INTELLIGENT SUPERVISION OF ADAPTIVE CONTROLLER

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Abstract: In this paper the algorithm for supervision of an indirect adaptive controller using pattern recognition is presented. Industrial adaptive controllers are known to operate unreliably in certain conditions. Even using a dedicated hardware and software, identifying the system at the right time still causes problems in certain cases. The main idea of this paper originates from the fact that a process and system only encounter a few different operating conditions during its life time. Therefore a feasible solution seems to be to "prescribe" strategies for these situations. This work presents development of an intelligent supervisor for adaptive controller, which is now in early stages. For illustration it has been applied for control of a simple room heating and cooling model.

1 INTRODUCTION

Adaptive control is still subject of thorough investigation. Advantages and disadvantages of different approaches to adaptation are presented in a survey study [5], while a very comprehensive description of adaptive control methods is given in [1]. Later work is focused on adaptation supervision and auto-tuning [4], [8], [9], [11] as well as on the advanced control employing pattern recognition techniques [2], [3], [10]. A general comparison study is given in [6].

In this field of research some academic approaches that use indirect adaptation are known. That is controller parameter tuning is based on (simultaneously) identified process parameters. Usually in such cases a supervisory function is added to control adaptation and increase its reliability. On the other hand there are industrial adaptive controllers. These are typical direct adaptive controllers, that employ pattern recognition techniques, [3], [6], [7]. Methods like conditional start/stop of adaptation, exponential and directional forgetting, leakage, covariance resetting, etc, ([1], p. 465-480) were developed as an upgrade to indirect controllers. They base on real-time data (signals) only. This makes them simpler but also disables them from being capable of handling exceptional working conditions, often met in industrial practice. As a result in such cases the response is not adequate.

Short invasive (massive) disturbances are examples of situation when most indirect adaptive controllers fail to avoid adaptation, which results in detuning the controller. Furthermore adaptation in such condition causes more troubles when followed by a period of signals that carry little to zero information. Proposed algorithm monitors the process behavior and reacts accordingly to current working conditions. As soon as these change, the data in buffer is analyzed in aspect of previously gathered experience and predefined knowledge. Then the decision upon adaptation is taken.

For the early studies of discussed problem a simple room temperature control model was built. Two kind of disturbances were implemented. First one was representing window-opening operation (as a massive disturbance) and the second one was representing operation of splitting the room in two parts (and merging back together), i.e. lowering the process model order and speeding up its dynamics.

In the first case one does not want the controller to keep room temperature. Even less appropriate would be to adapt the controller parameters at that time. At the second disturbance the process structure and gain are significantly altered, but the conditions are considered normal and controller is supposed to work properly in such conditions.

In this paper first the adaptive controller algorithm with supervisory function is presented. Then the room model, built for simulation purposes, is described. Finally the results of simulation tests are presented in the last part of the article.

2 THE ALGORITHM

Most of supervision algorithms make decisions upon adaptation based on current data and its features, but without a human-like wider aspect. With the algorithm being developed, we want to make a step forward and support the decision-making procedure with more information and past experience. Not like some universal solutions, this work concentrates to treating one exact case (process). Therefore we are expecting to benefit from a small number of known possible issues that our process can encounter. Then analyzing the buffer of real-time datasets such situations can be detected and treated properly.

The algorithm consists of three modules:

- module for updating buffer and calculating statistical values and features,
- adaptation supervision module,
- module for process identification and controller parameter setting.

2.1 Module for buffer updating and calculations

The supervision algorithm is based on checking the buffer – as a moving window and this module shifts the buffer each time step. It serves as a short archive of measurable data; In our case these are the reference temperature, controller output and the actual room temperature. The buffer length can be changed to satisfy the process time constants and sampling time constrains. This module also detects transients (at the moment only in reference signal), oscillations and calculates current noise variance, process gain sign and error at the first and last part of the buffer (Figure 1).

2.2 Adaptation supervision module

The supervision module exploits the main advantage of data logging; that is ability to survey a larger set of data. It employs pattern recognition techniques and takes decisions only when collected data has useful content. This way every transient is analyzed as a whole. Figure 2 shows a part of decision tree.

First condition before taking any action is existence of adequate information quantity in process input signal. That is usually related to the change in reference signal and is indicated/detected via increased standard deviation. Adaptation decision is also based on the amount of error before and after transient. As presented in Figure 1, adaptation is initiated when integral of error before step stays in certain limits. The opposite would point to the fact that the system is not under control and consequently the transient would not demonstrate the real process dynamics. On the other hand the unnecessary adaptation is avoided by minimal error condition as well as the minimal time since the last adaptation.

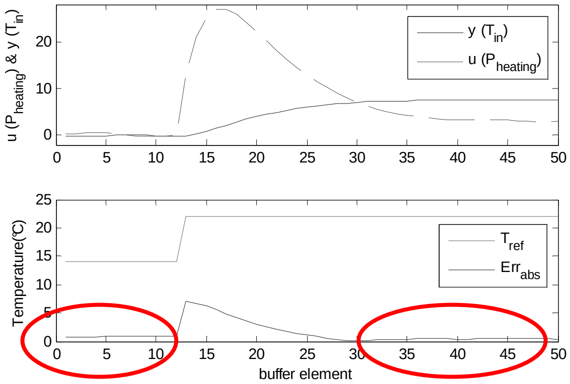

Figure 1: Trace of signals in buffer. Top: signals for identification – process input and output; their initial values are equalized to zero. Bottom: Reference signal and current error – difference between ref. signal and process output

At the same time the system state in (u,y) plane is being surveyed. The situation when u is saturated and y shows little dynamics suggests that the process deviated towards irregular conditions. This is another moment when the adaptation brings zero benefit, rather the opposite since the system elements are expected to be dimensioned properly during installation.

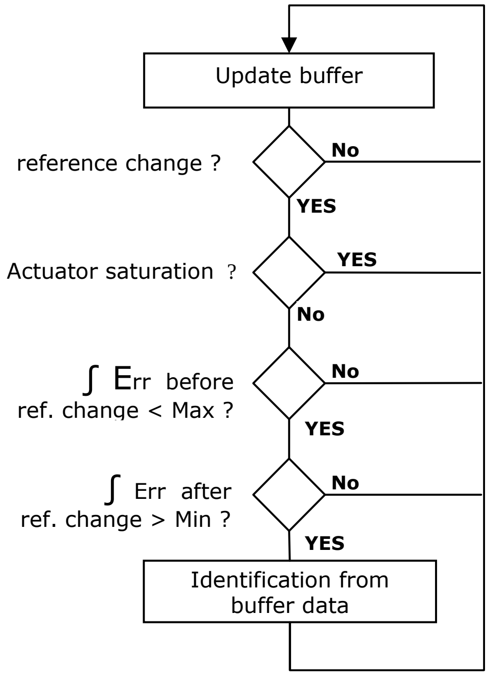

Figure 2: Decision-making tree scheme implemented in adaptation and identification supervision algorithm. The procedure is executed each time step.

2.3 Module for process identification and controller parameter setting

This part is executed on demand by supervision module. It estimates the process parameters from buffer data. When call for identification is issued firstly process input and output values from moments before transient are subtracted from all buffer elements, so both signals start with zero.

Looking for minimal CPU usage a recursive least-squares method is used for process parameter estimation. Based on these the PID controller is tuned using the MOMI [12] method.

3 TEMPERATURE ROOM MODEL

For the study and development of adaptation supervision algorithm a temperature control of 2 coupled rooms (divided by removable barrier) has been modeled (Figure 3.). It is represented as a 2nd order process with a short time delay and small nonlinearity on controller output. It includes the outside temperature with its year and daily cycle. To introduce time-variable properties two types of immeasurable disturbances have been implemented. The first one represents the open/close operation on the barrier between the rooms. This changes the model structure from 1st to 2nd order (or vice versa) and, since it is considered normal, demands adaptation. The second disturbance represents the open/close operation on the window of either first or the second room. It is more invasive and short-term type, therefore one wants to avoid adaptation in such moments.

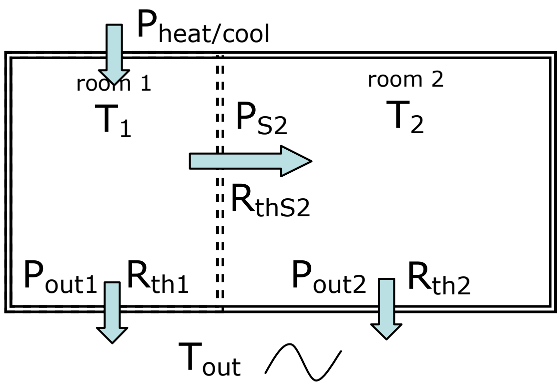

Figure 3. Scheme of the developed energy/temperature model of two coupled rooms

Some noise (low-pass filtered white noise) is added to the process output to imitate measurement noise and the actuator power is limited (up and down) with temperatures of heating and cooling water of the air-conditioning system.

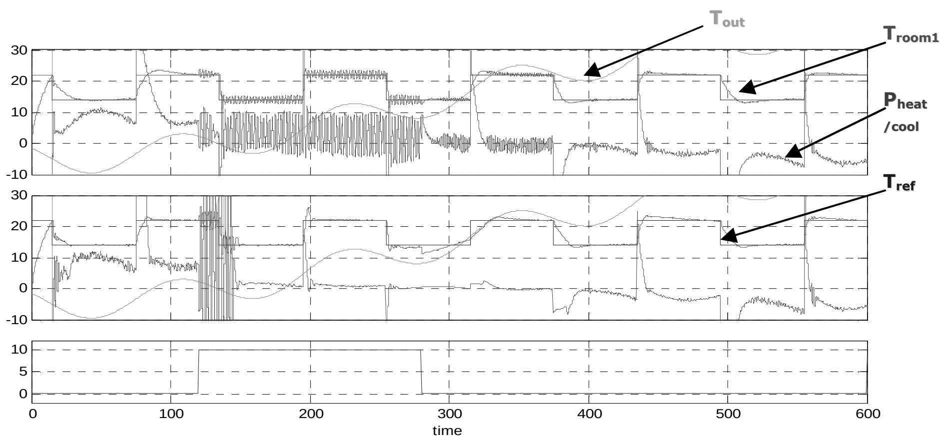

Figure 4. Time plots of essential signals using PID (upper diagram) and adaptive (middle diagram) controller. The lower diagram shows the time plot of thermal resistance of the wall between the rooms.

4 SIMULATION STUDIES

In the example, discussed in this paper both types of disturbance were realized. Figure 4 shows time plots for situation when the room is split in two parts (from time 120 tol 280). The gain increases and the loop becomes faster. It is obvious that a constant PID (upper diagram) controller cannot manage it while an adaptive controller settles down quickly.

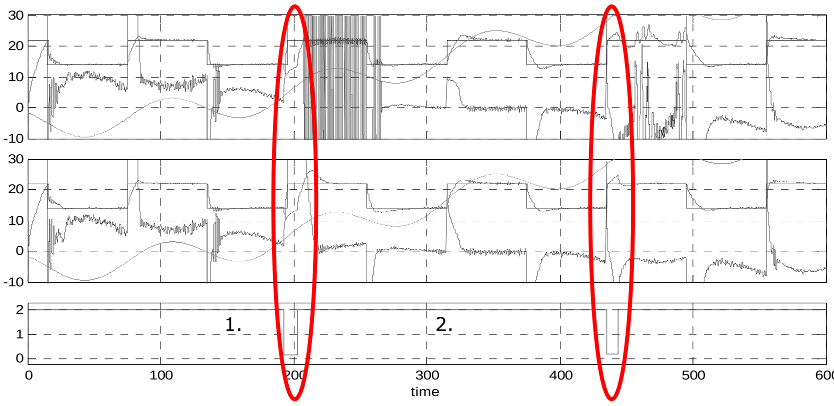

Figure 5. Time plots of essential signals using an ordinary (upper diagram) and supervised (middle diagram) adaptive controller. The lower diagram shows the time plot of thermal resistance of the outside wall and represents an action of opening a window.

Then we have a different situation (Figure 5) when the window is opened for a short time period (at times 195 and 435), just when the adaptation is under way. In both cases the signals in buffer resemble different dynamics from the one of the process. At first one (Figure 6., plot a) the room temperature has fallen to outside level and consequentially the actuator output peaks towards saturation. Obviously it can not compensate the disturbance – the room temperature responds very slowly – so the identified process gain is very small. The second disturbance has inverse effect – in same direction as reference change, but it is too large (Figure 6., plot b). The controller tries to reduce that effect; signals resemble negative process gain, which is, in this example impossible. Both issues can be seen in on the identified process gain diagram. (Figure 6., plot c). It is clear that the supervision algorithm prevents adaptation in both cases and manages to keep the system stable.

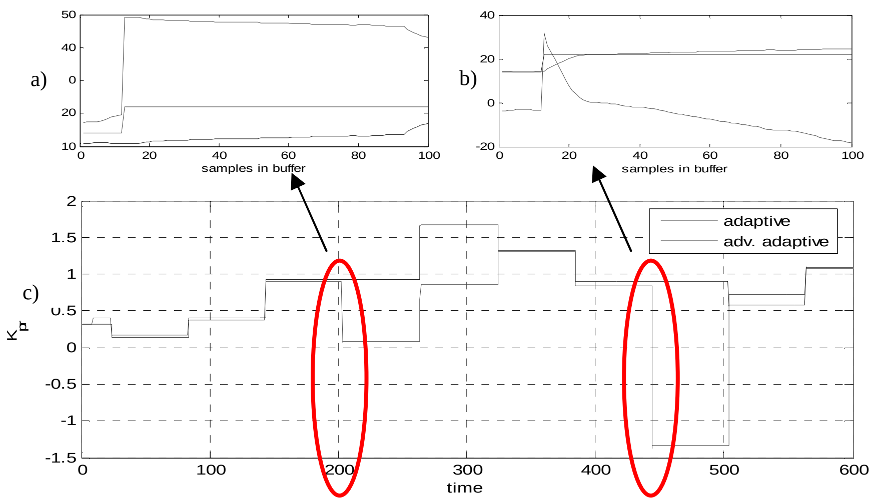

Figure 6. Upper left, right: examples of buffer in situations when the adaptation mast be avoided. Lower: time plot of identified process gain: supervised (blue) and ordinary (red) adaptive controller.

Figure 6 shows the time plot of identified process gain, i.e. K_{pr} of the following transfer function:

$$G(s) = \frac{K_{pr}(s+z_1)}{(s+p_1)(s+p_2)}$$

It can be seen that the supervised adaptive controller reacts to moderate condition change, while when encountering a massive disturbance, the adaptation is prevented.

5 CONCLUSION

The main idea of the presented approach to adaptation supervision is the memory buffer. Its content is always observed as a whole. Using pattern recognition techniques we analyze it and look for characteristic phenomena, defined in advance and thus distinguish between normal and unusual operating condition. Primary goal is consistent and reliable triggering of adaptation in proper condition as well as avoiding it in irregular situations. At the moment we only focus on the adaptation after a step in the reference signal although in future work the algorithm is supposed to work on signals with continuing dynamics. Further work objective is development of an on-line learning algorithm that will facilitate and automate the procedure of predefining discussed special conditions.

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