PREDICTIVE CONTROL FOR INTEGRATED ROOM AUTOMATION

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ABSTRACT

In order to operate buildings more energy and cost effective, *predictive* integrated room automation can be used instead of conventional – possibly integrated – room automation. Thereby the predictive integrated room automation controllers operate the buildings' passive thermal storages based on predicted future disturbances (e.g. weather forecast) by making use of low cost energy sources.
A specific predictive integrated room automation application is considered here: The room temperature can – technically – be controlled by heating, cooling with chiller, free cooling and blind positioning. To satisfy the thermal comfort demand, the room temperature is controlled within a defined comfort range. This is achieved by a model predictive control strategy which makes use of the passive thermal storage of the building: To reduce the energy costs the thermal capacity of the building can be loaded or unloaded with low cost energy (free cooling, solar gains influenced by blinds) as long as the room temperature remains in the comfort range. The predictive controller periodically calculates an optimal future profile of the manipulated variables while constraints on the manipulated variables and predicted disturbances are taken into account. The optimization problem is solved numerically by applying linear programming (LP) algorithms.
A performance bound is determined by simulations. Furthermore conventional (non-predictive) control strategies are compared and assessed using the performance bound as a benchmark. These analyses show that predictive control is promising to be a substantial improvement compared to non-predictive control regarding cost and energy efficiency.

KEYWORDS: predictive control, integrated room automation, passive storage management, integrated blind/light/HVAC control

INTRODUCTION

Predictive control in building applications has a potential to be more energy and cost effective (while maintaining equal or better control performance) than non-predictive control where

- the controlled system has distinctive storage properties,
- there are ranges for the controlled variables instead of single set points,
- future ranges for the controlled variables are known,
- future disturbances of the controlled system are known or can be estimated (predicted) by the controller,
- costs for control actions are time dependent and/or depend on variables that are known or can be estimated in advance,
- future costs for control actions are known or can be estimated.

In thermal control of buildings these conditions are often fulfilled. Therefore many specific applications of predictive control in building systems have been investigated: E.g. predictive heating controllers [1-4] or blind controllers [5]. The influence of forecast accuracy and of modeling errors on predictive control performance for building systems has also been analyzed [6]. In particular building system applications where there are means for low and high cost heating and cooling are potentially rewarding when using predictive control.

The specific building system considered here is primarily thermally conditioned by cold and hot water, i.e. through chilled ceilings for cooling and radiators for heating. The cold water for cooling can be produced either by chiller operation (high cost) or by free cooling using only wet cooling tower operation (low cost). The hot water for heating is produced by boiler operation (high cost). Moreover blinds can be used to control thermal comfort in the building (low cost). The room temperature is allowed to float within the room temperature comfort range, e.g. 21°C to 26°C. For systems with passive thermal storages as the considered system, a non-zero comfort range is a pre-condition to benefit from predictive control at all. The wider the comfort range, the more energy and cost effective predictive control can be since there is also a larger range where the thermal capacities of the building can be operated. E.g. given a comfort temperature range wide of 5 K, the maximal heat difference stored in a typical concrete ceiling is already more than 1 kWh/m^2. Besides the thermal capacity of the ceilings further capacities (inner and outer walls, furniture etc.) are effective in buildings.
If the high cost heating and cooling systems are fast and well dimensioned, i.e. the room temperature can be controlled without significant time delay within the comfort range, there is no risk of not fulfilling comfort demands. Wrong predictions based on modeling errors or incorrect estimated disturbances will therefore lead – temporarily –to more energy and/or cost demand but no discomfort. For this reason this type of predictive control is predestined for (prototype) application in real buildings since the building users' comfort is not perturbed.
In conventional control strategies for integrated room automation, blind control is independent of HVAC control. More sophisticated blind controllers also take into account the artificial lighting control task and some controllers additionally make decisions based on actual heating or cooling loads [7-8].
The investigated control concept has a hierarchical structure with typically one high-level controller and typically several sub-level controllers. High-level control is done by model based predictive control whereas mainly low cost energy sources such as solar gains (via blinds) or free cold (via dry or wet cooling towers) are under high-level control. Sub-level control for individual zone control is done by operation the remaining – mainly high cost – energy sources. Here only high-level control is considered, sub-level control is assumed to be ideal.

METHODS

The basic building model used by a high-level controller is typically a simple model that reproduces the buildings' essential static and dynamic thermal properties. An example of such a model is introduced below. The same model is also employed here to explore the potential of predictive control for integrated room automation.

Building Model

The model inputs are divided into manipulated variables and disturbance inputs. Manipulated variables are the heating power u_1, the cooling power u_2, the blind position u_3 (closed = 0, open = 1) and the normalized free cooling power u_4 (no free cooling = 0, maximum free cooling = 1). For this study the high cost cooling and heating sources are assumed to have no limitation in power output. Constraints for the manipulated variables are listed in (1)-(2).
Disturbances are the outside air temperature ϑ_{oa}, the outside air wet bulb temperature ϑ_{oawb}, the solar gains for fully closed blinds $\dot{q}_{s0}$ (secondary heat transmission), the additional solar gains for fully open blinds $\dot{q}_{s1}$ (radiation) and the internal heat gains $\dot{q}_i$.

$$0 \le u_1(t) \qquad 0 \le u_3(t) \le 1 \tag{1}$$

$$0 \le u_2(t) \qquad 0 \le u_4(t) \le 1 \tag{2}$$

A schematic diagram of the building model is shown in Figure 1. Heat flow is modeled through outside walls and windows as well as into and from inner parts of the building. Heating power u_1 and internal heat gains $\dot{q}_i$ act directly on the lumped thermal room knot which is associated with the operative (= sensed) room temperature ϑ_r . Cooling power u_2 and free cooling u_4 act on the ceiling thermal knot (chilled ceiling) while the solar radiation $\dot{q}_{s1}$ acts both on the floor and ceiling thermal knots. Secondary solar heat gains $\dot{q}_{s0}$ act on the inner outside envelope. The window and free cooling system heat transfer coefficients are changing with blind position u_3 and free cooling activity u_4, respectively. To represent the dynamic behavior of a real building, thermal capacities are assigned to the lumped thermal room knot (C_r), the outside envelope (C_{o1}, C_{o2}, C_{o3}) and the inner parts of the building (C_{i1}, C_{i2}, C_{i3}). The modeled windows have no thermal capacity. The building model can be written in a pseudo-linear state space representation (3), where the state vector $\underline{x}$ is given by (4), the disturbance input vector $\underline{v}$ by (5) and the state space matrices by (6)-(9).

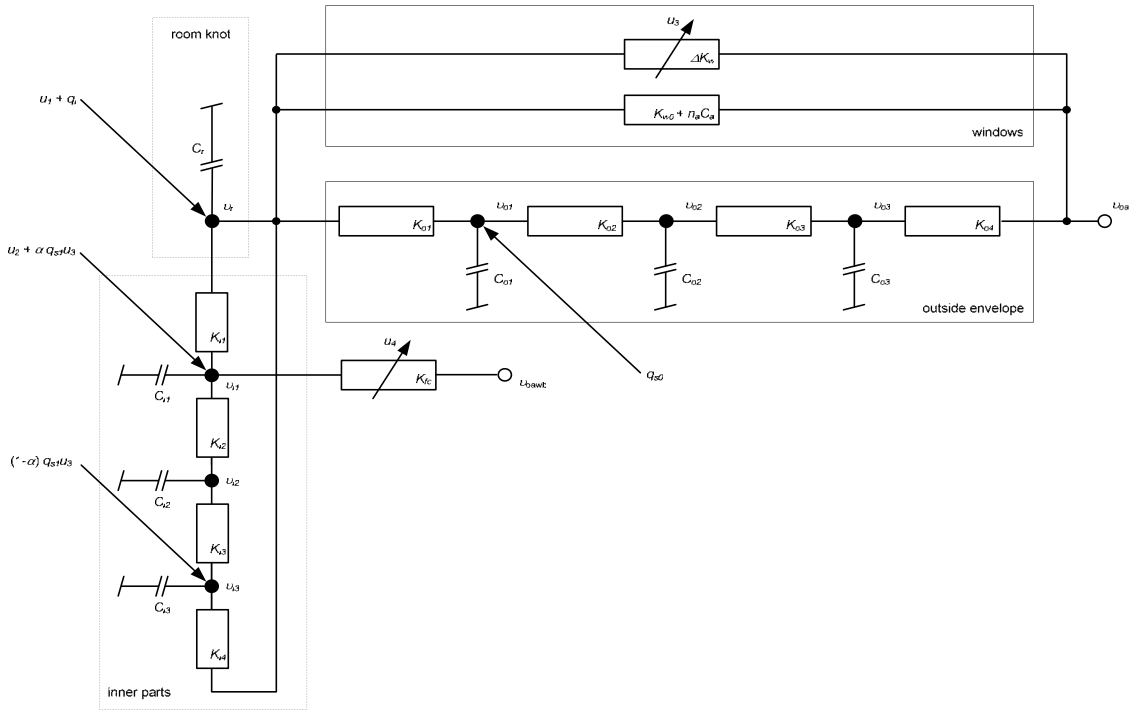

Figure 1. Schematic diagram of the building model

$$\dot{\underline{x}}(t) = A\underline{x}(t) + B_u \underline{u}(t) + B_v \underline{v}(t) + \underbrace{\sum_{i=1}^{4} \left[\left(B_{vu,i}\, \underline{v}(t) + B_{xu,i}\, \underline{x}(t) \right) u_i(t) \right]}_{B_u^*(\underline{x}(t), \underline{v}(t))\, \underline{u}(t)} \tag{3}$$

$$y(t) = C\underline{x}(t)$$

$$\underline{x}^T(t) = \left[\vartheta_r(t) \quad \vartheta_{i1}(t) \quad \vartheta_{i2}(t) \quad \vartheta_{i3}(t) \quad \vartheta_{o1}(t) \quad \vartheta_{o2}(t) \quad \vartheta_{o3}(t) \right] \tag{4}$$

$$\underline{v}^T(t) = \left[\vartheta_{oa}(t) \quad \vartheta_{oawb}(t) \quad \dot{q}_{s0}(t) \quad \dot{q}_{s1}(t) \quad \dot{q}_i(t) \right] \tag{5}$$

$$A = \begin{bmatrix} -\frac{\dot{n}_a C_a + K_{w0} + K_{i1} + K_{o1} + K_{i4}}{C_r} & \frac{K_{i1}}{C_r} & 0 & \frac{K_{i4}}{C_r} & \frac{K_{o1}}{C_r} & 0 & 0 \\ \frac{K_{i1}}{C_{i1}} & -\frac{K_{i1} + K_{i2}}{C_{i1}} & \frac{K_{i2}}{C_{i1}} & 0 & 0 & 0 & 0 \\ 0 & \frac{K_{i2}}{C_{i2}} & -\frac{K_{i2} + K_{i3}}{C_{i2}} & \frac{K_{i3}}{C_{i2}} & 0 & 0 & 0 \\ \frac{K_{i4}}{C_{i3}} & 0 & \frac{K_{i3}}{C_{i3}} & -\frac{K_{i3} + K_{i4}}{C_{i3}} & 0 & 0 & 0 \\ \frac{K_{o1}}{C_{o1}} & 0 & 0 & 0 & -\frac{K_{o1} + K_{o2}}{C_{o1}} & \frac{K_{o2}}{C_{o1}} & 0 \\ 0 & 0 & 0 & 0 & \frac{K_{o2}}{C_{o2}} & -\frac{K_{o2} + K_{o3}}{C_{o2}} & \frac{K_{o3}}{C_{o2}} \\ 0 & 0 & 0 & 0 & 0 & \frac{K_{o3}}{C_{o3}} & -\frac{K_{o3} + K_{o4}}{C_{o3}} \end{bmatrix} \tag{6}$$

$$B_u = \begin{bmatrix} \frac{1}{C_r} & 0 & 0 & 0 \\ 0 & -\frac{1}{C_{i1}} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad B_v = \begin{bmatrix} \frac{\dot{n}_a C_a + K_{w0}}{C_r} & 0 & 0 & 0 & \frac{1}{C_r} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{C_{o1}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ \frac{K_{o4}}{C_{o3}} & 0 & 0 & 0 & 0 \end{bmatrix} \quad B_{vu,1} = B_{vu,2} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad B_{vu,3} = \begin{bmatrix} \frac{\Delta K_w}{C_r} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{\alpha}{C_{i1}} & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1-\alpha}{C_{i3}} & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{7}$$

$$B_{vu,4} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{K_{fc}}{C_{i1}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad B_{xu,1} = B_{xu,2} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad B_{xu,3} = \begin{bmatrix} -\frac{\Delta K_w}{C_r} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad B_{xu,4} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -\frac{K_{fc}}{C_{i1}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{8}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{9}$$

Control Optimization Problem

Linear programming is used to determine the solution of the control optimization problem with the cost function J in (10) to minimize. For each step, weightings $\underline{w}$ (costs per unit) are assigned to the manipulated variables at this step. n is the number of optimization time steps. The related time steps define the partition of the optimization horizon while larger time steps at the end of the horizon offer to reduce the optimization problem size (and therefore calculation time) with small impact on the solution. Besides maintaining the constraints of the manipulated variables $\underline{u}$ given in (1)-(2), there can be optimization constraints on the state vector $\underline{x}$ or the output vector $\underline{y}$. With these constraints the modeled physics of the system (3) is taken into account when optimizing. Here the optimization problem is formulated so that the sensed room temperature ϑ_r remains in the comfort range (11). Since linear programming is used to solve the optimization problem, the future states to calculate the manipulated input matrices B_u^* are fixed – e.g. to the actual state vector – to obtain a linear optimization problem. In order to find the optimal solution for the nonlinear problem an iterative procedure can be applied where the solution of the state vector of the linear problem is used to calculate B_u^* for the next iteration step.

The optimization problem is solved repeatedly with a sampling time t_s that is usually much smaller than the optimization horizon length. Only the optimized manipulated variables for the next sampling time are applied after each optimization (moving horizon).

$$J(u) = \sum_{i=0}^{n-1} \left((t_{i+1} - t_0) \underline{w}^T (t_i) \underline{u}(t_i) \right) \tag{10}$$

$$\vartheta_{r,\min} \le \vartheta_r \le \vartheta_{r,\max} \tag{11}$$

RESULTS

The parameters in (6)-(9) are set based on a typical office building in Switzerland. Measured data for solar radiation, outside air temperature and outside air wet bulb temperature is taken from Zurich. Internal heat gains are set to 25 W/m^2 from 8 a.m. to 8 p.m. on workdays, otherwise 5 W/m^2 are present. A constant weighting $\underline{w}$ (12)– within the optimization horizon and for each optimization – is applied. 1 kW heating power serves as the normalization for the weighting. A negative weighting factor for the blind position is chosen because closed blinds correlate with higher artificial lighting demand. Thus artificial lighting is treated indirectly as a cost for closed blinds. Maximal free cooling is causing costs equal to 10 kW heating power.

$$\underline{w}^T = \begin{bmatrix} 1 & 3 & -0.1 & 10 \end{bmatrix} \tag{12}$$

Fundamental for exploring the energy (costs) saving potential of predictive control is a comparison between ideal non-predictive and ideal predictive control. Here ideal means that a model based (predictive) controller with a model equal to the controlled process model is applied; disturbances are known exactly for each optimization horizon. Thus the main difference between non-predictive and predictive control is given by the length of the optimization horizon. The following three control solutions will be discussed further below:

I. *performance bound*: ideal predictive control with sampling time t_s = 0.5 h, optimization horizon length t_{opt} = 72 h
II. *short term optimal control*: t_s = 0.5 h, t_{opt} = 0.5 h
III. *representative example for conventional control algorithm*: blinds are used as “cooling device” (close blinds when solar radiation is present, otherwise open blinds) when last active action was cooling (u_2 > 0 or u_4 > 0), blinds are used as “heating device” (open blinds when solar radiation is present, otherwise close blinds) when last active action was heating (u_1 > 0), free cooling is favored when ϑ_{oawb} > 15 °C; this has been approximated here by setting the blind position weight to 0.1 when last active action was cooling and back to –0.1 when last active action was heating and by setting the free cooling weight to –10 when ϑ_{oawb} > 15 °C, $\vartheta_r > (\vartheta_{r,\min}+\vartheta_{r,\max})/2$, otherwise back to 10, t_s = 0.5 h, t_{opt} = 0.5 h

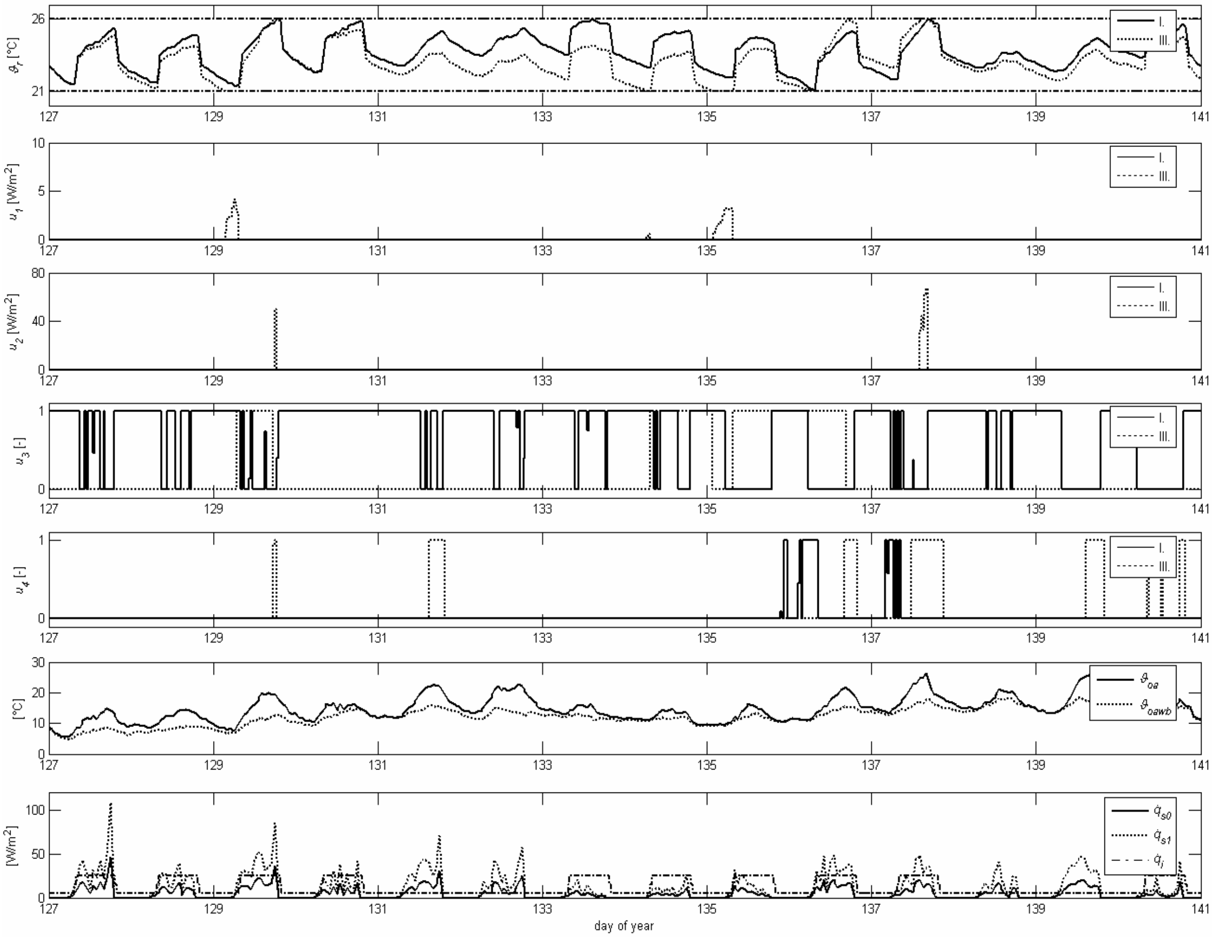

Figure 2. Simulation results for strategies I. and III.

Energy costs – according to the weighting (12) except no blind position weighting is included – accumulated in whole year simulations for the three strategies were determined: For strategy I (performance bound) an average cost of 6.44 · 10^{-3}/m^2 resulted, strategy II caused average costs of 13.6 · 10^{-3}/m^2 and for strategy III 9.19 · 10^{-3}/m^2 average costs resulted.

Figure 2 shows a comparison between the performance bound predictive strategy I and the non-predictive strategy III for 14 days in spring. The predictive strategy manages to control the room temperature within the comfort range by only using low cost heating (open blinds when radiation is present) and cooling sources (free cooling instead of cooling with chiller, open blinds during nights when no radiation input is present and ϑ_{oa} is relatively low). Therewith it keeps the room temperature ϑ_r high when the coming days are cooler and less solar gains are present (days 131-135), and it keeps the room temperature lower when the next days are warm and high solar gains are effective (days 136, 137). In doing so the buildings thermal capacities are emptied and loaded with low cost energy.

DISCUSSION

The presented results show that predictive integrated room automation has substantial potential to exploit. The predictive control solution is superior to non-predictive control especially when low cost heating and low cost cooling can be used to cool or heat the building at an early time (before high-cost heating or cooling is necessary). If there are fast (high-cost) heating and cooling devices, a predictive controller of the presented type is not compromising comfort – even if the controllers building model is bad and future disturbances are estimated wrong.

To further investigate the subject, realistic predictions of disturbances will be used for different building types and different climates. More (simpler) building models will also be studied regarding their robustness and sensitivity to model errors as well as possible tuning methods. In addition the users' behavior – in particular in respect of glare protection, desire of daylight and a small numbers of blind repositions – will be treated more realistic. This will lead to fewer possibilities for a predictive controller to use blinds as low cost heating or cooling device and therefore reduce the energy (cost) savings.

The outcomes will be helpful not only to design and justify predictive controllers for real-world application but also to design and evaluate simple heuristic integrated room automation controllers.

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