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Model Predictive Control of thermal comfort as a benchmark for controller performance

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ABSTRACT

Assessing controller performance in normal operation needs reproducible conditions and comparison with the best possible result. Tests in emulation are reproducible. Model Predictive Control (MPC) gives the best possible performance when the future inputs and the model of the process are known. When the benchmark is used for building energy management, the cost function of MPC becomes a linear programming problem with constraints given by the comfort. In emulation, the model of the building used in MPC may be obtained by gray-box parameter identification, using signals which excite all the modes of the complete model. The proposed benchmark was used to test a PID and a scheduled start PID-based energy management system. During the test periods, the MPC benchmark always outperformed the PID controllers. It reduced the occupants' discomfort by up to 97%, the energy consumption by up to 18%, and the number of on–off cycles of heat pump by up to 78%.

1. Introduction

Building thermal behavior is characterized by, generally, great inertia and it is strongly influenced by the weather and occupation type. Most often, the occupation is intermittent, which implies variable indoor temperature set-point. Since space heating is responsible for over 50% of the total energy consumption in residential and tertiary sectors [1], thermal control has an important impact on energy consumption. Nevertheless, energy savings must not affect the comfort during the occupied periods because the cost of people discomfort is much higher than the operational cost of the building [2].

Several surveys on the current building thermal control strategies have shown that these are, generally, room thermostats or thermostatic valves on radiators [3–5]. In the best case, radiator valves are driven by PID controllers to cope with room overheating. Although these controllers are omnipresent in the field, they are not specifically designed or adjusted to minimize the energy consumption. Furthermore, their feedback loops introduce a lag between the indoor temperature and the set-point, which affects negatively the comfort.

Ideally, a building thermal controller should take a maximal advantage of the weather and the building inertia in order to provide the comfort with minimal energy consumption. Model Predictive Control (MPC) is regarded as being one of the most suited for the thermal control of intermittently occupied buildings. It inherently minimizes criteria that may be related to discomfort and energy; it may include weather forecast, future set-point schedule and constraints in the optimization. In simulation studies, MPC outperformed the other tested controllers in terms of energy consumption and comfort criteria [6–9]. Field tests confirmed the trend obtained in simulations [10–16].

Three different approaches can be used to test an innovative algorithm — simulation, in-situ test and emulation. The advantage of simulation models is to obtain repeatable test conditions which allow testing and comparing different controllers. If the same model is used for the simulation and for the MPC, there are no modeling errors in the MPC algorithm and, therefore, the robustness of the controller to modeling errors cannot be assessed. On the other hand, in-situ tests permit to capture model uncertainties which usually are not considered in low-order simulation models. However, besides the fact that in this case testing is much more expensive, it is difficult to have repeatable test conditions in order to make valid comparisons of different controllers. Therefore, it is difficult to quantify the improvements of MPC control structure over the other ones.

Testing in emulation combines the advantages of simulation and in-situ experiments. The principle is to simulate the building and its afferent heating system by a detailed model which was calibrated on existing buildings and to implement the model on a process computer which has electrical signals (0–10 V) as inputs and outputs. Then, the physical controllers are tested by connecting them through electrical

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signals to the emulated building running in real time, i.e. one emulation second equals one real-time second. In these conditions, the tested controller will make no difference between a real building and a simulated one. The advantage is that the real controller is tested in reproducible conditions.

This allows comparing different controllers operating in the same conditions but does not answer the question of how a controller behaves in comparison with the best possible performance obtainable in the given situation. This paper suggests that MPC with a known evolution of the future inputs and high accuracy of the internal model of the process can be used as a benchmark or a yardstick to assess the performance of any controller. The proposed benchmark uses a new cost function for MPC, recently introduced in [17], which ensures the thermal comfort with minimal energy consumption. The cost function is formulated so that MPC becomes a linear optimization problem solved by Linear Programming (LP). This paper focuses on buildings with hydronic heating systems. Due to the hydronic systems, the control problem is more delicate because the overall model is nonlinear. However, it is possible to represent the building by a Hammerstein model. Thereby, physical knowledge is used for the identification of the nonlinear part of the model and linear least squares identification method for the linear part of the model. Then, the inverse of the identified nonlinear characteristic is used to remove the nonlinearity from the control loop. We have already presented the control algorithm [17] and the identification procedure [18] used in this paper. They were tested by simulating only the building (without its heating system) by using a low order model. This paper presents results by using a real-time emulator of the building and of its heating system. The elements of our previous work which are necessary in order to explain the findings presented hereafter are resumed in Section 2–4.

The proposed MPC is embedded in a Building Energy Management System (BEMS), tested and compared in emulation with two classical PID based management systems. For the assessment of the overall performance, the heating system that prepares the hot water is also considered in the tests. The controller adjusts the energy flow from the maximum available power down to zero. Therefore, the heating system has an important impact on the overall control performance.

2. Control problem formulation

2.1. Requirements in building thermal control

Usually, the requirements in building temperature control refer to two aspects: thermal comfort and energy savings. The comfort requirements are generally imposed as a temperature range, defined by an upper and a lower bound, within which should lie the indoor temperature. This range has different width for occupied and unoccupied periods which changes instantly (Fig. 1). During the occupied period (occupancy), this

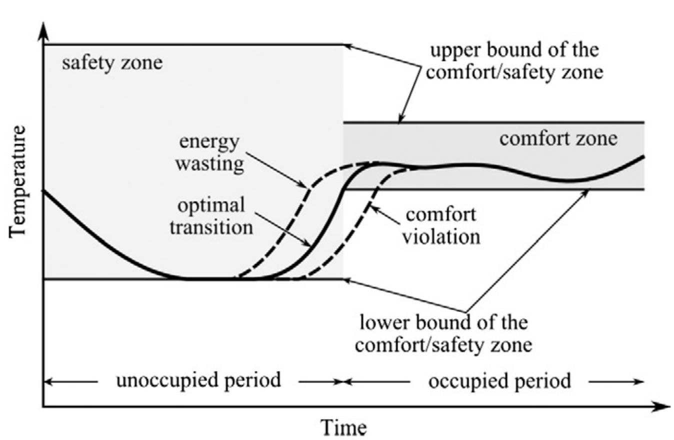

Fig. 1. Comfort requirements and possible scenarios for indoor temperature.

temperature range will be called comfort zone and during the unoccupied period — safety zone.

Since the building has a rather slow dynamics, the heating must be restarted in advance so that the indoor temperature does not remain below the comfort zone at the beginning of the occupancy. If, due to the heating system, the temperature reaches the lower bound of the comfort zone before the occupancy starts, then excessive energy is consumed. Consequently, an optimal heating restart generates a temperature variation that attains the lower bound of the comfort zone just around the beginning of the occupied period (Fig. 1).

In order to increase the indoor temperature, the heating system consumes energy. Therefore, it can be admitted that a minimal energy control strategy acts against temperature rise and will tend to keep it at the lower acceptable bound. Thus, since in this paper building cooling is not considered, for comfort requirements it is sufficient to define only the lower bound of the comfort and of the safety zones. The minimal energy control strategy naturally constraints the temperature for the upper bound.

The economic criterion can be formulated for fixed or variable energy price as:

$$J_e = \int_t \lambda(t)\,\Phi(t)\,dt \tag{1}$$

where $\lambda(t)$ represents the energy price and $\Phi(t)$ is the heat flux injected into the building. The criterion J_e is related through the efficiency of the heating system to the energy bill. When the energy cost is constant, minimizing J_e results in minimizing the energy consumption. In this paper, only energy consumption minimization is considered ($\lambda(t) = 1$). Thus, the second performance requirement in building thermal control is to minimize the criterion J_e from the relation (1).

2.2. A cost function for thermal comfort with minimal energy consumption

MPC calculates a command sequence which minimizes a cost function over a finite future time horizon. The performance, which is embedded in the cost function, is predicted by using the system model, the future variations of the set-points and, if available, the future variations of disturbances. Since the system model is indispensable, there are several MPC algorithms that are built around different model representations. We can find algorithms that use artificial neural networks [19,20], genetic algorithms [21], fuzzy logic [22,23] or classical formulations using transfer functions, state–space or convolution models [24,25]. Building models are naturally defined in state–space representations and discrete-time MPC is easier to understand than the continuous one [24]. Therefore, in this paper the discrete-time MPC algorithm is used based on the state–space model.

The goal of ensuring thermal comfort with minimal energy consumption can be mathematically formulated as the minimization of the heat flux integral subject to constraints on the indoor temperature. The indoor temperature should be above the lower bound of the comfort/safety zone. The physical limitations of the heating system also should be considered in the optimization. Therefore, additional constraints are imposed on the heat flux, which should be in the feasible range of the heating system. Considering that the heat flux is the manipulated variable, u, and the indoor temperature is the system output, y, the new MPC problem formulation is [17]:

$$\begin{aligned} &\text{minimize} : J(k) = \sum_{i=1}^{N_u} u(k+i) \\ &\text{subject to} : 0 \le u(k+i) \le u_{\max}, \quad i = 1 \ldots N_u \\ &\qquad\qquad \hat{y}(k+i) \ge \theta_{\min}(k+i), \quad i = 1 \ldots N_y \end{aligned} \tag{2}$$

where $\theta_{\min}$ is the lower bound of the comfort/safety zones and $u_{\max}$ is the maximal power of the heating system, $\hat{y}$ is the predicted output