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ADAPTIVE FUZZY CONTROL OF PRESSURE AND LEVEL

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Abstract. Due to high complexity of chemical processes and their control systems, adaptive controllers are frequently applied in practice. The present paper describes the design and implementation of adaptive fuzzy controllers for the control of a coupled level and pressure process. Expert knowledge is applied to form an adaptation mechanism which tunes the fuzzy controller based on process data. The results of the experiments on the physical plant prove the practical relevance of the design strategy of an adaptive fuzzy controller.

Keywords: adaptive fuzzy control, process control, nonlinear level and pressure plant.

1. Introduction

With the increase of the computation power the more complex control algorithms can now be applied to today's highly nonlinear, sometimes even not well explored systems that are affected by unexpected internal or external disturbances, to systems whose dynamics is changing in time. At the design stage of controller, for such systems in most cases only general information about the plant is available so the problem becomes to analyze and learn information about the plant during the control process. This paper analyses the control of level and pressure in a closed tank.

A model derived from physical principles, even if available, can show significant differences from the working physical system, which can lead to errors in the control design [1]. The approach when model based control is applied is not always practical as the identification of an adequate model of a level-pressure system is a challenging task and the lack of precision of the model in that case results in a decrease of control effectiveness [2]. Besides as research show, due to the coupling and non-minimum-phase behavior, plus the nonlinearities from valves, the specifications that can be obtained in practice are very poor, further worsened by the high amount of noise present in sensor readings (caused by the bubbles and turbulence). Noise in level-pressure systems forbids derivative action, and non-minimum-phase limits bandwidth. A common choice for the control of level-pressure system is a low gain feedback PI controller. Any improvement would need a substantial modeling effort, non-linearity cancelation, etc. and will also meet with the noise and non-minimum-phase fundamental limitation so the model-based approach will not, in many cases, significantly improve the results (comparing to PI control) [3].

As an alternative solution of a problem, a fuzzy control approach that strives to design an input-output dynamic feedback controller and tune it using expert knowledge and system input-output data is considered. As the incorporation of expert knowledge in the control systems is quite efficient using fuzzy logic principles, fuzzy controllers are selected.

2. The plant

A plant analyzed in this paper is an important part of the albumen processing technological process in a confectionery manufacture. The plant's structure is shown in Figure 1. It contains a close tank, 0.5 meters in height, with the adjustable liquid level and the air pressure. The variables of the process "pressure" and "level" are varied using the inlet liquid flow, F_{i_in} and the inlet airflow, F_{p_in}. Liquid and air flow are varied with separate pumps. The pumps are the actuators and have an electrical input-range of 0 to 10 V. The tank has two outlets, one for the liquid flow and one for the airflow.

The exit liquid flow F_{l_out} depends on the liquid input flow and the pressure in the tank. The manipulation of pressure is performed through the air pump, which affects the air flow, F_{p_in}. The pressure in the tank is also affected by the change of liquid level as it increases or decreases the air volume.

The plant is two inputs two outputs coupled system, where each input affects both outputs. The outflow of liquid is also affected by the varying temperature of the liquid and the fact that the liquid outflows through the convoluted pipe.

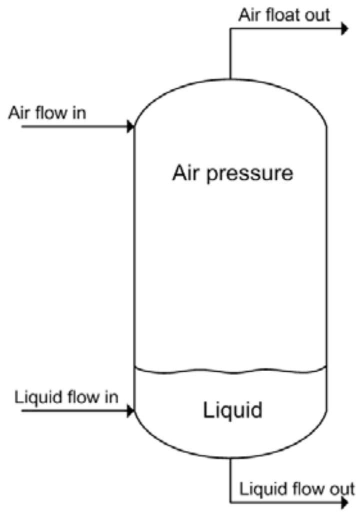

Figure 1. Plant's scheme

The control objectives in this part of the manufacturing process are to maintain a pressure and a level around the reference values in the tank.

3. Adaptive control system

3.1. Control system configuration

From the earlier experiments on the plant, controlled with two independent PI and fuzzy controllers [4], Figure 2, it was evident that the level control with independent controller was satisfactory even if the process was coupled, but in order to get a satisfactory control of the pressure it is necessary to take into account the level control action [5].

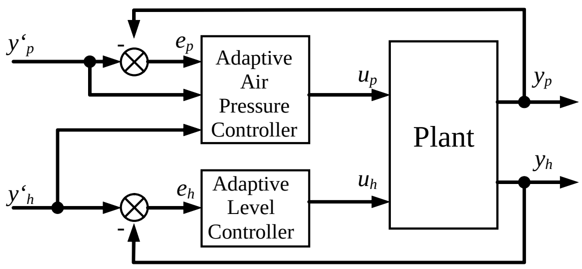

Figure 2. Closed-loop control system

A popular approach to dealing with control loop interactions is to design decoupling control schemes, Figure 3 [6].

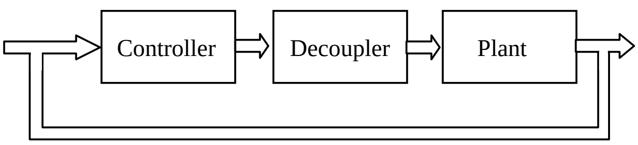

Figure 3. Structure of decoupling control system

Decouplers decompose a multivariable process into a series of independent single-loop sub-systems. In such a case the multivariable process can be controlled using independent loop controllers. Decouplers are derived from a mathematical model of a plant and the model itself should be not complicated [3, 6, 7]. But the coupling and non-minimum-phase behavior, the nonlinearities from valves, high amount of noise present in sensor readings (caused by turbulent water flow) complicate mathematical modeling of the system. It was experimentally shown in [4] that the derived mathematical model of the analyzed level-pressure system is adequate only at the designed operating regime and requires tuning of its parameters each time the set points changes. Considered that, and the fact, that the model-based control approach will not, in this case, significantly improve the level-pressure control results in practice, comparing to PI control (noise forbids derivative action, and non-minimum phase limits bandwidth) [3], fuzzy logic was introduced to control level-pressure system. To overcome the problem with the loop interactions, a fuzzy compensator was used instead of the pressure loop decoupler. The control system is shown in Figure 4.

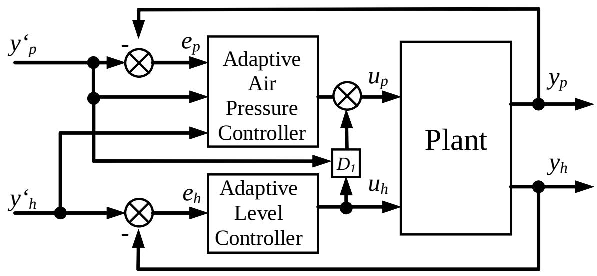

Figure 4. Closed-loop control system with compensator

As expert knowledge in a linguistic form is more convenient to represent with Mamdani type fuzzy structures [8] than with Takagi type structures [9], the Mamdani type fuzzy rule bases are used throughout this paper. Every rule is presented by a conjunction and the aggregation of the rules by a disjunction. Triangular fuzzification and center of gravity defuzzification on implied fuzzy sets are used for the calculation of crisp outputs [10].

3.2. Level fuzzy controller

For the control of liquid level, a direct adaptive fuzzy controller was used [4]. Fuzzy controller has 2 inputs and 1 output, Figure 5. Each of the inputs is covered with nine triangular symmetric membership functions across the universes of discourse. Membership functions are normalized and uniformly distributed, see Figure 6.

The fuzzy controller uses adaptation mechanism to observe numerical data from fuzzy control system. Using this data, the mechanism characterizes system's current performance and automatically adjusts controller parameters so that given performance objectives are met.

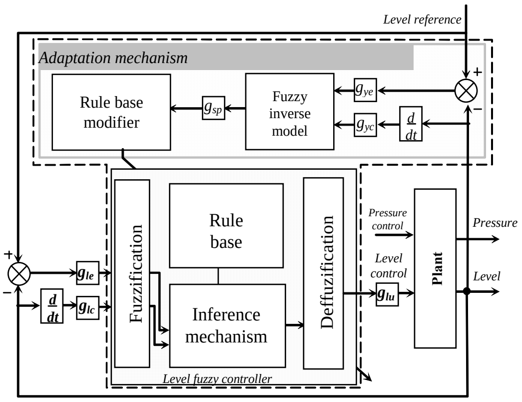

Figure 5. Level fuzzy controller

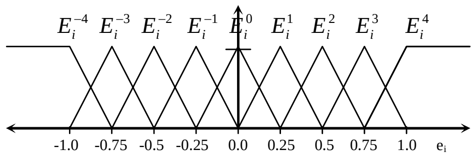

Figure 6. Inputs membership functions

The adaptation 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 in the process input, that are necessary to force process error to zero. The knowledge-base modifier directly adjusts the fuzzy controller's rule-base to affect the changes needed in the process inputs [4].

3.3. Pressure controller

3.3.1. Controller's structure

For the control of pressure in the tank, a more complex fuzzy controller, shown in Figure 7, is used.

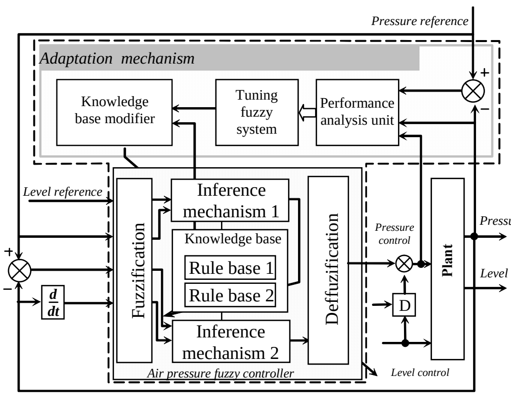

Figure 7. Pressure fuzzy controller

This fuzzy controller has 4 inputs and 1 output. The inputs are: the actuating error, linguistically named "*pe*", the change of actuating error, linguistically named "*pc*", and the level and pressure reference values, linguistically named "*l*", and "*p*". These reference inputs are used to identify the plant's operating mode. The output is the air pump rotation speed control signal $u_{pressure}$. For all these signals, the scaling gains are defined and their values are stored in the controller's knowledge base.

Linguistic variables are described using membership functions of the triangular form. The "effective" universes of discourse for the air pressure actuating error and the changes of error linguistic variables are defined by experiment, taking into account the dynamical characteristics of the plant.

For the pressure actuating error "*pe*", the effective universe of discourse is set to [-5.0, 5.0], for the change of actuating error linguistic variable "*pc*", the range is set to [-1.09, 1.09]. The "effective" universes of discourse for reference inputs linguistic variables are chosen taking into account the plant's physical parameters, so for the water level linguistic variable the universe of discourse is set to [0.0, 25.0], for the air pressure linguistic variable – [0.0, 50.0]. The "effective" universes of discourse of the output linguistic variable are chosen taking into account the physical characteristics of actuating mechanisms (the control signal can take values from the interval 0-10V), so it is set to [0.0, 10.0]. According to the defined effective universes of discourse, scaling gains are chosen so that input universes of discourse are normalized to interval [*-1; 1*], and the output – to interval [0, 1]. The linguistic variable of the actuating error is composed of 9 membership functions, the change in error, and reference inputs – of 7 membership functions.

The linguistic values of the second inference mechanism are calculated on-line, using the basic, defined in advance, 9 linguistic values that vary depending on the decision of the first inference mechanism, u_1, Figure 8.

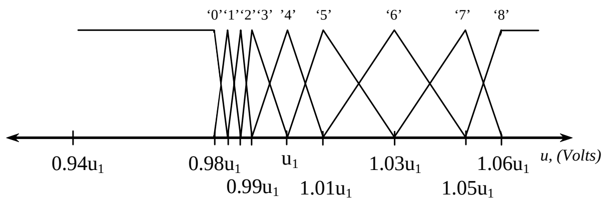

Figure 8. Output membership functions

3.3.2. Controller's knowledge base

The knowledge base of the fuzzy controller stores information about the scaling gains of the universes of discourses of linguistic input and output variables and the rule bases. The difference of the proposed fuzzy controller is that it has two rule bases where the first rule base is used to online form the main rule base of the controller.

The first rule base links the pressure and level reference signals with the basic control signal value and it contains 49 rules. These rules are tuned online based on the process data. The rules of the second rule base specify the values of the output depending on the current values of the actuating error and the change of the actuating error. This rule base is recalculated every time the reference signals are changed or after the tuning mechanism was activated.

The second rule base has 63 linguistic rules, where the centers of the conclusion membership functions of each of the rule are calculated according to formula:

$$c_{ij} = b_i \cdot (1 - (sk \cdot (3 - j))), \quad (1)$$

where c_{ij} is the center of the area of the output's implied fuzzy set, b_i – the center of area of the i-th basic output membership function, that are defined in advance (Figure 8), the index i is related with the linguistic-numeric value of the actuating error, j is related with the linguistic value of the controlled variable, and sk defines how much in percent to correct the center position of the calculated output membership function. Here sk is set to 0.0004. The second rule base of the controller inference mechanism physically stores only 9 rules, i.e. 9 values of the centers of output membership functions. These values describe control signal membership functions when the change in error is 0. These nine rules (the centers of output membership functions) are adjusted by the adaptation mechanism. The other 54 rules are defined on line. At the start up of the controller, the assumption is made that the controller knows nothing about how to control the process. This form of the rules generation reduces the number of rules in the controller's rule base and easy its tuning process.

3.3.3. Adaptation mechanism

Even if a large amount of expert knowledge about the process is presented, the synthesis of a tolerable fuzzy controller for this process in most cases is a challenging task due to many parameters of fuzzy controller. As research and experiments show, an expert knowledge in most cases has to be tuned in order to reach the desired performance of a controller. In order to effectively select the correct values for these parameters, tuning mechanism for fuzzy controller is implemented.

Fuzzy controller's adaptation mechanism contains performance analysis unit, fuzzy decision making systems and knowledge base modifier. The performance analysis unit operates like an input preprocessing unit that keeps track on the plant's operation, analyses data and provides the fuzzy decision making system with the relevant statistical data, in this case current pressure, the pressure error, and control signal values. Fuzzy decision making system is used for the calculation of the necessary adjustment values for the particular rules. According to the information from the process analysis unit, it calculates the adjustment value for the appropriate data. Fuzzy decision making system uses triangular fuzzification, min-max inference and center of gravity defuzzification techniques. In case of a rule correction in a fuzzy controller's knowledge base, fuzzy decision making system calculates a shift values for centers of the output membership functions of the rule.

The tuning fuzzy system of the adaptation mechanism is synthesized using an expert knowledge: an expert decides what inputs are essential for the tuning process of particular data structures, what the speed of tuning should be. The role of the knowledge base modifier is to correct the appropriate rules by the provided values. The adjustments are performed on the first rule base of the controller and, because the first rule base is used for the online synthesis of the controller's rules the, change of these values directly affect the controller performance. In order to prevent the controller from the over tuning, the knowledge base modifier is complimented with the tuning supervisory system.

3.3.4. Control loop interaction compensation

For the level control action compensation in the pressure loop, a simple two input-one output fuzzy system is used, Figure 9.

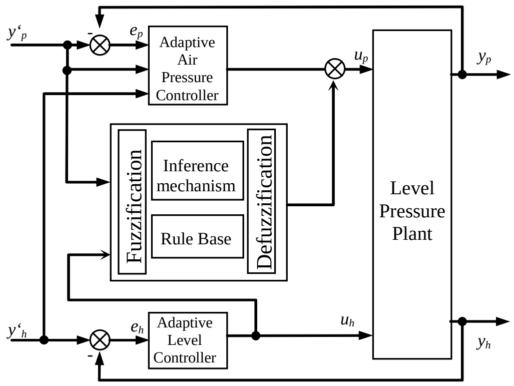

Figure 9. Interaction fuzzy compensator

Taking into consideration the air pressure reference signal and level control action, fuzzy decision making system calculates adjustment value for the air pressure control action. The rule base of this fuzzy system is made of 63 Mamdani type fuzzy rules (7 membership functions for pressure reference input and 9 membership functions for level control signal input), that are chosen and tuned experimentally.

4. Experiments

The performance of the controllers was experimentally tested and the results were compared with the performance of the controllers that control the plant independently of each other.

For the analysis of the controllers, 400 seconds of control data were examined. The reference values were changed every 57 seconds; the data from the plant were collected at one-second intervals. The level and the pressure reference signals are chosen to have a step form.

The efficiency of the controllers was evaluated calculating the standard deviations of pressure errors and level errors, Table 1. The response of the plant, controlled with the independent controllers, see Figure 2, is shown in Figure 10 [4]. Figure 10 shows the response of the plant, controlled with the decoupled adaptive air pressure fuzzy controller. Liquid level is this case was controller not taking into consideration pressure control. The standard deviations were calculated according to formulas

$$STD_{e_p} = \sqrt{\frac{1}{400}\sum_{t=1}^{400} e_p^2(t)} \text{ and } STD_{e_h} = \sqrt{\frac{1}{400}\sum_{t=1}^{400} e_h^2(t)}\,.$$

The experiment shows that the overall control of the plant is more efficient when air pressure is controlled taking into consideration the level control action. The visual difference of the control quality in this case is noticeably better than comparing the standard deviation values, but these are also smaller in values: pressure error is decreased by 22%. As the same controller was used for the control of level, level error remained almost unchanged. The smaller standard deviation value here is because level and pressure processes are strongly related and, as the variation of pressure decreased, level variation slightly decreased too.

Table 1. Comparison of controllers

Standard deviation \ Controller type	Independent control of level and pressure	With compensated pressure control
Pressure error , e_p	1.2629	0.9943
Level error, e_h	0.9110	0.9070

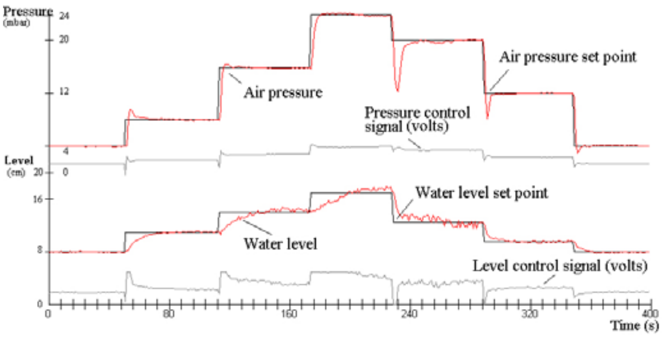

Figure 10. Independent control of level and pressure in a 2x2 system

5. Conclusions

In this paper the synthesis and application of the adaptive fuzzy controllers with a fuzzy loop interaction compensator for the in multiple input-multiple output level-pressure plant was presented. The efficiency of the controllers and the fuzzy system as a loop interaction compensator was experimentally tested and compared with the performance of the uncoupled controllers. The results of experiment proves that fuzzy logic can be used for the design of loop compensators in control systems for the control of multiple input-multiple output plants in case there is no adequate mathematical model of that plant. It was experimentally shown that the adaptive fuzzy pressure control using fuzzy compensator makes sense and can increase the control efficiency of the level-pressure system.

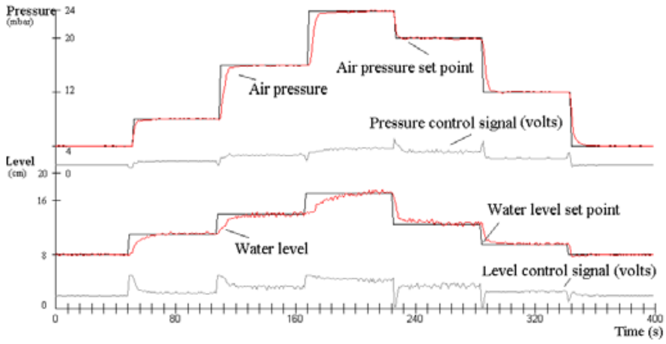

Figure 11. Level and pressure control in a 2x2 system with the level control action compensation in the pressure loop

References

[1] **G. Stephanopoulos.** Chemical process control, an introduction to theory and practice. *PTR Prentice Hall (UK), London*, 1984.

[2] **B. Roffel, B. Betlem.** Process Dynamics and Control. Modeling for Control and Prediction. *John Wiley & Sons, England*, 2006.

[3] **P. Albertos, A. Sala.** Multivariable Control Systems. *Springer*, 2004, 159.

[4] **V. Kaminskas, R. Liutkevičius.** Adaptive fuzzy control of nonlinear plant with changing dynamics. Informatica, **13**(3), 2002, pp.287-298.

[5] **V. Kaminskas, R. Liutkevičius.** Learning fuzzy control of nonlinear processes. *Informatica*, 16(4), 2005, 571-586.

[6] **K. Warwick, D. Rees (Eds.).** Industrial Digital Control Systems, 2nd Edition. *IEE Control Engineering Series* 37, *Peter Peregrinus*, 1988.

[7] **O.N. Gasparyan.** Linear and nonlinear multivariable feedback control, a classical approach. *John Wiley & Sons, England*, 2008.

[8] **E.H. Mamdani.** Application of fuzzy algorithms for control of simple dynamic plant. *Proceedings IEE, D-*121, 1974, 1585-1588.

[9] **T. Takagi, M. Sugeno.** Fuzzy identification of systems and its applications to modeling and control. *IEEE Trans. on Systems, Man, and Cybernetics*, 15(1), 1985, 116-132.

[10] **K.M. Passino, S. Yurkovich.** Fuzzy control. *Addison-Wesley, USA*, 1998.

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