Design and Implementation of a Hybrid Control Strategy

Traditionally there is a trade-off in design objectives when choosing controller parameters. It is usually hard to achieve the desired step change response and at the same time get the wanted steady-state behavior. An example of contradictory design criteria is tuning a PID controller to achieve both fast response to setpoint changes, fast disturbance rejection, and no or little overshoot. In process control it is common practice to use PI control for steady-state regulation and to use manual control for large setpoint changes. Fig. 1 shows a system that is controlled (left) by a PID controller and (right) with manual control combined with a PID controller. The simulations show a step response at time zero and a load disturbance rejection at time 80. This article describes a hybrid control structure which combines a steady-state PID controller with a minimum time controller for the setpoint changes. Both good response to setpoint changes and good disturbance rejection are achieved.

Design and implementation of such a hybrid control strategy for two different plants are presented. The ideas were first tested in the laboratory on a double tank system, and later applied to a heating/ventilation system in a public school. The experiments were performed in two different software environments but with the same basic control algorithm.

The main focus of this work has been to apply optimal control theory and hybrid control theory to realistic processes using as simple methods as possible. This means taking hardware and software limitations into account when designing the control.

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algorithm. In practice we have been forced to simplify and approximate the control strategy. A positive aspect of this has been that we have found a fairly easy way of synthesizing our controller. This in turn makes the control strategy much more accessible for industrial use. A Lyapunov-based strategy is first investigated theoretically and simulated. A simplified version of this controller is then implemented for two different processes.

This paper is based on work found in [18], [8], and [19].

The Controller Structure

Using a hybrid control scheme it is possible to combine several control algorithms and thus get a controller that consists of several subcontrollers, each designed for a special purpose. An example of a multi control architecture is shown in Fig. 2. The basic idea here is that the process outputs y are fed back to a set of controllers. Then each controller calculates a candidate control signal. Which control signal is finally used is decided by the supervisor. For an overview of hybrid systems see [5], [3], [2], and [6].

A Two-Mode Hybrid Controller

A controller structure with two subcontrollers and a supervisory switching scheme will be used. The time-optimal controller is used when the states are far away from the reference point. Coming closer, the PID controller will automatically be switched in to replace the time-optimal controller. At each different setpoint the controller is redesigned, keeping the same structure but using reference point dependent parameters.

Fig. 3 describes the algorithm with a Grafcet diagram, see [7]. Grafcet, also known as Sequential Function Charts (SFC), is a graphical language for implementation and specification of sequential algorithms. A Grafcet consists of steps and transitions. A step corresponds to a state and can be active or inactive. Each state may be associated with an action which is executed when the step is active. A transition may fire if its condition is true and the preceding step is active. The Grafcet diagram for our hybrid controller consists of four states. Initially no controller is in use. This is the Init state. Opt is the state where the time-optimal controller is active and PID is the state for the PID controller. The Ref state is an intermediate state used for calculating new controller parameters before switching to a new time-optimal controller. The signal Close tells if the controller should use the PID controller or the time optimal controller. Two different ways to calculate Close are given in the section on Lyapunov function modifications.

Stabilizing Switching-Schemes

It is well known that switching between stabilizing controllers may lead to an unstable closed loop system. It is therefore necessary to have a switching scheme that guarantees stability. Consider the system

$$\dot{x} = f(x, t, u)$$

$$u = c_i(x, t)$$

$$u(t) \in [1, \ldots, n],$$

where the $c_i(x, t)$ represent different controllers. In a hybrid control system different controllers are switched in for different regions of the state space or in different operating modes. There exist some switching schemes that guarantee stability, see for example [13] and [11]. For the applications in this paper the min-switch strategy described below is used.

The min-switching strategy is defined as follows. Let there be a Lyapunov function $V_i$ associated with each controller $c_i$ in (1). Furthermore let the controller $c_i$ be admissible only in the region $\Omega_i$. The idea is then to use the controller corresponding to the smallest value of the Lyapunov function. More formally:

**Definition 1 (The min-switching strategy).** Let $f_i(x, t)$ be the right-hand side of Eq. 1 when control law $c_i$ is used. Use a control signal $u$ such that,

$$\dot{x} = \sum_{i=1}^{n} \alpha_i f_i(x, t),$$

where $\alpha_i$ is the weight of the controller $c_i$.

**Fig. 1.** In the design of a PID control system there is often a choice between a fast controller giving a large overshoot or a slow controller without overshoot. In the left figure this is illustrated by two examples of PID control. The right figure shows a PID controller combined with manual control. The top figures show the setpoint $y_{ref}$ and the measured variable $y$. The bottom figures show the control signal $u$.

**Fig. 2.** A multi controller architecture, used in [20]. Several controllers $C_i$ execute in parallel and a supervisor is used to select which control signal $u = u_i$ to be fed to the process.
where $\alpha_i \geq 0$ satisfies $\sum \alpha_i = 1$, and $\alpha_i = 0$ if either $x \notin \Omega_i$ or if $V_i(x,t) > \min[V_j(x,t)]$. If only one controller achieves the minimum then $\alpha_i = 1$ for that controller and all the other $\alpha_i$ are zero.

**Theorem 1 (Stability of Hybrid Systems)**

Let the system be given by Eq. 1. Introduce $W$ as

$$W = \min(V_1, V_2, \ldots, V_n).$$

The closed loop system is then stable with $W$ as a non-smooth Lyapunov function if the min-switch strategy is used.

For a proof of the theorem and a more detailed description of the strategy, see [18]. The case where several Lyapunov functions achieve the minimum is discussed in [18].

**Lyapunov Function Modifications**

From a control designer’s point of view the design of a hybrid control scheme using the min-switching strategy can be reduced to separate designs of $n$ different control laws and their corresponding Lyapunov functions. To improve performance it is often convenient to change the location of the switching surfaces. This can, to some degree, be achieved by different transformations of the Lyapunov functions. One example is transformations of the form $V_i = g_i(V_i)$, where $g_i(\cdot)$ are monotonically increasing functions.

In some cases there can be very fast switching, known as chattering, between two or more controllers having the same value of their respective Lyapunov function. The hybrid controller is still stabilizing, but it may not lead to the desired behavior in a practical implementation. One way to avoid chattering is to add a constant $\Delta$ to the Lyapunov functions that are switched out and subtract $\Delta$ from the Lyapunov functions that are switched in. This works as a hysteresis function. For two controllers with Lyapunov functions $V_1$ and $V_2$, the equations are $V_i = V_i + \Delta$ and $V_i = V_i - \Delta$ if controller two is in use and $V_i = V_i + \Delta$ and $V_i = V_i - \Delta$ if controller one is controlling the process. This guarantees that a controller is used for a time period $t > 0$ before it is switched out. It is easily shown that the hybrid controller is globally stabilizing with this addition, if it is stabilizing without it. More information on chattering in hybrid systems can be found in [12] and [21].

**The Processes**

The first process is a double tank system, a standard laboratory process. The second is a real process, a heating-ventilation system at a public school.

**A Double Tank System**

The first process is the double tank system from our laboratory. It consists of two water tanks in series, see Fig. 4. The goal is to control the level, $x_1$, of the lower tank and indirectly the level, $x_2$, of the upper tank. The two tank levels are both measurable. The following state space description is derived

$$\dot{x} = f(x, u) = \begin{bmatrix} -\alpha_1 x_1 + \alpha_1 x_1 + u \\ \alpha_1 x_1 - \alpha_2 x_2 \end{bmatrix}$$

where the flow $u$ into tank 1 is the control variable. The inflow can never be negative and the maximum flow is $u = 27 \cdot 10^{-6}$ $m^3/s$. Furthermore, in this experimental setting the tank areas and the outflow areas are the same for both tanks, giving $\alpha_1 = \alpha_2$.

The square root expression is derived from Bernoulli’s energy equations.

**A Heating/Ventilation Process**

The second process is a heating/ventilation system in a public school in Klippan, Sweden. The process (see Fig. 5), is a combined heating and ventilation system where pre-heated air is blown into the classrooms. The control problem here is to design a controller that has both the desired steady-state behavior and transient behavior. The participating company was interested in new ways of improving start-up and reference change performances.

Specifically, the control problem is that two different settings for the ventilation air temperature are desired, one during the day and one during the night. Another related problem is that when the system has been shut down for some reason it is necessary to start from considerably lower temperatures. The air is heated in a heat-exchanger and the incoming air has outdoor temperature, which can be very low in Sweden during the winter. The variation in outdoor temperature will cause considerable variation in the process parameters.

![Fig. 3. A Grafcet diagram describing the control algorithm.](image-url)
The existing PID controller was tuned very conservatively to be able to handle these cold starts without excessive overshoot. This was exactly the problem type that the fast setpoint hybrid controller previously discussed was designed for.

The control signal, $u$, is the setpoint for the opening of the valve. Hot water flows through the valve to a heat exchanger and the air is heated. The output of the system is the air temperature, $T$, after the fan, which blows the air into the classrooms. The final temperatures in the classrooms are controlled with radiators on a separate control system.

While the double tank system was well known, there was no model available for the heating/ventilation system. A system model was identified. The identification data was logged running the system in manual control mode and then uploaded over a modem connection. System identification data was collected by exciting the system with the input profile sketched in Fig. 6. The identification software used is described in [23]. The only measurable state of the system is the outlet air temperature. During normal use the reference temperature varies between 17 and 22 degrees centigrade. The goal of the experiment was to be able to also handle the start-up phase from considerably lower temperatures. Therefore the transfer function was estimated at a much lower temperature as well.

The actual modeling was done by fitting step responses of low order to match the input-output data. The identification data was separated into several sets, each covering different working-points. In fact there were actually two sets for each working-point, one for raising the temperature and one for lowering the temperature. There was no significant difference in the models estimated from raising or lowering the temperature or at different setpoints. Basically the only difference was in the static gain. The identification experiments showed that

$$G(s) = \frac{b}{(s + a_1)(s + a_2)} = \frac{0.03}{(s + 0.01)(s + 0.05)}$$

was a reasonable model of the system. During the experiments the parameter $b$ had a variation of ±20%. At least part of the variation in this parameter is due to the outdoor temperature changes. To raise the temperature, more energy needs to be added to the outdoor air when it is colder.

The chosen model is complicated enough to capture the dynamics of the system and still simple enough to allow an analytical solution to the time-optimal control problem.

There is some freedom in choosing a state space representation for the transfer function in (4). In the real process only one state, the temperature, is measurable, and to simplify the filtering needed in the real-time implementation, the second state was chosen as the derivative of the temperature. A suitable state-space representation for simulation and implementation is the controllable form:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -a_1 a_2 & -(a_1 + a_2) \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ b \end{bmatrix} u$$
$$y = [1 \ 0]x.$$  \hspace{1cm} (5)

The parameters $a_1$, $a_2$, are almost constant and only the gain $b$ contributes to the process variations as a function of the working conditions.

**Controller Design**

This section describes the design of the subcontrollers for each of the processes. First, the design of the PID controller for both the double tank system and the heating/ventilation process is presented. Next, the time optimal controller is discussed for both plants.

**PID Controller Design**

A standard PID controller of the form

$$G_{PID} = K \left( 1 + \frac{1}{s T_I} + s T_D \right).$$
with an additional low-pass filter on the derivative is used. The
design of the PID controller parameters $K$, $T_d$ and $T_i$ is based on
the linear second order transfer function,

$$G(s) = \frac{k}{(s + a_1)(s + a_2)}.$$  

Both the double tank system and the heating/ventilation system
may be written in this form. The PID controller parameters are
then derived with a pole-placement design method, where the
desired closed loop characteristic equation is

$$(s + \alpha \omega)(s^2 + 2\zeta \omega s + \omega^2).$$

For the double tank system the subcontroller designs are
based on a linearized version of (3):

$$x = \begin{bmatrix} -a & 0 \\ a & -a \end{bmatrix} x + \begin{bmatrix} h \\ 0 \end{bmatrix} u.$$  

(6)

For the tank system $a_1 = a_2 = a$, and $k = b$, compare (6).
The parameter $b$ has been scaled so that the new control variable
is in $[0,1]$. The parameters $a$ and $b$ are functions of $\alpha, \beta$ and the
reference level around which the linearization is done. It is later
shown how the neglected nonlinearities affect the performance.
To be able to switch in the PID controller, a fairly accurate
knowledge of the parameters is needed. The parameters
$(\alpha_1, \zeta_1, \alpha) = (0.06, 0.7, 1.0)$ are chosen to get a good behavior under
load disturbances.

For the heating/ventilation process the parameters in the
closed loop characteristic equation are
$(\alpha_0, \zeta_0, \alpha) = (0.025, 1.0, 1.0)$. The controller parameters are chosen to give a well damped
closed loop system but with approximately the same speed as the
open system. The controller could be more aggressively tuned
than the currently used PID controller, as the error and control
signal are never large.

Time-Optimal Controller Design

The problem of setpoint response can be viewed as a purely
deterministic problem: to change the process from one state to
another in the shortest possible time, possibly without any over-
shoot, subject to constraints on the control signal. The con-
straints are typically bounds on the control signal or its rate of
change. This is an optimal control problem, and the theory of op-
timal control (see [17] and [16]) is applied to derive minimum
time strategies to bring the system as fast as possible from one
setpoint to another. The time-optimal control is the solution to
the following optimization problem

$$\max \int_0^T r dt$$  

under the constraints

$$x(0) = [x_1^0 \ x_2^0]^T$$  

$$x(T) = [x_1^T \ x_2^T]^T$$  

$$u \in [0,1].$$

This, together with the system dynamics, gives the control law.

For a wide class of systems the solution to (7) is of bang-bang
character where the optimal control signal switches between its
extreme values. For problems with a two-dimensional state
space the strategy can be expressed in terms of a switching curve
that separates the state space into two subsets, where the control
signal assumes either its high or low value. This changes the con-
trol principle from feedforward to feedback.

Equilibrium points and switching curves around these may be
derived from the state space representations. These switching
curves may then be used as reference trajectories. For many sys-
tems, analytic expressions for the switching curves are hard to
derive. The solution is then to use approximate switching curves.
If the system is known it is easy to get numerical values for the
switching curves through simulation.

The Hamiltonian, $H(x,u,\lambda)$, for the double tank system de-
scribed by (3) is

$$H = -1 + \lambda_1 (a\sqrt{x_1} + bu) + \lambda_2 (a\sqrt{x_2} - a\sqrt{x_2})$$

with the adjoint equations,$\dot{\lambda} = \frac{\partial H}{\partial x},$

$$\begin{bmatrix} \dot{\lambda}_1 \\ \dot{\lambda}_2 \end{bmatrix} = \begin{bmatrix} -a & a \\ 2\sqrt{x_1} & 2\sqrt{x_1} \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix}.$$  

(8)
The complete solution to these equations is not needed to derive the optimal control signal. It is sufficient to note that the solutions to the adjoint equations are monotonic. The switching function from solving (8) is \( \sigma = \lambda^T b u \). It gives the optimal control signal sequence that minimizes \( H(u) \), and the possible control sequences are then

\[
(0,1), (1,0), (0,0), (1,1).
\]

For linear systems of order two, there can be at most one switch between the maximum and minimum control signal value (it is assumed that the tanks never are empty, i.e., \( x_i > 0 \)).

The switching times are determined by the new and the old setpoints. In practice it is preferable to have a feedback loop instead of precalculated switching times. Hence an analytical solution for the switching curves is needed. For the linearized equation for the double tank systems it is possible to derive the switching curve

\[
x_s(x_i) = \frac{1}{a} \left[ \frac{(ax_i - b \bar{u})}{1 + \ln \left( \frac{ax_i - b \bar{u}}{ax_i - b \bar{u}} \right) + b \bar{u}} \right]
\]

where \( \bar{u} \) takes values in \([0,1]\). The time-optimal control signal is \( u = 0 \) above the switching curve and \( u = 1 \) below, see Fig. 7.

The fact that the nonlinear system has the same optimal control sequence as the linearized system makes it possible to simulate the nonlinear switching curves and to compare them with the linear switching curves. Simulation is done in the following way: Initialize the state to the value of a desired setpoint and simulate backwards in time.

Note that the linear and the nonlinear switching curves are quite close for the double-tank model, see Fig. 7. The diagonal line is the set of equilibrium points, \( x_s = x_i \). Fig. 7 shows that the linear switching curves are always below the nonlinear switching curves. This will cause the time-optimal controller to switch either too late or too soon.

It is not necessary to use the exact nonlinear switching curves since the time-optimal controller is only used to bring the system close to the new setpoint. When sufficiently close, the PID controller takes over.

The heating/ventilation system is a linear, second order system with real poles, and a time optimal controller for such a system is known to be of bang-bang type. The switching curves for the heating/ventilation system were derived through simulation, and a simple linear function was fitted to the simulated curves. The approximate linear function is simply a function of the steady-state coordinate. Both the simulated switching curves and the linear approximations are shown in Fig. 8.

### Simulations

In this section some different switching methods are evaluated. In all simulations a switching surface for the time-optimal controller based on the linearized equation is used.

All simulations have been made in the OmoldOmsim environment [1], which supports hybrid systems.

The Double Tank System

A natural simple switching strategy would be to pick the best parts from both PID control and time-optimal control. One way to accomplish this is to use the time-optimal controller when far from the equilibrium point and the PID controller when close to it.

As a measure of closeness the function \( V_{\text{close}} \) is used,

\[
V_{\text{close}} = \frac{x^*_i - x_i}{x^*_i - x_i}
\]

where

\[
P(\theta, \gamma) = \begin{bmatrix}
\cos^2 \theta + \gamma \sin^2 \theta & (1 - \gamma) \sin \theta \cos \theta \\
(1 - \gamma) \sin \theta \cos \theta & \sin^2 \theta + \gamma \cos^2 \theta
\end{bmatrix}
\]

Fig. 7. Switching curves, for different setpoints, for the double tank system. The setpoints lie on the diagonal \( x_1 = x_2 \). The full lines show the switching curves for the nonlinear system, while the dashed lines show the linearized, approximate switching curves. Above the switching line the minimum control signal is applied and below it the maximum control signal is used.

Fig. 8. The switching curves for the heating/ventilation system. The figure shows both the actual simulated switching curves (dashed) and the approximate, linear ones (full).
The switching strategy here is to start with the time-optimal controller and then switch to the PID controller when $V_{\text{ciose}} < \rho$. The size and shape of the catching region may be changed with the $\gamma$ and $\theta$ parameters. The $P$ matrix above gives ellipsoidal catching curves. In this simulation switching back to the time-optimal controller is not allowed until there is a new reference value. See Fig. 3 for a graphical description of the algorithm. The simulation results in Fig. 9 show how the best parts from the subcontrollers are combined to give very good performance.

In this second simulation set, the min switching strategy that guarantees stability for the linearized system is used. The two Lyapunov functions are defined as

$$V_{\text{PID}} = \begin{bmatrix} x_1^8 - x_1 \\ x_2^8 - x_2 \\ x_3^8 - x_3 \end{bmatrix}^T P(\theta, \gamma) \begin{bmatrix} x_1^8 - x_1 \\ x_2^8 - x_2 \\ x_3^8 - x_3 \end{bmatrix}$$

$$V_{\text{to}} = \text{remaining time to reach new setpoint}.$$

The second Lyapunov function is associated with the time optimal control law and is the time it takes to reach the new setpoint starting from the current position in the state space if time optimal control is used. The state $x_1$ is the integrator state in the PID controller and $x_1^8$ is its steady-state value. As in the previous simulation set, the parameters $\gamma$ and $\theta$ are used to shape the catching region. The new state $x_1$ is preset to its value at the new equilibrium point, i.e., $x_1^8$, any time there is a setpoint change. This state is not updated until after the first switch to PID control. Using this method a similar two-dimensional catching region, as in the case with the simple switching strategy, is created. The simulation results are presented in Fig. 10.

This supervisory scheme may lead to two types of chattering behavior. One is only related to the time-optimal controller and is due to the nonlinearities. The nonlinear switching curve lies above the linear, see Fig. 7. This causes the trajectory of the nonlinear system to cross the linear switching curve and the control signal goes from 0 to 1 somewhat too late or too early. One way to remove this problem is to introduce a hysteresis when going from minimum to maximum control signal in the time optimal controller. There can also be chattering between the PID and the time-optimal controller if their corresponding Lyapunov functions have the same value. One solution to this problem is to add and remove the constant $\Delta$ as discussed in the section on Lyapunov function modifications.

The Heating/Ventilation Process

In practical applications it can be an advantage to approximate the switching curves with simpler functions. To investigate the behavior for such approximations, the switching curves for the system in (5) were approximated with five straight lines. As can be seen in Fig. 11 the overall performance did not deteriorate very
much. The main difference from using the theoretically correct switching strategy is that a few extra \((\min, \max)\) switches are needed. Simulations to test the method's robustness to process variations were also made. There was no significant decrease in performance for process parameter variations of \(\pm 50\%\).

**Implementation**

The traditional way of implementing real-time systems using languages such as C or Ada gives very poor support for algorithms expressed in a state machine fashion. The need for a convenient way to implement hybrid systems is evident. The programming language must allow the designer to code the controller as a state-machine, as a periodic process, or as a combination of both. The latter alternative is particularly useful in the case where the controller is divided into several controllers sharing some common code. A typical example of this is a state feedback controller for a plant, where it is not possible to measure all states. To get information about the non-measurable states an observer or a filter can be used. Typically, this information is needed by the whole set of controllers, and thus the controller itself can be implemented as a hybrid system, consisting of one global periodic task that handles the filtering of process data, and a set of controllers that can be either active or inactive. Many hybrid controllers have the same sort of demands on the programming language.

Implementing complex control algorithms puts high demands on the software environment. Automatic code generation and verification are needed together with advanced debugging and testing facilities.

**The Double Tank System**

The hybrid controller for the double tank system was implemented in PAL for use in the PALSJØ real-time environment.

PAL [4] is a dedicated control language with support for hybrid algorithms. Furthermore, the language supports data types such as polynomials and matrices, which are extensively used in control theory. PAL has a run-time environment, PALSJØ [9], that is well suited for experiments with hybrid control. PALSJØ was developed to meet the needs for a software environment for dynamically configurable embedded control systems. PALSJØ features include rapid prototyping, code re-usability, expandability, on-line configurability, portability, and efficiency. For a more exhaustive description of PAL and PALSJØ, see [8].

**The Heating/Ventilation System**

The hybrid controller was implemented in the Forth language on a Diana ADP 2000 system and tested against a process simulation using real-time SIMNON, see [10].

The control system, Diana ADP 2000, manufactured by Diana Control AB Systems, is mainly used in heating-ventilation applications. The system is flexible, modular and well suited for testing of new software. It is possible to install new controller code without having to rebuild the whole system for input/output handling, logging, and so on.

The controller hardware Diana ADP 2000 is modular. One unit can itself have several control loops, and on large installations several Diana ADP 2000 systems can be interconnected in a network. In the network configuration, one of the control units is a master and the others are slaves. This master unit could be reached over a modem connection, and from the master it is possible to communicate with the others. Over the telephone line and via a user interface it is possible to log data, change parameters, and down-load new code for every controller.

The programming of both the real-time operating system and the application programs is done in Forth. Amongst its good properties are that it is both interactive and compiled. Structure can be built with the notion of "words." Words are executable functions or procedures that can be arranged in a hierarchical structure. Diana ADP 2000 comes with some predefined objects and a limited number of mathematical functions.

**Experiments**

The theory and the simulations have been verified by experiments. For simplicity only the simple switching strategy previously presented was implemented. Fig. 12 shows the results of that experiment with the double tanks.

The measurements from the lab process have a high noise level, as can be seen in Fig. 12. A first-order low-pass filter

\[ G_f(s) = \frac{1}{s + 1} \]

is used to eliminate some of it. To further reduce the impact of the noise, a filter is added to the derivative part of the PID controller in a standard way.

The parameters in the simulation model were chosen to match the parameters of the lab process. It is thus possible to compare the experimental results directly with the simulations. A compar-

![Fig. 11. Simulation of the ventilation model for the school in Klippan. The affine approximation of the ideal switching curves is seen together with two setpoint change trajectories in the last sub-plot.](image-url)
The double tank system. The simple switching strategy is used. The noise level is rather high, which is visible during PID control.

Fig. 12. The double tank system. The simple switching strategy is used. The noise level is rather high, which is visible during PID control.

Fig. 13. A 5 degree setpoint change using the hybrid controller. Air temperature (left) and control signal (right).

Comparison of Figs. 9 and 12 shows a close correspondence between simulation and experimental results.

During experiments it was found that the model mismatch, i.e., the difference between the linear and the nonlinear switching curves, did not affect the performance in the sense of fast tracking. It resulted in a few more \((\text{min, max})\) switches before reaching the target area where the PID controller took over. However, a good model of the static gain in the system is needed. If there is a large deviation it cannot be guaranteed that the equilibrium points are within the catching regions. The catching region is defined as an ellipsoid around the theoretical equilibrium points.

Field Test

Finally, the hybrid control strategy was tested at the school in Klippan. The results are shown in Fig. 13. As expected, there were a few extra \((\text{min, max})\) switches due to approximation of the switching curve and probably also due to unmodeled dynamics and nonlinearities. The parameter \(b\) was estimated from steady-state values of the air temperature and the control valve position.

A similar setpoint change for the controller currently in use at the school showed that it took approximately twice as long to reach the new setpoint. However, the main advantage with the proposed method is that it will not give a large overshoot even if started from a very low temperature.

It is not difficult to incorporate some process parameter estimation functions in the code. This would give a good estimate of the static gain. Points on the switching curves could be stored in a table instead of using the analytical expressions. If the switch is too early or too late because of the nonlinearities, this information could be used to update the switching curve table.

Summary

Hybrid controllers for a double-tank system and a heating ventilation process have been designed and implemented. Both simulations and real experiments were presented. It was shown that a hybrid controller consisting of a time-optimal controller combined with a PID controller gives very good performance. The controller is easy to implement. It gives, in one of its forms, guaranteed closed loop stability.

The proposed controller solves a practical and frequent problem. Many operators switch to manual control when handling start-up and setpoint changes. It is fairly easy to combine this method with a tuning experiment that gives a second order model of the system. From the tuning experiments it is easy to automatically generate a PID controller and an approximate time-optimal controller. The model mismatch was not serious. The nonlinearity led to some additional \((\text{min, max})\) switches.

The simple hybrid controller was tested on a fast setpoint problem in a school. Simulations indicated that the theoretically derived switching curves could be approximated with simple functions without too much performance deterioration. Measurements at the school showed that the process variations were not significant and the variation in steady-state gain could be estimated from input-output data before or during a setpoint change.

A fairly crude model of the system together with approximate switching curves gave significant improvements for setpoint changes. The speed was doubled without large overshoots. At this first test, no attempts were made to smooth the control signal. The extra \((\text{min, max})\) switches could have been avoided with a hysteresis function.

References


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