FUZZY EXPERT SYSTEM FOR SUPERVISION IN ADAPTIVE CONTROL

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Abstract: As several problems arise at the application of adaptive controllers to real industrial processes, for a successful implementation the standard control algorithms have to be combined with heuristically derived safety jackets. These safety nets are often realized in expert systems. This paper presents such an intelligent supervision system, where the heuristic knowledge is represented by fuzzy rules. The fuzzy system designed for adaptive control of a simulated fermenter supervises the semi-continuous identification and the controller tuning procedure. Simulation results show that the application of the proposed algorithm results in a robust and good control performance.

Keywords: adaptive control, supervision, fuzzy systems

1. INTRODUCTION

Adaptive control has been proven to be an efficient approach for dealing with time-varying, nonlinear, and/or unknown processes. However, several problems arise at the implementation of parameter adaptive controllers to industrial processes. In order to avoid these problems, the standard control algorithms have to be combined with heuristically derived safety jackets. These safety nets are often implemented as supervisory expert systems introduced to monitor and co-ordinate the adaptation process and guarantee satisfactory control behaviour.

The first steps in this direction in connection with parameter bursting were proposed in (Fortesque *et al.*, 1981). Timmons has introduced a constrained adaptation algorithm to constrain the model parameters to lie within a reliable region, and incorporate important *a priori* knowledge about the process into the control-relevant model (Timmons *et al.*, 1997). The basic ideas about supervision of adaptive controllers were first presented by Isermann (Isermann and Lachmann, 1985). In order to handle heuristic knowledge utilized by these methods, an expert system approach has been suggested (Astrom *et al.*, 1986) and applied to relay auto-tuning method (Arzen, 1989).

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These expert control algorithms utilize performance measures extracted from on-line input-output process data. Some of them were proposed by Isermann (Isermann and Lachmann, 1985), Doraiswami (Doraiswami and Jiang, 1989), and Gertler (Gertler and Chang, 1986) to detect signal and parameter trends and instability of the control system.

The "AtRequestTuner" is a simple approach to Intelligent Adaptive Control (Tuleken, 1992). Instead of the usual philosophy of continuous adaptation, it features automatic control re-tuning at (user) request only. The idea of this structure is discussed and analyzed in great detail by Hilhorst (Hilhors, 1992). This semi-continuous adaptation approach was also suggested in (Zhu *et al.*, 2000) for adaptive control of bioreactors, because the continuous adaptation considered practically infeasible, too costly, and too risky under hard circumstances.

Most of the expert or knowledge-based control solutions developed to handle heuristic supervision knowledge are closer in spirit to conventional adaptive control than fuzzy control (Arzen, 1989). However, Isermann showed that fuzzy systems can be useful tools in supervision (Isermann, 1988). Moreover, recently fuzzy systems have been successfully applied to the supervision of a recursive parameter estimator (Abdennour *et al.*, 1998).

Hence, the aim of the research presented in this paper is to design an intelligent supervision system for adaptive control of bioreactors based on the 'AtRequestTuner' and the expert system concept, where the heusristic knowledge is represented by a fuzzy system.

The paper is organized as follows. In Section 2 the basic scheme of the proposed modular supervisory algorithm is described. Section 3 presents an application example, where the proposed approach is applied to the pressure control of a simulated fermenter. Conclusions and discussion on future improvement possibilities are given in Section 4.

2. THE SUPERVISION SYSTEM

2.1 *The structure of the supervision system*

The basic scheme of the designed supervision system is shown in Figure 1.

When the supervision system operates in a semi-automatic way, the supervisor estimates the current status of the process and reports about its performance and current and planned parameters of the control algorithm to the operator. If the operator agrees with such initiative, he acknowledges it, and the process will be controlled with the newly identified and adjusted parameters. If

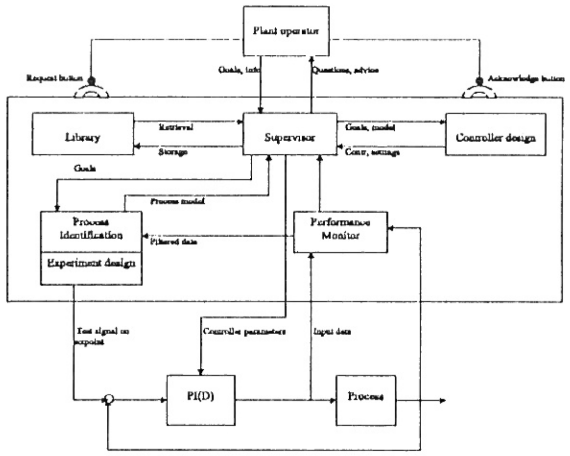


Fig. 1. Architecture of the supervision system

the operator based on his own perception is dissatisfied with the resulted control performance, a request can be made for automated improvement of the closed loop behaviour. In this case the operator coordinates the identification and control design procedure, while the supervisor gives only advice to take an action.

During automated operation, the control algorithm runs without any operator intervention. This means, the main task of the algorithm is the decision on when and how a closed-loop identification has to be performed, and the design and tuning the parameters of the controllers. According to these tasks, the control scheme consists of the following modules:

- *Supervisor*
- *Performance monitor*
- *Controller designer*
- *Identification block*
- *Experiment designer and test signal generator*

The most important modules of the presented algorithm are briefly described in Table 1.

According to the general structure of a real-time expert controller (Doraiswami and Jiang, 1989), these building blocks can be grouped into the following main elements.

- *Real-time information preprocessor*
- *Knowledge base and inference engine*
- *Control and identification algorithm*

In the following subsections these elements will be described in more details.

2.2 *Information preprocessor, the utilized performance measures*

The real-time information preprocessor consists of a collection of signal processing algorithms which are responsible for providing the rele-

Table 1. Functions of the supervision system

Name of the function	*Goal*	*Required tools for realization*
Model performance monitor	Characterization the modeling performance of the control relevant model	Methods for model validation
Control performance monitor	Characterization of the performance of the controller	Pattern recognition of control trajectory (e.g. steady-state error and ringing detector)
Process identification	Generating the model parameters and the test signal	Model identification and perturbation signal generation methods
Controller tuning	Design and re-fine the parameters of the PI(D) controller	Advanced controller tuning methods

vant information about the current status of the system. If the supervision system does not use any process-relevant knowledge, these performance measures are obtained based only on the measured input-output signals (Isermann and Lachmann, 1985),(Doraiswami and Jiang, 1989), (Gertler and Chang, 1986). In the following, only some of them will be reviewed that is applied in our case study.

Let's $z(k)$ denote the value of a signal used for obtaining the performance measure at the kth discrete time instant. By using a sliding window of N_w samples, the following measures can be obtained:

- mean value:
  $\bar{z}(k) = E\{z(k)\} = \frac{1}{N_w} \sum_{i=k-N_w+1}^{k} z(i)$
- variance:
  $\sigma_z^2 = E\left\{[z(k) - \bar{z}(k)]^2\right\}$
- trends:
  $h(k) = h_1(k) - h_2(k)$
  $h_1(k) = (1 - a_1) \sum_{i=k-N_w+1}^{k} a_1^{i-k} z(k-i)$
  $h_2(k) = (1 - a_2) \sum_{i=k-N_w+1}^{k} a_2^{i-k} z(k-i)$
  $1 > a_2 > a_1 > 0$

Based on these simple measures, steady-state and oscillation (ringing) detectors can be designed by choosing $z(k)$ the control error $e(k)$ and $|e(k)|$.

- The measure of steady-state error:
  $|E\{e(k)\}|$
- The measure of oscillation:
  $E\{|e(k)|\} - |E\{e(k)\}|$

Measures based on the modeling error, e_m, of the process model used for controller design can be also utilized (Isermann and Lachmann, 1985). Beside the presented average, variance and tend measures,

- auto-correlation:
  $\phi_{e_m e_m}(\tau) = E\{e_m(k)e_m(k+\tau)\}$
- cross-correlation:
  $\phi_{u e_m}(\tau) = E\{u(k)e_m(k+\tau)\}$

measures can be defined.

In order to obtain a supervision algorithm that is less sensitive to measurement noise, the modeling error is obtained by $n$step ahead prediction.

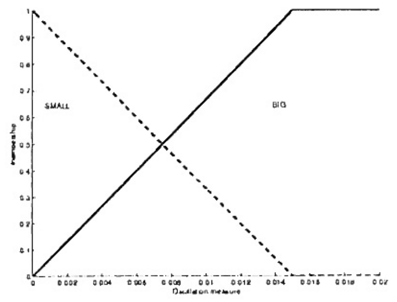
2.3 *Inference engine*

Based on the obtained performance measures the supervisory system decides about whether to continue the normal operation, perform an identification experiment, and/or re-tune the controller. This decision is often made by an inference engine or an expert system. According to (Arzen, 1989), two approaches exist to represent the knowledge utilized in such algorithms. The first approach expresses the control heuristics in terms of if-then rules, which are implemented with more or less standard programming techniques, while the second approach uses expert systems for the implementation.

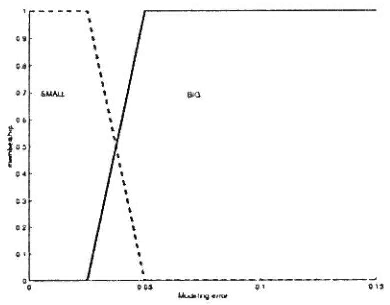
As most of these techniques utilize if - then rules for a comparison of the performance measure with a crisp threshold, the possibility of the application of fuzzy logic in these systems is naturally arises. The fertilization of the supervisor with fuzzy techniques could result in easily interpretable and transparent algorithm. Because the fuzzy system operates with linguistic variables, the *a priori* knowledge of the operators and their control specifications can be easily incorporated as fuzzy if - then rules.

To deal with fuzzy inference mechanism that operates with fuzzy sets, the fuzzy system must be equipped with conversion interfaces, the fuzzification and deffuzzification units. This means at first the performance measures obtained in the previous section has to be fuzzified. In this paper triangular and trapezoidal membership functions (MF) were used. An example for fuzzy values of performance indexes is presented in Figure 2.

By using the fuzzified values of the performance indexes, fuzzy if-then rules can be defined for the representation of the heuristic knowledge. According to our example, by using the previously defined linguistic variables, the following rules can be defined:



(a) MF defined on oscillation measure



(b) MF defined on the average of the absolute modeling error

Fig. 2. Example for MFs

R_1 : **If** oscillation is BIG
and modeling error is BIG
then Change the model and the controller

R_2 : **If** oscillation is BIG
and modeling error is $SMALL$
then Redisign the controller

2.4 *Control and identification algorithm*

Obviously, the rules applied in the inference system are highly dependent on the applied control and identification method. As the aim of our research is to design an intelligent adaptive controller for bioprocesses, and the continuous adaptation is suggested to be too costly and too risky under hard circumstances, semi-continuous adaptation approach is used (Zhu *et al.*, 2000). This results in an "AtRequestTuner" (Tuleken, 1992) that features automatic control re-tuning at the request of the supervisor only.

The process is controlled by independent PID control loops. The parameters of the PID controllers are designed by IMC tuning rules introduced by Rivera (Rivera and Gaikwad, 1996). The idea is to derive PID parameters based on a low order model of the process. The PID parameters are determined so that the closed-loop behavior approximates the behavior given by a first order filter

$$G(s) = \frac{1}{\tau_{cl}s + 1}.$$

Hence, for controller tuning, only the time constant of the desired closed-loop performance, τ_{cl}, and the low order model of the system has to be determined.

For obtaining the low-order process model, closed-loop identification is used in order to avoid the drift of the system away from the required operating point. During the identification experiment the system is perturbed using a test signal superposed to the setpoint. Due to an incorrect disturbance model, the standard equation error (ARX) model estimation methods are biased for closed-loop data. In order to avoid this problem, the parameters of the low-order model were obtained by using the ASYM method (Zhu, 1998), where a high order equation error model estimation is combined with a model reduction algorithm. Based on the error bound matrix of the high order model, the method gives an estimation of the quality of the reduced model. As the ASYM implementation grades the identified models between A-D according to they estimated validity, the information about the quality of the estimated model can be easily incorporated to the supervision system. For instance, models graded C and D are not applicable to design a controller. Hence, in this case the supervision system gives an order to continue the identification experiment by doubling the amplitude of the applied excitation signal. This example shows, that the excitation signal design plays crucial role in practical identification. Hence this task also has to be managed by the supervision system. The following heuristic rules were used. Set the average switch time to be equal to the 1/3 of the settling time of model identified in the previous identification experiment, set the length of the excitation signal to be the 12 times of the settling time, and determine the amplitude of the signal according to the estimated noise-signal ratio.

3. APPLICATION TO THE PRESSURE CONTROL OF A FERMENTER

In this case study, the pressure control of a laboratory fed-batch fermentor is studied. Figure 3 shows a schematic diagram of the setup.

The simulation model of the fermetner is described in (Babuska *et al.*, 1996), where this process is used as a case study for comparision of different intelligent control schemes. The volume of the fermenter tank is 40 l. At the bottom of the tank, air is fed into the reactor. This flow-rate is assumed to be unknown and handled as an unmeasured disturbance. The air pressure above the

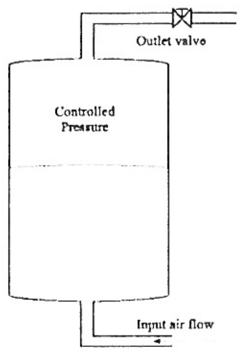


Fig. 3. The control setup

liquid phase is controlled by the outlet valve at the top of the tank. Because of the underlying physical mechanism and the characteristic of the valve, the process has nonlinear steady-state and dynamic characteristic. The smallest time constant of the process is about $45s$, which allows for a sample time of $T = 5s$.

The fuzzy expert supervisory system is based on the building blocks presented in the previous section and implemented to the process through the following steps:

- Calculation of the performance measures (PM)
- Fuzzification of the PMs
- Decision of the future tasks based on the fuzzy inference engine

If it is needed, a closed-loop identification experiment is performed according to the following schedule:

- Experiment design based on parameters of the previously identified model and user specifications
- Processing the process signals resulted from the closed-loop identification experiment (data de-trending, cutting the outliers, and filtering
- Identification using the ASYM method
- If the model grade is A or B than go to the controller design step
- If the model grade is C or D redesign the test signal and continue the identification experiment

The length of the applied sliding window was set to $N_w = 50$ that is nearly equal to the settling time of the process. Based on the fuzzified oscillation and modeling error measure (see, Figure 2), the supervisor decides about the identification and controller redesign. During normal situation, the controller is designed by choosing τ_{cl} to be equal to the 1/4th of the time constant of the identified model. However, because only a single tuning parameter is used by the PID control design method, the operator has the opportunity to define the closed-loop performance in qualitative terms, e.g. "as fast as possible" because this term can be easily represented as a ratio between the time constant of the model and the desired closed loop behaviour.

Figure 4 presents one of the performed simulation experiments. As Figure 4 shows, the performance monitor was switched off during the identification experiment. The identification and controller redesign task were performed if the degree of the corresponding rule was greater than 0.5. During the short operating time presented in this figure, the supervision system required two identification experiments. One at around the beginning operation, and an another around the 1500th second. In both cases, the firstly identified models had bad estimated performance (grade C), hence the identification experiments were extended. This can be seen from the output of the supervisor and the increased amplitude of the set-point perturbation. After the introduction of a new model and controller, the suggestions of the supervision system has not been taken into account for a small period, because the mowing window used by the oscillation detector requires data generated by normal operation. As Figure 4 shows, the oscillation detector works really good, because it is not sensitive to set point chances and disturbance rejection actions (in this case its output is zero, because $E\{|e(k)|\} = |E\{e(k)\}|$), hence it is only signs if there is a large oscillation around the set-point.

4. CONCLUSIONS AND DISCUSSION

In order to handle problems arise at the application of adaptive controllers to real industrial processes, a fuzzy supervision system has been introduced and applied to a simulated fermenter. The work is motivated by control problems resulted from the complexity of biotechnological processes and problems with standard adaptive control.

The application of fuzzy techniques on the supervisory level of an adaptive controller resulted in an easily interpretable and transparent algorithm. As the fuzzy system operates with linguistic variables and rules, the *a priori* knowledge of the operators and their control specifications can be easily incorporated to the algorithm. Because of the modular structure of the supervisor, the elements of the algorithm can be maintained and developed almost separately. The proposed algorithm contains only the basic elements of the supervision system that we would like to design for adaptive pH, dissolved oxygen, and temperature control of commercial bioreactors. The aim of our further theoretical research is to examine the possibility of the application of bioprocess specific knowledge and multiple-model adaptive control techniques (Narendra *et al.* 1995) where the supervision

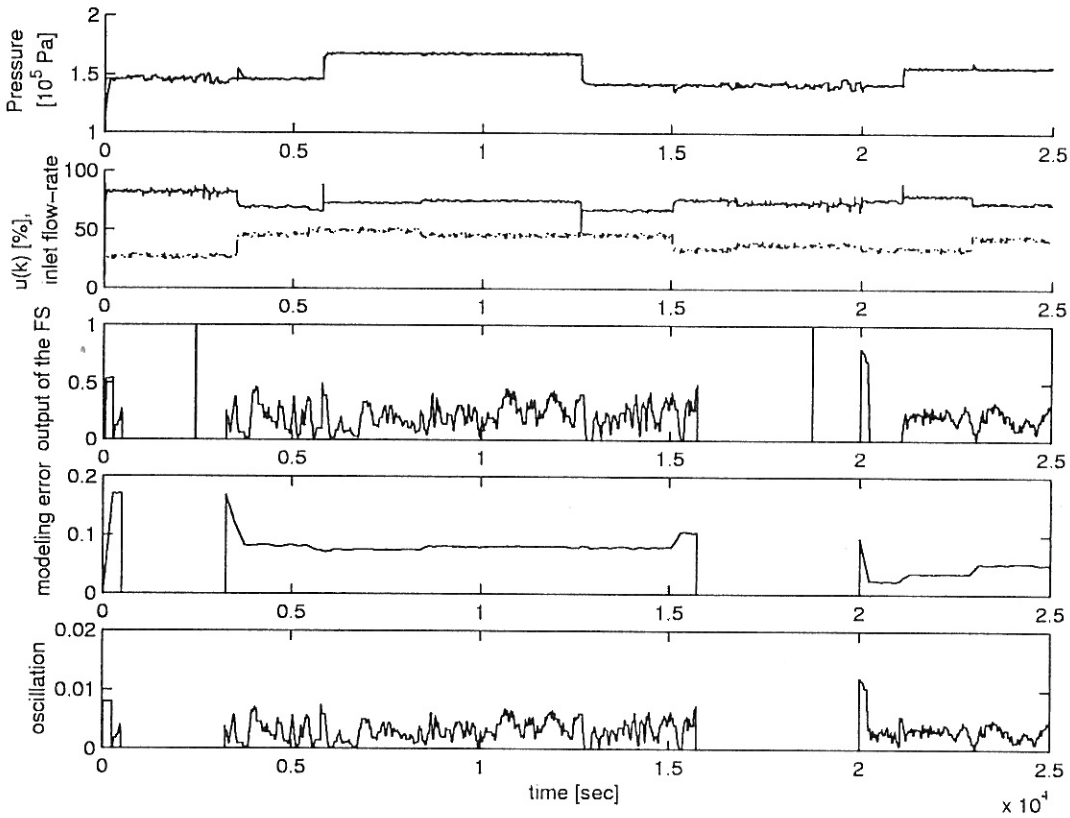


Fig. 4. Application of the supervision system

algorithm requires identification and control tuning only for new working points, because the old parameters are stored in a model and controller library. By using this methodology batch-to-batch learning will be realized.

5. REFERENCES

Abdennour, R.B, G. Favier and M. Ksouri (1998). Fuzzy trace identification algorithm for non-stationary systems. *Journal of Intelligent and Fuzzy Systems* **6**, 403–417.

Arzen, K.E. (1989). An architecture for expert system based feedback control. *Automatica* **25**, 813–827.

Astrom, K.J., J.J. Anton and K. Arzen (1986). Expert control. *Automatica* **22**, 277–286.

Babuska, R., H.J.L van Can, A.J. Krijgsman and H.B. Verbruggen (1996). Comparison of intelligent control schemes for real-time pressure control. *Control Engineering Practice* **4**, 1585–1592.

Doraiswami, R. and J. Jiang (1989). Performance monitoring in expert control systems. *Automatica* **25**, 799–811.

Fortesque, T. R., L.S. Kershenbaum and B.E. Ydstie (1981). Implementation of self tuning regulators with variable forgetting factor. *Automatica* **17**, 831–935.

Gertler, J. and H.S. Chang (1986). An instability indicator for expert control. *IEEE Control Systems Magazine* (August), 14–17.

Hilhors, R. (1992). *Supervisory Control of Mode-switch Processes*. Ph.D. Thesis, University of Twente.

Isermann, R. (1988). On fuzzy logic applications for automatic control, supervision, and fault diagnostic. *IEEE Transactions on Systems Man and Cybernetics, Part A* **28**, 221–235.

Isermann, R. and K.H. Lachmann (1985). Parameter-adaptive control with configuration aids and supervision functions. *Automatica* **21**, 625–638.

Narendra, K.S., J. Balakrishan and M.K. Ciliz (1995). Adaptation and learning using multiple models, switching and tuning. *IEEE Control Systems Magazine* (August), 105–127.

Rivera, D.E. and S.V. Gaikwad (1996). Digital PID controller design using ARX estimation. *Computers and Chemical Engineering* **20**, 1317–1334.

Timmons, W.D., H.J. Chizeck and P.G. Katona (1997). Parameter-constrained adaptive control. *Ind. Eng. Chem. Res.* **36**, 4894–4905.

Tuleken, H. (1992). *Gray-box Modelling and Identification Topics*. Ph.D. Thesis, Delft University of Technology.

Zhu, Y. (1998). Multivariable process identification for MPC: the asymptotic method and its applications. *Journal of Process Ccontrol* **8**, 101–115.

Zhu, Y., P.J. Bosch and A. Oudshoorn (2000). Identification and adaptive control of bioprocesses. *Journal A*, p. to appear.