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LEARNING ALGORITHM IN FUZZY CONTROL

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Abstract: Fuzzy controllers were proposed in several papers [1]. The control algorithms were usually based on the operator's experience. The operators's experience can be described by a set of rules in the form of "IF-THEN" statements. A learning algorithm which helps in the process of gathering experience has been derived and proposed. Its application cuts the time needed for collecting the operator's experience.

Keywords: Batch fermentation, fuzzy control, learning algorithm, adaptive fuzzy control

1. INTRODUCTION

In the chemical industry there are many technologies which can not be controlled by traditional control elements, because of the difficulties in measurements, complicated processes and rapidly changing parameters. In these cases processes are usually controlled by operators. Quality of the control and product depends on the operator's experience. Collecting the operator's experience a controller can be developed by means of the fuzzy set theory to solve this control problem. In Section 2 we introduce the control problem and the fuzzy controller. The learning algorithm is discussed in Section 3.

2. FUZZY CONTROL

2.1. Control problem

The control problem is dissolved oxygen control in a batch fermenter.

At the beginning of the process the operator fills the substrate into the fermenter. In the next step the solution is saturated by oxygen. After the saturation the operator inoculates the micro-organisms in the fermenter. The micro-organisms can be multiplied by reproduction in the fermenter. During the fermentation the dissolved oxygen concentration (c) and substrate volume (s) decrease, the biomass volume (x) increases in the fermenter (Figure 1). At the end of process the substrate is exhausted so the biomass stops increasing while the dissolved oxygen concentration increases. If the value of the oxygen concentration goes under a critical value, the micro-organism will not be able to reproduce itself, to avoid this effect the required oxygen feed must be increased significantly.

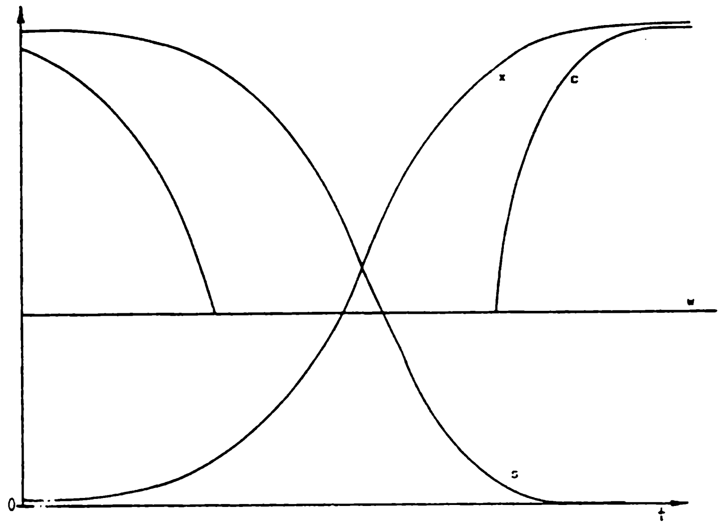

Fig. 1. Fermentation process

2.2 Linguistic and fuzzy control

The operator uses the following algorithm to control the process. He watches the actual value of the dissolved oxygen concentration and adjusts the revolution of the impeller and feed rate of the air. The operator decides about what to do? Every operator has his own control algorithm. This algorithm depends on the operator's experience. The algorithm contains a lot of rules. These rules may be changed in time. Every operator has his own set of rules.

The case presented here is a simulation example. A simulation model and program of the fermenter was developed to study the operator's activities [2]. The operator didn't know the model and program of the fermenter; for him it was only a black-box model. The operator knew only the actual value of the dissolved oxygen concentration and process variables (feed rate of the air, revolution of impeller). During the process he decided about when and how to adjust the process variables.

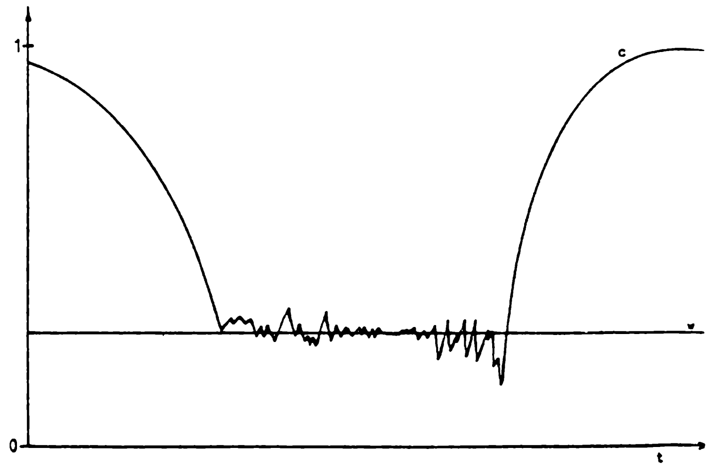

Fig. 2. Manual Control (AE=3.2)

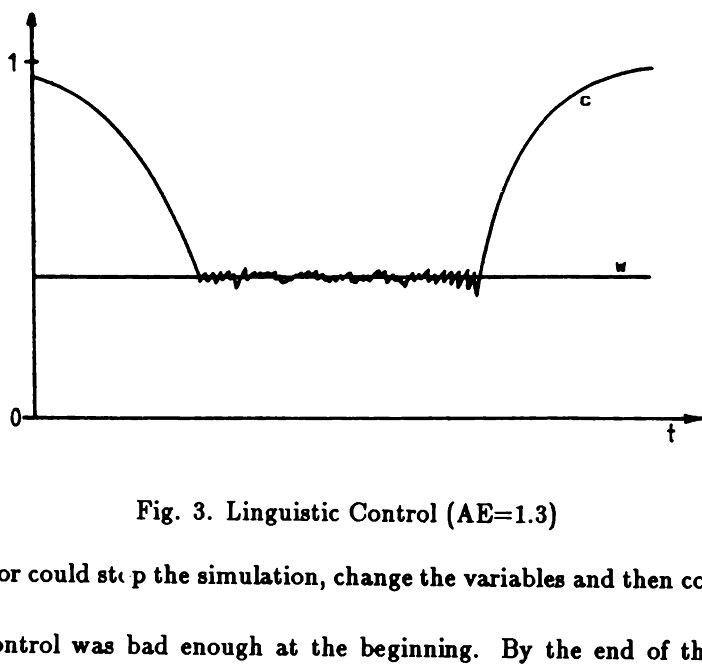

Fig. 3. Linguistic Control (AE=1.3)

The operator could stop the simulation, change the variables and then continue the simulation.

The control was bad enough at the beginning. By the end of the learning period the operator could learn how to control the fermenter (Figure 2). After the learning period the operator's experience was described in form of the "IF-THEN" rules. The state of each variable was represented qualitatively by five

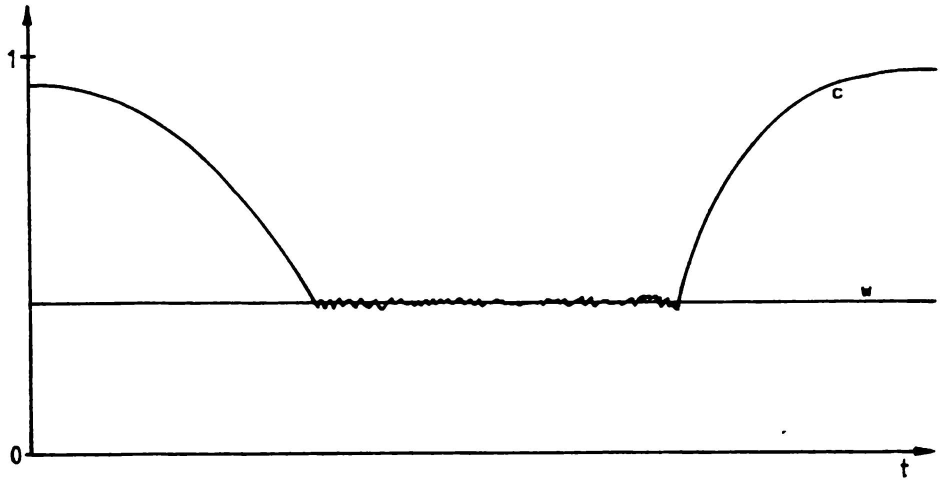

Fig. 4. Fuzzy Control (AE=0.9)

ranges: positive large (PL), positive small (PS), good (0), negative small (NS) and negative large (NL). Altogether 25 control rules were set up. Figure 3 shows the operation of the fermenter controlled by the linguistic controller, where the average control error (AE) decreased to 1.3 from 3.2.

The membership functions were defined by the "bell-shape" function:

$$\mu_1(x) = \exp\left[\frac{(x - \mathrm{m}_1)^2}{2\sigma_1^2}\right]$$

where m_1 denotes the fuzzy mean and
σ_1 is responsible for the spread.

Universe of variables are divided into five parts by membership functions.

The fuzzy controller was generated by fuzzy composition:

Generation:

$$R : \mu_R(\tilde{e}, \triangle\tilde{e}, \triangle\tilde{L}) = \max_{i=1}^{25}\left[\min\left(\mu_{e_i}(\tilde{e}), \mu_{\triangle e_i}(\triangle\tilde{e}), \mu_{\triangle L_i}(\triangle\tilde{L})\right)\right]$$

control:

$$\triangle\tilde{L}_k : \mu_{\triangle L_k}(\triangle\tilde{L}) = \max_j\left[\min\left(\mu_{e_k}(\tilde{e}), \mu_{\triangle e_k}(\triangle\tilde{e}), \mu_R(\tilde{e}, \triangle\tilde{e}, \triangle\tilde{L})\right)\right]$$

The quality of the fuzzy control was better than that of the linguistic controller (Figure 4). The controller was tested in several ways (Figure 5), for example the set point (w) was changed and some substrate (s) was fed into the fermenter.

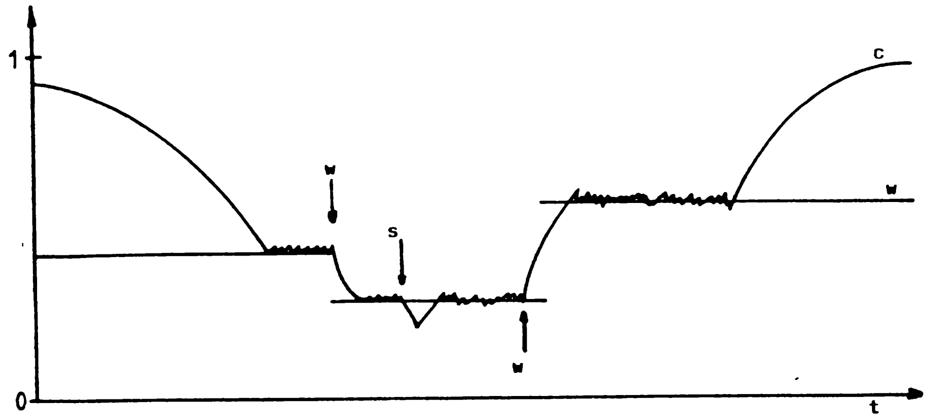

Fig. 5. Test of the Fuzzy Cont.

3. LEARNING ALGORITHM

In this section an algorithm that automatically generates the fuzzy controller and modifies the set of rules and the fuzzy controller in real time is introduced. This way the fuzzy controller can adapt itself to the change of the process.

a) First the universe of the variables, the membership functions and the rules were defined. In the learning period the process was controlled by the operator (Figure 6). The operator selected a rule every time he wanted to intervene.

During this period the operator also learned about how to control the process. The algorithm monitored the operator and collected the rules applied in the period. After the learning period the rules were evaluated. It was assumed that good rules were applied more often than bad rules, since the operator gained experience. Consequently the evaluation algorithm chose the rule applied most often from the rival ones. After the learning period the algorithm generated a fuzzy controller by fuzzy composition. In the example we had 125 rules. In the learning period the algorithm collected about 500-600 operator's decisions and chose about 17-20 unambiguous rules.

b) In the other experiment the operator was excluded from the learning period (Figure 7). An evolution algorithm which could select the good rules from the set of rules and generate the fuzzy controller in real time was developed.

This algorithm can be considered as an adaptive fuzzy controller. First the rules were defined. Every rule got a "goodness value" in the [0,1] interval by an expert. 0 represented the bad rules while 1 represented the good rules. ε was a

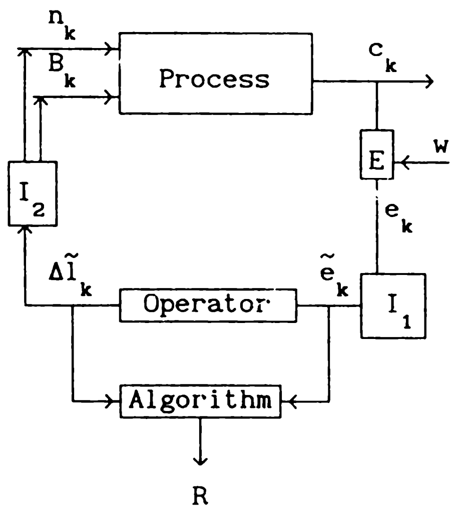

Fig. 6. Structure of the learning process

critical value. If the "goodness value" of a rule was higher that ε then the rule was regarded as a good one. Thus the algorithm generated an initial controller by fuzzy composition. Then the algorithm monitored the active rule and its effect at the next sampling time. If the effect of the active rule was good then the rule collected a few good points according to the evaluation table (Table 1).

For example if the previous control error was NL and the actual change of the error was PL then the rule active previously was given 10 points. After the learning period the algorithm changed the goodness values according to the collected points and regenerated the fuzzy controller. The learning time was higher than or equal to the sampling time but it was less the processing time of a batch. Figure 8 shows the operation of the fermenter controlled by the adaptive fuzzy controller with a sampling time equal to the learning time.

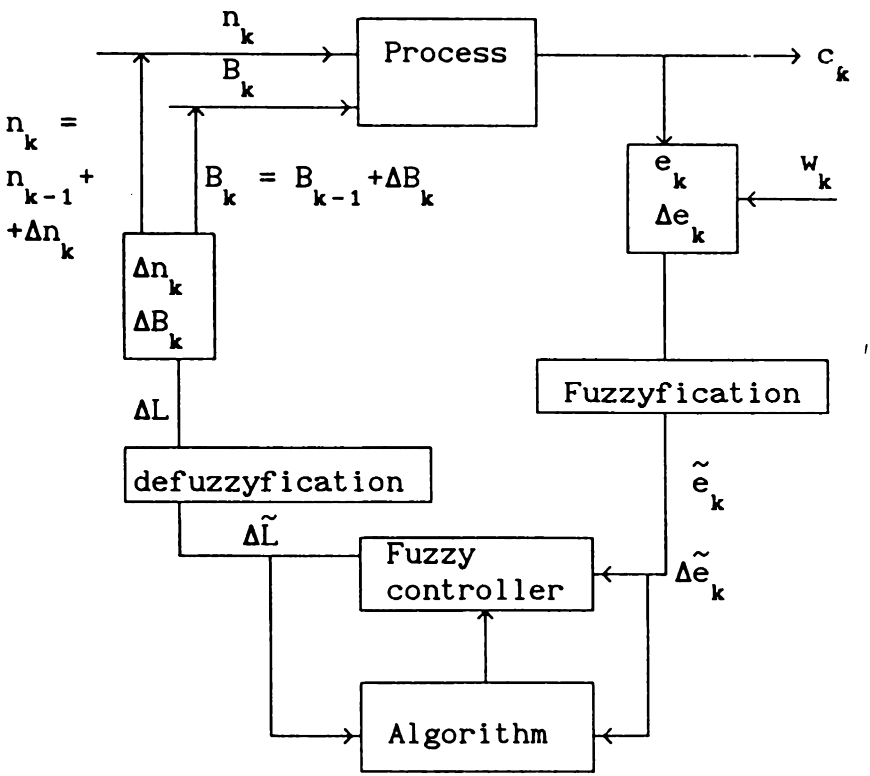

Fig. 7. Adaptive Fuzzy Controller

Table 1. Evaluation table

$\Delta\tilde{e}$ / $\tilde{e}$	NL	NS	O	PS	PL
NL	-10	-10	-1	5	10
NS	-10	-10	1	5	0
O	-10	0	5	0	-10
PS	0	5	1	-10	-10
PL	5	2	-1	-10	-10

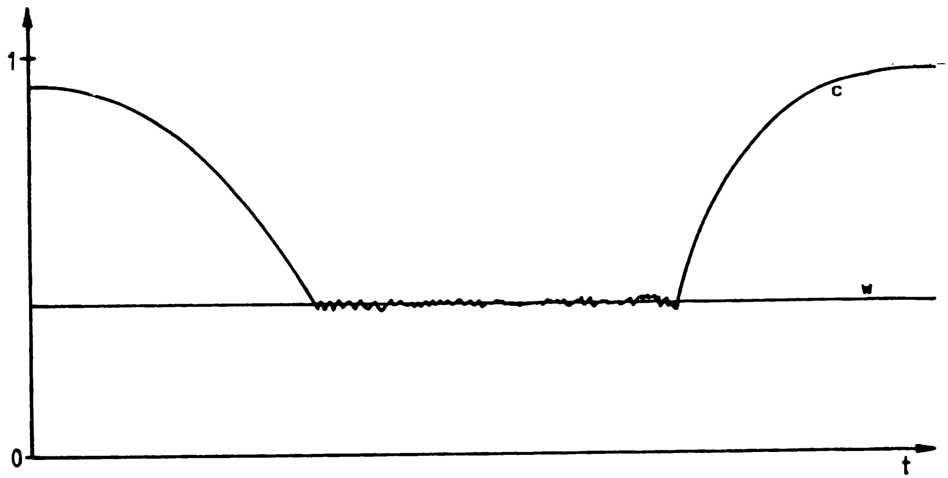

Fig. 8. Adaptive Fuzzy Control (AE=0.64)

SUMMARY

In the paper a simulation example for application of the fuzzy set theory in the chemical engineering was presented. The fuzzy controller was developed by fuzzy composition. An adaptive fuzzy controller was introduced in the Section 3.

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