USE OF PREDEFINED KNOWLEDGE IN ADVANCED ADAPTIVE CONTROL

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Abstrac: An advanced pattern recognition based supervision algorithm for an indirect adaptive controller is proposed. It was developed to improve control performance under certain conditions that are common in the industrial environment, in which indirect adaptive controllers with simple supervision are known to perform poorly or unreliably. Specifically, the problem of large invasive unmeasured disturbances of short or longer duration is addressed. The supervisor is designed recognize such events by analysis of recent control signals with no additional measurements used. Based on predefined features and thresholds, it switches to appropriate strategy. This way it prevents model degradation by learning from misleading data and to maintain acceptable performance under unfavorable conditions. As an illustration, it has been applied to the control of a model of a semi-cleanroom HVAC installation subsystem.

1. INTRODUCTION

Adaptive control was introduced to handle processes with varying parameters and it is still the subject of scientific examination. An adaptive controller adjusts its parameters in order to retain good performance throughout the varying operating conditions operation. The main advantages and disadvantages of several common approaches to adaptation are presented in a survey study [6] and a comprehensive description of adaptive control methods is given in [1]. There are two main types of adaptive controllers:

- indirect adaptive controllers that compute controller parameters based on on-line identified plant model parameters, and
- direct adaptive controllers that directly update controller parameters from process signals.

Adaptive controllers are present in industrial applications but are not as widespread as was once expected. Despite the obvious need for controller self-tuning and adaptation, the percentage of adaptive controllers remains small due to their complexity and the practical problems associated with application to specific processes [7], [9].

Available industrial adaptive controllers typically belong to the direct type [4], where the tuning rules for adaptation of controller parameters are based on features of the process signals, such as rise-time, overshoot, damping ratio and noise band, determined using heuristics and pattern recognition techniques [3], [8], [11]. Usually they are pre-configured for specific applications in order to decrease the complexity of implementation. One comparison study of such algorithms is given in [7].

Indirect adaptive controllers are not as common as the direct type in industrial use, mostly because they are less suitable for handling specific problems of practical process operations and exceptional working conditions. Short unmeasured invasive disturbances are examples of situations where most indirect adaptive controllers fail to stop the adaptation and consequently degrade the model. Several methods of adaptation supervision were developed, such as conditional start/stop of adaptation, exponential and directional forgetting, leakage and covariance resetting ([1], p. 465-480; [9]). However, these methods appear to be less effective and robust in selecting useful signal segments for tuning than pattern recognition based approaches used by industrial direct adaptive controllers. On the other hand, for certain industrial applications there is a need for indirect adaptation since it does not require the special step-like shape of excitation signals, for example in cascade control inner loops.

Related literature on the supervision of adaptive controllers was found, but the issue of response to short unmeasured invasive disturbances is not elaborated in detail. Comprehensive work concerning the building of higher-level information and using it for adaptation supervision is presented in [12]. Expert control is applied to a self-tuning voltage regulator in a case study [5]. A supervisory scheme for an indirect adaptive controller for fermentation control is presented by Babuška et al. [2], in which a supervisor based on a state automaton with a fuzzy rule-based inference system is used. Related approaches are also found in fault detection and isolation literature [18], [19].

Most supervision algorithms for indirect adaptive controllers only decide whether to update the model parameters or freeze adaptation based on current data and possibly the state of the supervisor automaton. This approach extends the decision-making with the detection of events in the buffer of process signals, using pattern recognition techniques [22] and predefined expert knowledge about the process. It is able to recognize critical events (e.g. unmeasured disturbances) from the shape of the signals and react quickly with appropriate action.

The proposed adaptive system consists of a basic adaptive controller, a diagnostic module and supervision module. The diagnostic module scans the signal buffer, analyzing recent values, statistics and the transient behavior of the process signals to detect characteristic events. The supervisor is a finite state machine (FSM) [20], [21]. Based on the calculated features, the supervisor evaluates the situation in light of predefined knowledge about the characteristic disturbances. Therefore, the whole adaptive system may be seen as a discrete hybrid automaton.

For performance illustration, the operation of the system is presented in a simulation case-study of a heating-ventilating-air conditioning (HVAC) process. Nevertheless, the phenomenon of short invasive disturbances is common in many industrial processes, and the approach is essentially not model-specific, so it can be easily modified for other applications.

The outline of the paper is as follows: in Section 2, the model of the HVAC subsystem is presented. Sections 3 and 4 briefly present a fixed outer cascade loop controller and a basic adaptive inner loop controller, respectively. Section 5 focuses on the advanced diagnostic and supervision modules of the adaptive controller. The simulation study in Section 6 compares control performance with fixed parameters, the basic adaptive controller and the supervised adaptive controller. Finally, conclusions are given in Section 7.

2. PROCESS DESCRIPTION

The performance of the adaptive system is evaluated on a model of the relevant subsystem of a semi-cleanroom HVAC installation in Fig. 1.

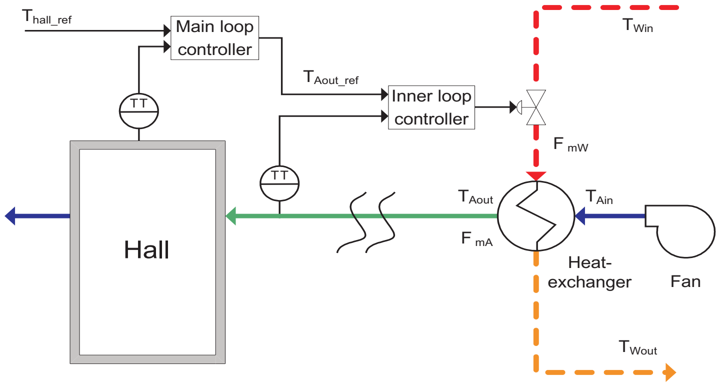

Fig. 1. Process scheme.

The model describes the hall heating process using hot air with constant flow Φ_{mA}, which is defined by the ventilation requirements. The air path starts with the fan blowing air (at temperature T_{Ain} of outside (environmental) air) into the heat exchanger. Heated air at T_{Aout} then flows through the duct (whose length causes a time delay; in reality it also affects the temperature, which is neglected here) leading to the hall. Finally the air exits the hall at the outlet. In the heat exchanger, the air is heated by water coming from the heating station with a mean temperature T_{Win} of 85°C. Two sensors measure hall temperature T_{hall} and hall inlet air temperature T_{Aout} before it enters the hall.

A counter-flow heat exchanger ([15], [16], [17]) is used. Its model is based on the following equation

$$P = \mu \cdot \Delta T_{\ln} \cdot A_{TOT} \tag{1}$$

where P is the heat transfer rate [W], μ the overall heat transfer coefficient [W/m^{2}K], ΔT_{ln} the logarithmic mean temperature difference [K], and A_{TOT} the total effective heating surface area [m^2].

The logarithmic mean temperature difference is calculated via

$$\Delta T_{\ln} = \frac{\Delta T_1 - \Delta T_2}{\ln \frac{\Delta T_1}{\Delta T_2}} \tag{2}$$

with

$$\Delta T_1 = T_{Win} - T_{Aout} \qquad \Delta T_2 = T_{Wout} - T_{Ain}\,, \tag{3}$$

where:

T_{Ain}, T_{Aout} are the heat exchanger inlet and outlet air (cold side) temperatures and

T_{Win}, T_{Wout} are the heat exchanger inlet and outlet water (hot side) temperatures.

Presuming known hot (water) and cold (air) stream mass flows in the heat-exchanger Φ_{mW} and Φ_{mA}, respectively, the output temperatures are calculated from the power transfer equation

$$P = (T_{in} - T_{out}) \cdot \Phi_m \cdot c_p\,, \tag{4}$$

yielding

$$T_{Aout} = T_{Ain} + \frac{(T_{Win} - T_{Wout}) \cdot \Phi_{mW} \cdot c_{pW}}{\Phi_{mA} \cdot c_{pA}}\,. \tag{5}$$

The water flow Φ_{mW} is set by the valve position u and the relation

$$\Phi_{mW} = u \cdot \Phi_{mW,\max}\,, \tag{6}$$

where the range of u is from 0 to 1. The hall heating model is represented by

$$\frac{dT_{hall}}{dt} = \frac{(T_{Aout} - T_{hall}) \cdot \Phi_{mA} \cdot c_{pA} - (T_{hall} - T_{outside}) \cdot G_{th}}{C_{th}}\,, \tag{7}$$

where T_{hall} is the hall temperature, $T_{outside}$ the outside air temperature, m the mass of air in the hall, c_{pA} the heat capacity of the air, C_{th} the thermal capacity of the hall and G_{th} the thermal conductivity of the hall walls.

The nature of the process is time-varying and non-linear. The process dynamics can be divided into two parts: the faster – heating of the hall inlet air by water, and the slower – heating of the hall by the hall inlet air. A cascade control scheme is used. The outer loop controls the temperature of the hall by setting a reference for the hall inlet air temperature. The latter is controlled in the inner loop by the heating water flow valve. In the inner loop, adaptive control is applied with the purpose of achieving efficient control over a wide range of operating conditions and reducing the effect of disturbances as quickly as possible.

Two types of external influence on local process dynamics must be considered. Firstly, there are several gradually changing parameters that are considered as regular, and the controller is expected to adapt to them. Two of them are considered in the model:

- outside air temperature (daily and yearly cycle, noise)
- heating water temperature (small step changes represent switching on/off of other systems connected to the heating station).

The second type is short invasive disturbances. In this process, such disturbances are caused by temporary cut-outs of the heating station, which is a common problem due to switching of another large consumer of heat. These disturbances have large amplitudes but short duration and require special treatment in order to minimize deviation from the set-point and the degradation of model parameters in the adaptive controller.

3. OUTER LOOP CONTROLLER

The hall temperature is controlled using a constant continuous-time PI (proportional-integral) controller (proportional gain $K = 2.2$, integral constant $T_i = 2.75$). The controller reads the room temperature sensor and sets a reference temperature for the air blown into the hall. This temperature represents the set-point for the inner heat exchanger loop. The outer loop controller also includes an anti-windup function [14]. The control scheme is given in Fig. 2.

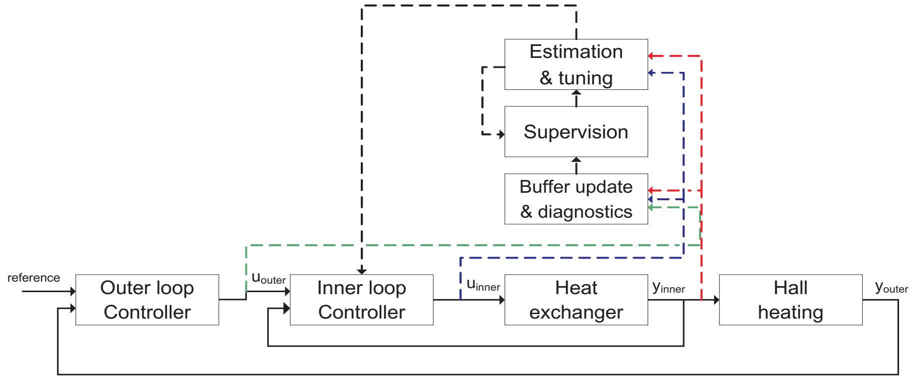

Fig. 2. Scheme of supervision and adaptation modules applied to the inner loop controller

4. INNER LOOP CONTROLLER – BASIC INDIRECT ADAPTIVE CONTROL

In the inner loop, a P controller is used. The integral term is omitted for the sake of simplicity, because offset-free tracking is not required in the inner loop, since it is provided in the outer loop controller. Due to the presence of noise, the use of the derivative term is not in place.

A. Identification and controller tuning

A standard recursive least-squares (RLS) method is used for estimation of the model parameters from on-line data [10]. After a thorough examination, the structure of a first order model with offset and predefined time delay was selected, due to the nonlinear nature of the process.

The RLS estimator is executed as follows:

$$\Psi = [u(k) \quad y(k-1-d) \quad 1]$$

$$K = \frac{P \cdot \Psi}{(\lambda + \Psi' P \Psi)} \qquad , \tag{8}$$

$$\vartheta(k+1) = \vartheta(k) + K(y - \Psi' \cdot \vartheta)$$

$$P(k+1) = \frac{(I - K\Psi')P}{\lambda}$$

where Ψ is the regressor vector, P the covariance matrix, K the correction factor, and θ the vector of estimated parameters. Basic supervision of adaptation is employed: if the freshly updated model parameters are outside specified limits (unstable, too high or negative gain), then the last good θ and P are retained. Sufficient excitation is provided by the outer loop.

Based on the estimated parameters, the inner loop proportional gain is tuned using the Magnitude Optimum Multiple Integration (MOMI) method [13] (PI or PID tuning would also be possible). To prevent the rapid change of controller parameters, the tuned controller parameters are passed to the controller through a low-pass filter.

5. INNER LOOP CONTROLLER – DIAGNOSTICS AND SUPERVISION

A. Diagnostic module

The function of this module is to gather as much information as possible from the process signals. It maintains a memory buffer of the recent values of the process signals (reference *r*, process input *u* and output *y*); see Fig. 2. Its length is set so that it includes approximately 5–10 dominant time constants of the process. The module examines the buffer and calculates certain signal features, listed in Table 1. At the end their values are compared to prescribed thresholds and converted to logic variables for the decision-making procedures in Table 2.

TABLE 1
SIGNAL FEATURES PREPARED BY THE DIAGNOSTIC MODULE

Buffered signal	Feature	Calculated from
(u)	oscillation	energy of the main nonzero frequency component
(u, y)	difference	max. difference of the signal from two parts of the buffer
(u, y)	mean value	moving average (MA) of both signals
(u, y)	variance	variance of the last part of the buffer
(r, y)	mean error	MA of the error

TABLE 2
LOGIC VARIABLES CALCULATED FROM THE FEATURES FOR AUTOMATON STATE TRANSITION CONDITIONS

Discrete state / variable	short.	Information included
saturation	sat	signal on its upper/lower limit
oscillations	osc	oscillations present in the buffer
change/transition	trans	larger transient present in the buffer
process gain change	gch	process gain sign change detected
within limits	inlim	recent values of signals within limits around MA
low variance	low_var	low variance (in the last part of the buffer)
low performance	low_perf	MA of error exceeds the limit

Since a P controller is used, efficient supervision is even more difficult because the steady-state offset is not eliminated. Therefore, the calculation of the moving average (MA) of the error was introduced to evaluate process condition, as the error value alone is not relevant. The MA of the control error signal stays within limits during slow changes due to adaptation, while it changes considerably in a more radical change of the environment.

B. Supervision module

This module monitors controller operation and controls the adaptation of model parameters in order to retain good performance in spite of imperfect conditions for adaptation. It is structured as an FSM that changes between modes of operation based on performance analysis logic signals from the diagnostic module and a table of expert rules.

Signs of short disturbance can be read from the data in the closed loop. Several test statements were made to distinguish invasive disturbances from regular conditions:

- change of y is fast and large enough
- change in u follows after a change of y
- u changes in the opposite direction of y with almost no lag – compensates for the disturbance (presuming a minimum-phase process with positive gain)
- u comes into saturation.

When an invasive disturbance is recognized, the adaptation of model parameters is stopped until the disturbance is over. By design the controller and the actuator are not required to maintain control performance under such conditions. It is important to retain control as soon as possible after the disturbance stops. In case of a short invasive disturbance, this is best achieved by continuing operation from the last set of model parameters. If the disturbance remains present for a longer time, a reset of model parameters and covariance is required.

The FSM consists of four states, summarizing the process operating conditions. In these states different types of control are executed as shown in Table 3.

TABLE 3
FSM STATES AND CONTROL MODES

Mode (state)	Process condition	Control type
operational (I)	normal	adaptive
oscillation (II)	presence of oscillation	adaptive, low gain
disturbance-wait (III)	large disturbance detected	fixed parameters held
disturbance (IV)	large disturbances	fixed parameters held

The states, and possible (admissible) transitions between them, are shown in the hybrid automaton state graph in Fig. 3. In case of disturbance, the supervisor switches from an operational (1) to a disturbance-wait state (3) for a short time. There, the estimator and consequently controller parameters are held and no checking is performed. After a defined amount of time the automaton switches to state 4 (estimation and tuning still held), where it waits until all signals return to near-normal values before it switches back to normal operation. If control performance degrades, the estimator covariance is reset at the switch to speed up controller retuning.

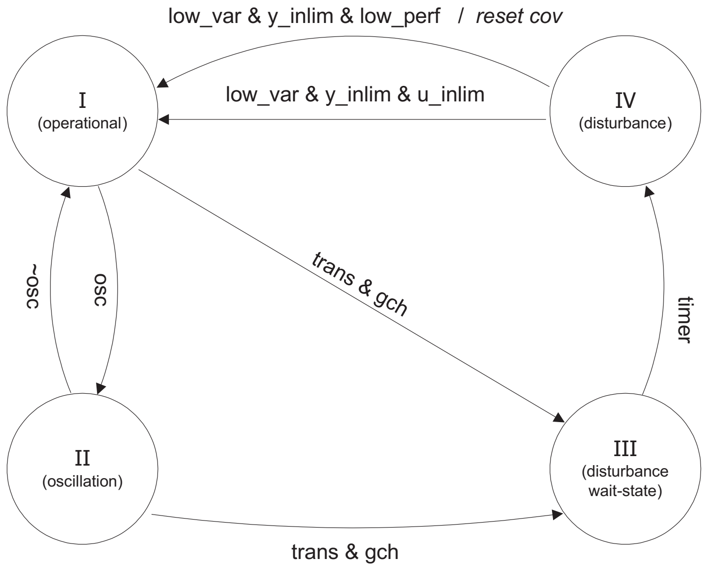

Fig. 3. Transition diagram of the finite state machine (FSM) and control modes.

6. SIMULATION STUDY

Three different types of inner loop controllers were compared: a fixed P-controller, a conventional indirect adaptive P controller (with basic supervision only) and an adaptive controller with advanced supervision. The model described in Section 2 was used. The sample time was 36 s.

First the comparison of both adaptive controllers and the fixed controller under the influence of the gradually changing environment is shown across a longer time interval. Time plots of outside temperature and heating water temperature are shown in Fig. 4.

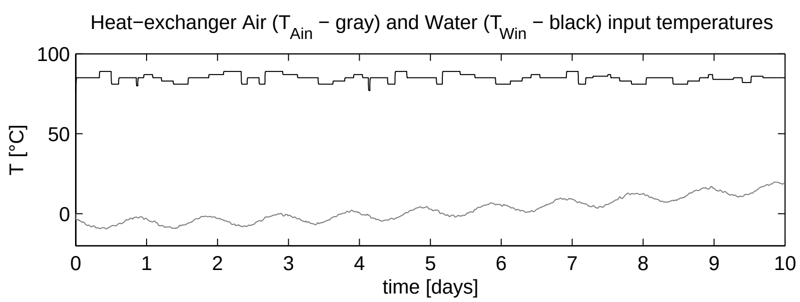

Fig. 4. Inputs to the heat exchanger representing disturbances

Fig. 5 of the fixed controller indicates that the process parameters change considerably during process operation. While controller output u_{inner} is sluggish at the beginning of the simulation, it becomes oscillatory towards the end of the simulation. The estimated process gain (K) rises from 50 at the beginning towards 300 at the end of simulation and the estimated time constant (τ) from 15 to almost 100.

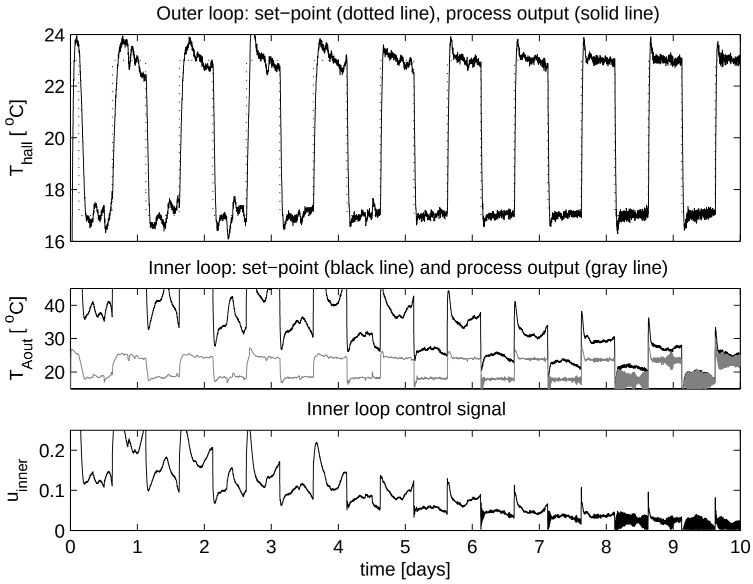

Fig. 5. Simulation using a fixed-gain controller in the inner loop.

The adaptive controller in Fig. 6 lowers its gain over time and provides more uniform performance over the whole range of operation. Aside from the visible difference, the measure *I* was used to evaluate control performance.

$$I = \sum_k \left[(r_{\text{outer}}(k) - y_{\text{outer}}(k))^2 + w \cdot \Delta u_{\text{inner}}{}^2(k) \right]. \tag{9}$$

The measure I comprises a sum of squared outer loop tracking errors and a weighted sum of squared changes of the inner loop actuator signal $u_{\text{inner}}(k)$, where $w = 100$ is a weighing factor. The results are $I_{\text{fixed P}, 1} = 13170$ and $I_{\text{adv\_superv}, 1} = 12796$.

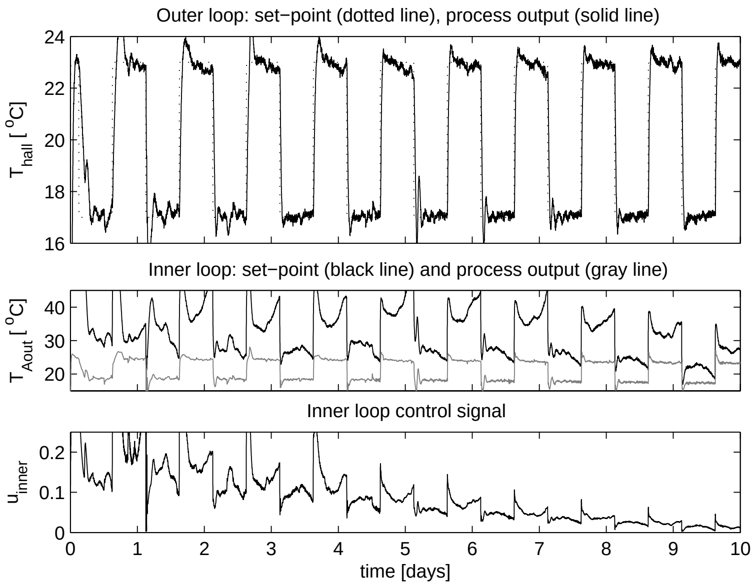

Fig. 6. Plots of simulation using a basic adaptive controller.

The second set of experiments in Fig. 7 is focused on a shorter time interval to test the ability of the two adaptive controllers to overcome short invasive disturbances. At time 0.9 day, a short drop in the temperature of the heating water supply appears (Fig. 7 d). The adaptive controller with advanced supervision (black line) freezes adaptation under inappropriate conditions and restores normal operation immediately after the signals settle to near-normal working conditions in less than 0.3 day. The adaptive controller with basic supervision (grey line) continues adaptation during the presence of the disturbance, which results in model degradation and a rise of controller gain lasting over 1 day. The performance measure I results for this test are: $I_{basic\ adapt,\ 2} = 7554$, $I_{adv\_adapt,\ 2} = 5918$.

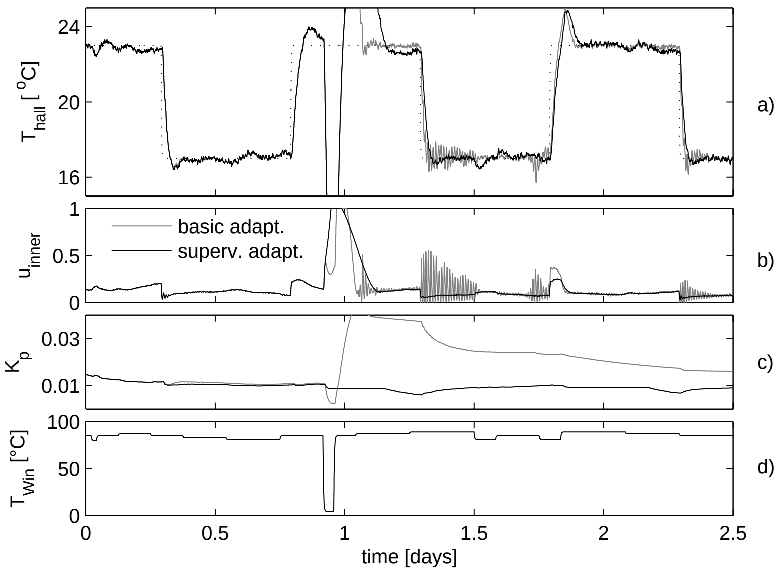

Fig. 7. a) Outer loop set-point and response to short invasive disturbance for the adaptive controller (gray line) and supervised AC (black line), b) Inner loop actuator signal, c) Inner loop controller gain, d) Disturbance: temperature of heat exchanger hot water input T_{Win}.

The next test in Fig. 8 shows the performance comparison of the two adaptive controllers in the case of an invasive disturbance of longer duration, starting at 0.5 day. The basic adaptive controller adapts the parameters relatively slowly, which results in some performance degradation for 1.6 day. The supervised adaptive controller recognizes the disturbance from the rapidly rising MA of the inner loop error signal, although the actuator does not saturate. Then, it waits until T_{Aout} returns close to the set-point. Since the error MA is above the specified threshold, the supervisor resets the covariance matrix P, allowing the estimator to obtain new parameters in less than 0.5 day. The comparison of the cost function I shows: $I_{basic\ adapt,\ 3} = 6429$, $I_{adv\_adapt,\ 3} = 4839$.

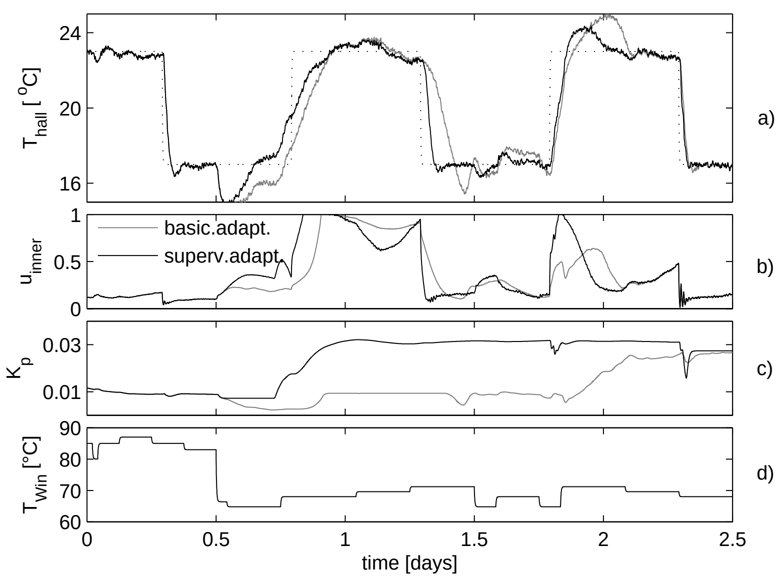

Fig. 8. System response to a moderate disturbance of longer duration (chart d). Signals are the same as in Fig. 7.

7. CONCLUSION

In this paper, an advanced algorithm for indirect adaptation supervision based on pattern recognition was described. The simulation study on an HVAC installation subsystem model shows that the supervised adaptive controller is able to cope with time-varying and nonlinear conditions as well as the invasive disturbances which are characteristic for the process. Comparisons made for three typical scenarios show that the supervised adaptive controller performs better than the basic adaptive controller and the controller with fixed parameters. The advanced supervisor successfully prevented estimator model degradation in the case of a short invasive disturbance and facilitated rapid learning after a change of the operating point.

As is typical in adaptive control practice, considerable performance improvements are achieved by tailoring the supervision system to the needs of the particular process, which requires a great deal of expert knowledge and time. However, the solutions presented are useful for a wider range of industrial control problems where invasive disturbances are present (massive load changes, temporarily unreliable measurements, etc.). Furthermore, the analysis is based on examining control signals r, u and y only, without the need for first-principles process modelling and additional measurements.

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