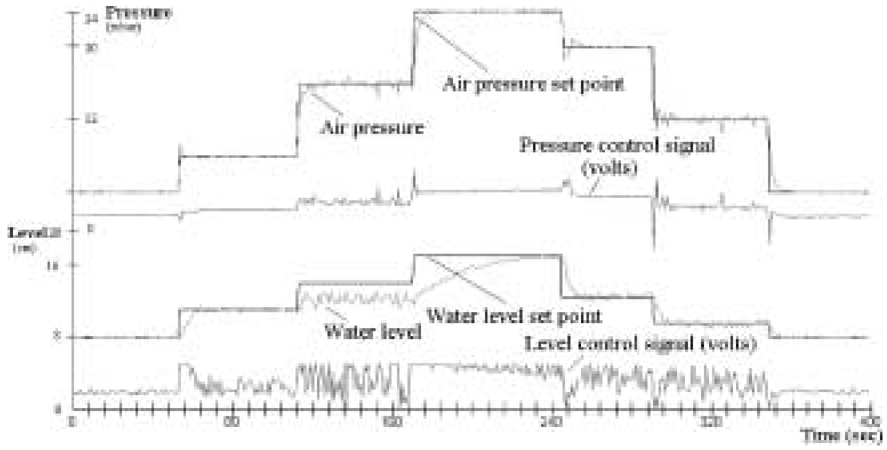


(a)

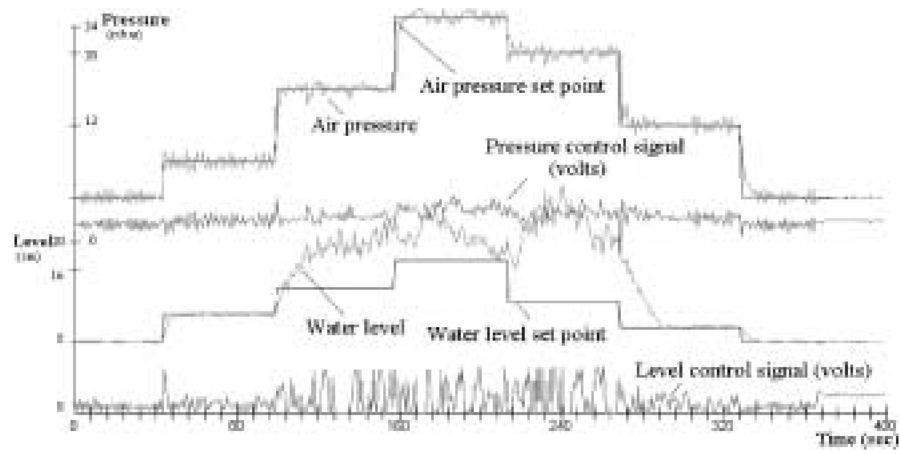


(b)

Fig. 6. Response of the plant to step form level and pressure reference signals: (a) – plant operates under normal conditions, (b) – plant's water and air outlets diameters are reduced. Plant is controlled with adaptive fuzzy controllers.



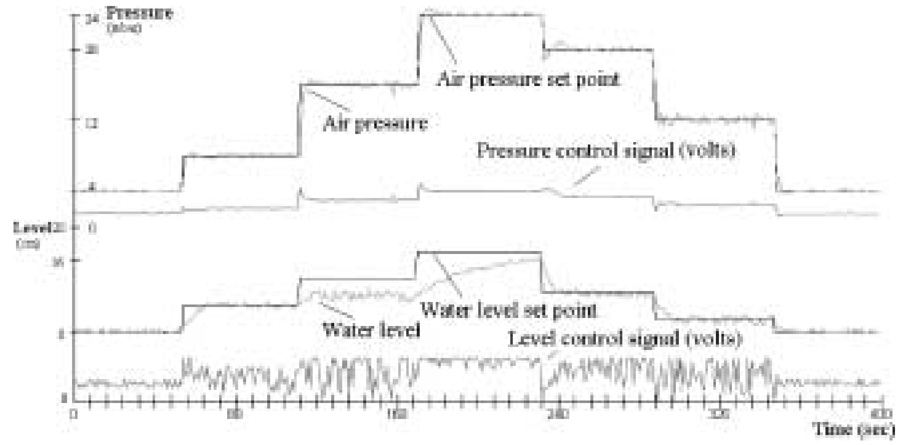
(a)



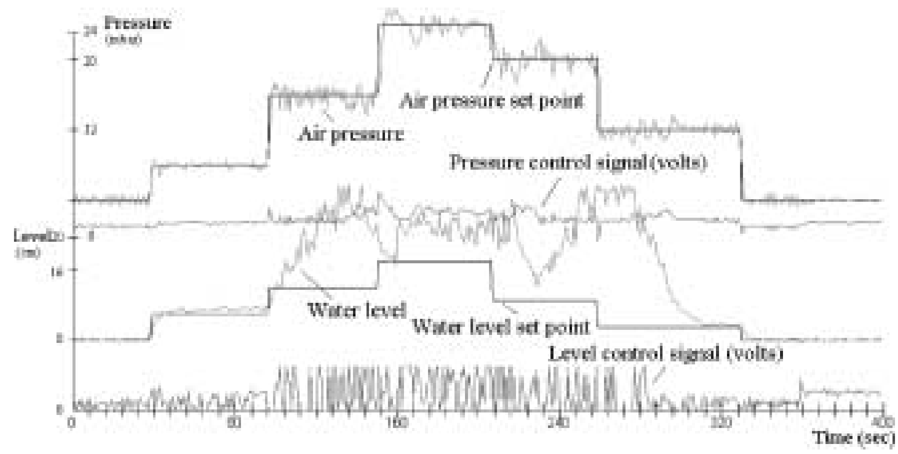
(b)

Fig. 7. Response of the plant to step form level and pressure reference signals: (a) – plant operates under normal conditions, (b) – plant's water and air outlets diameters are reduced. Plant is controlled with PI controllers.

signal; the lower part shows the plant's water level response to the water level reference signal, gray signal is the water level control signal. It is seen from the graphs that after the reduction of outlets' diameters the performance of PI and PID controllers visibly decrease, and higher reference signals are unable to track. The variations of control signals, both air pressure and water level, in case of fuzzy controller, are much smaller if compared with the PI and PID control signals. The actuating errors are in most cases smaller when the plant is controller with fuzzy controller (Table 1). The square root average errors of water level, air pressure, water level control, and air pressure control signals are



(a)



(b)

Fig. 8. Response of the plant to step form level and pressure reference signals: (a) – plant operates under normal conditions, (b) – plant's water and air outlets diameters are reduced. Plant is controlled with PID controllers.

calculated as

$$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\overline{x})^2}, \quad \overline{x}=\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}x_i \tag{7}$$

for plant's stationary working conditions, when water level reference signal is 11cm and air pressure – 8mbar. The results are given in Table 1.

Table 1

Square root average errors of stationary process

Controller type	Water level (cm)	Errors of water level and control signals				Air pressure (bar)	Error of air pressure and control signals			
		Normal outlets		Halved outlets			Normal outlets		Halved outlets	
		Level error	Control signal variation	Level error	Control signal variation		Pressure error	Control signal variation	Pressure error	Control signal variation
Fuzzy	11	0.09	0.02	0.08	0.01	8	0.09	0.002	0.15	0.003
PI		0.18	0.14	0.18	0.13		1.01	0.013	0.70	0.064
PID		0.20	0.23	0.58	0.15		0.14	0.009	0.31	0.011

From the Table 1 it is seen that water level error in case of adaptive fuzzy controller, before the reduction of outlets, is two times smaller that that of PI and PID controllers. The water level control signal variation is 8 times and 13.4 times smaller that of PI and PID controllers, respectively. The air pressure error in case of fuzzy controller is 10.3 times smaller than that of PI controller and 1.5 times smaller then that of PID controller. The air pressure control signal variations in case of fuzzy controller are 8.6 times and 5.9 times smaller than in case of PI and PID controllers, respectively. After the reduction of plant's water and air outlets, the advantage of the adaptive fuzzy controller increases.

The similar calculations were also made for the process, tracking the step form reference signals, including the transient response. The calculations are presented in Table 2.

The oscillations of water level and air pressure control signals during the whole process in case of adaptive fuzzy control were more than several times smaller than that of PI and PID controllers, Table 2. The same is with water level error signals. However, the air pressure error in case of fuzzy control was bigger than that of PI and PID controllers. This is due to the fact, that water level and air pressure fuzzy controllers are uncoupled – work independent of each other. Because of this feature, after the change of reference signal, the pressure signal overshoots the reference signal for a second, thus adding large instantaneous errors and disimproving the average error calculation results.

Table 2

Square root average errors of transient process

Controller type	Errors of water level and control signal				Error of air pressure and control signal			
	Normal outlets		Halved outlets		Normal outlets		Halved outlets	
	Level error	Control signal variation	Level error	Control signal variation	Pressure error	Control signal variation	Pressure error	Control signal variation
Fuzzy	0.79	0.10	0.66	0.08	0.92	0.01	1.00	0.01
PI	0.99	0.17	2.81	0.25	0.67	0.04	0.83	0.07
PID	1.01	0.19	4.33	0.29	0.81	0.02	0.99	0.04

6. Conclusions

Adaptive fuzzy controllers for water level and air pressure control in the nonlinear plant have been synthesized. The sufficient efficiency of adaptive fuzzy controllers is shown experimentally, controlling the plant at different working conditions. It is experimentally proved that adaptive fuzzy controllers are more powerful than conventional PI and PID controllers when working conditions and plant's dynamics changes in time.

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Netiesinio proceso su kintančia dinamika adaptyvus "fuzzy" valdymas

Vytautas KAMINSKAS, Raimundas LIUTKEVIČIUS

Nagrinėjami netiesinio objekto valdymo klausimai. Sudaryti "fuzzy" logikos pagrindu veikiantys adaptyvūs reguliatoriai oro slėgiui ir vandens lygiui valdyti ir eksperimentiškai parodytas jų pakankamas efektyvumas įvairiuose darbo režimuose. "Fuzzy" reguliatoriai palyginti su klasikiniais PI ir PID reguliatoriais.