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Model Predictive Climate Control of a Swiss Office Building: Implementation, Results, and Cost–Benefit Analysis

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***Abstract*— This paper reports the final results of the predictive building control project OptiControl-II that encompassed seven months of model predictive control (MPC) of a fully occupied Swiss office building. First, this paper provides a comprehensive literature review of experimental building MPC studies. Second, we describe the chosen control setup and modeling, the main experimental results, as well as simulation-based comparisons of MPC to industry-standard control using the EnergyPlus simulation software. Third, the costs and benefits of building MPC for cases similar to the investigated building are analyzed. In the experiments, MPC controlled the building reliably and achieved a good comfort level. The simulations suggested a significantly improved control performance in terms of energy and comfort compared with the previously installed industry-standard control strategy. However, for similar buildings and with the tools currently available, the required initial investment is likely too high to justify the deployment in everyday building projects on the basis of operating cost savings alone. Nevertheless, development investments in an MPC building automation framework and a tool for modeling building thermal dynamics together with the increasing importance of demand response and rising energy prices may push the technology into the net benefit range.**

***Index Terms*— Building energy, building modeling, model predictive control (MPC).**

I. Introduction

APPROXIMATELY 40% of the global energy consumption occurs in buildings [1], of which, in industrialized countries, roughly half is used for heating, ventilation, and air conditioning (HVAC) [2]. This level of consumption makes measures aimed at HVAC energy reduction very attractive. These can be realized by improving a building's HVAC systems and construction, its operation, or preferably some combination of both. Unfortunately, the majority of the building stock is already in place and refurbishments of buildings are expensive. Quite differently, control systems can be upgraded and their operation optimized at comparatively low cost. However, the interaction with building users, increasing comfort requirements, and the complexity of many modern buildings make the design of energy efficient, economic, robust, and easy to implement building control systems far from trivial.

A promising alternative to traditional building control is model predictive control (MPC). In recent years, many studies have analyzed the energy savings potential of MPC in simulations, often in a best case scenario where the simulation and the control model were identical. However, while these studies have demonstrated the potential benefits of MPC when compared with industry-standard *rule-based control* (RBC), many problems still remain to be solved that relate to the appropriate modeling of real buildings, plant-model mismatch, and the practical feasibility of MPC, as for instance its compatibility with preinstalled control systems. Moreover, the usefulness of any proposed controller must be measured by not only its benefits but also its incurred costs, such as the necessary hardware and software and the system's design, implementation, and maintenance effort.

In this paper, we report the results of the predictive building control project OptiControl-II[1] that aimed at answering these questions. The three-year project was done in close collaboration with a predevelopment and research team from Siemens Building Technologies as well as with building simulation experts from Gruner–Roschi AG. The project included seven months of MPC of a thermally activated building system (TABS),[2] an air handling unit (AHU), which was also used for heating and cooling, and blinds of a fully occupied typical Swiss office building. The MPC used a physics-based bilinear model constructed from building data. In addition to the experiments, the MPC strategy was compared in terms of comfort compliance and energy use to the previously installed industry-standard RBC strategy using whole-year simulations with the EnergyPlus simulation software [3]. Experiences with state-of-the-art integrated predictive RBC developed within the OptiControl-II project by the Siemens engineers were reported in [4].

This paper extends the results reported in [5] and summarizes the detailed final project report [6]. This paper makes the following contributions.

1) A comprehensive literature review of experimental building MPC studies.

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Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

[1] www.opticontrol.ethz.ch

[2] Pipes buried in the concrete floor slabs through which heated/cooled water is pumped.

TABLE I

SUMMARY AND COMPARISON OF EXPERIMENTAL MPC STUDIES

Study	System	Actuators	Exp. Time	MPC Model
[7]	One unoccupied test room	Radiator	3 hours	ESP-r
[8]	Two unoccupied test rooms	AHU, ice storage, chillers	4 days	TRNSYS
[9]	Two experiments with three and two occupied office rooms	Shading and window opening devices	60 days	HAMBase and Radiance
[10]	Four occupied rooms	AHU	3 days	Artificial neural network
[11]	Occupied commercial office building	Boiler supplying passive radiators	40 days	Linear SS model
[12]	Eight floors of an occupied university building	TABS heating	90 days	Linear SS model
[13]	Occupied student computer room	AHU	2 days	Linear SS model
[14]	Campus-wide cold water storage	Chillers and cooling tower	10 days	Nonlinear SS model
[15]	Occupied office room	Fan-coil unit	6 hours	Linear SS model
[16]	$650\,\mathrm{m}^2$ space of a research facility	AHU	21 days	Nonlinear SS model

2) A description and discussion of the chosen control implementation and modeling approach as well as of the main experimental and simulation results. This is an extension of the intermediate project results reported in [5].
3) A cost–benefit analysis of building MPC for cases similar to the investigated target building, backed by the practical experience of the Siemens team.

The rest of this paper is organized as follows. In Section II, we review the literature on experimental building MPC and put our project into context. Section III describes the building and its HVAC system. Sections IV and V outline the modeling approach and the implementation details, respectively. The experimental and simulation results are reported in Section VI and the cost–benefit analysis is provided in Section VII. Finally, in Sections VIII and IX, we discuss our results and present our conclusion.

II. REVIEW OF EXPERIMENTAL BUILDING MPC STUDIES

This section together with Table I summarizes all published experimental studies known to us in which buildings have been controlled by MPC.

In general, a building MPC aims to find at every control iteration the control input trajectory over a given prediction horizon that minimizes total operating costs (typically energy or money), while satisfying comfort constraints (typically upper lower bounds on the room temperatures). To evaluate the costs and constraint satisfaction of a particular control input trajectory, a model is needed. While the costs and comfort constraints are mostly similarly defined across the studies, the choice of the model arguably is the most distinctive feature in a building MPC. In the reviewed studies, the used models ranged from building simulation software models (e.g., EnergyPlus or ESP-r [17]) and artificial neural networks (ANNs) to the more commonly known linear and nonlinear state-space descriptions.

In this paper, we classify the studies according to the system that was controlled (whole building, test cells, and so on), the actuators, the total experiment time, and the MPC model.

The earliest work on experimental building MPC used building simulation software models. A practical proof of this concept was first reported in [7]. The authors used an ESP-r model to optimize the starting time of a radiator in an unoccupied test cell in a 3-h-long experiment. Henze *et al.* [8] extended the idea to a more complex HVAC setup in a four-days experiment using a TRNSYS model [18]. The primary system consisted of two chillers and an active thermal energy storage, while the secondary system comprised a ventilation unit serving two unoccupied test rooms. Schuss *et al.* [9] reported MPC experiments conducted over two months in two occupied Austrian office buildings mainly equipped with window shading and opening devices. In both cases, HAMBase [19] and radiance [20] models were used.

The only experimental application known to us of an MPC using an ANN model was reported in [10]. Several experiments were conducted in four occupied rooms of a university building equipped with independent AHUs over a total experiment time of around three days.

To our knowledge, the experimental application of an MPC using a state-space model has first been published in [11]. The authors report the control of a boiler supplying two commercial buildings equipped with radiators over a period of 40 days. MPC was based on a low-order linear state-space model predicting a building-wide average room temperature. Široký *et al.* [12] report the control of the TABS of an eight-floor building block of a university building over three months. Their setup provided the unique opportunity to systematically compare the MPCs performance to a baseline controller running in an identical nearby building block. The authors used a low-order linear state-space model. Aswani *et al.* [13] report an experimental proof of concept of an adaptive MPC approach where in each step the internal model was improved based on the measurements. The scheme used a scalar linear state-space model and was applied to an air conditioning unit of a student computer room. In [14], a nonlinear state-space model was used in an MPC controlling the chillers supplying a large campus-wide cold water storage tank over two five-day periods. The buildings' actuators were not controlled, instead the total campus cooling demand was

Fig. 1. Building used for the experiments.

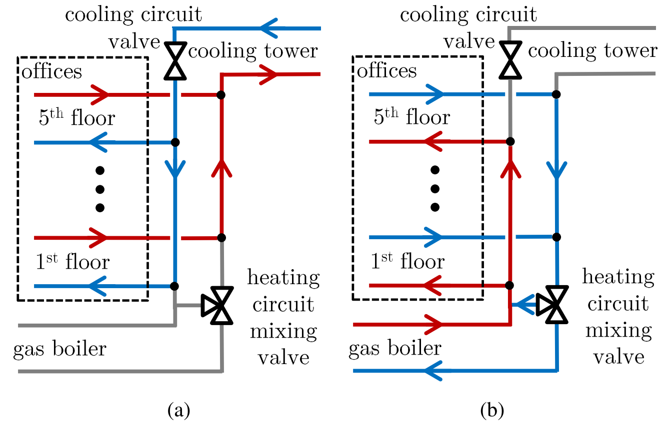


Fig. 2. Schematic of the TABS in heating and cooling operation. Arrows indicate the directions of the water flow. Blue and red indicate, relative to each other, hot and cold water flow, respectively. The pumps (not shown) and valves are operated such that at no time hot water from the boiler enters, while the cooling tower is active and vice versa. (a) Cooling operation. (b) Heating operation.

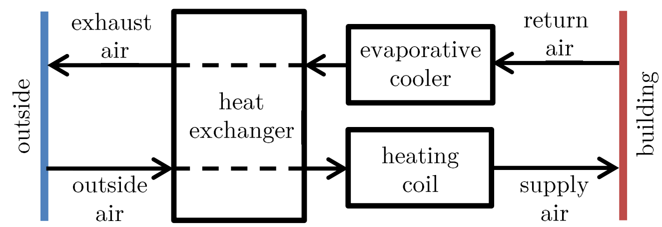


Fig. 3. Schematic of the AHU. Arrows indicate the directions of the air flow. No air mixing takes place in the heat exchanger.

estimated as a function of the weather forecast and then considered as a predictable disturbance. Castilla *et al.* [15] report experimental results obtained over 6 h in a single test room actuating the mass flow and cooling of a fan-coil unit using a linear state-space model. Bengea *et al.* [16] report MPC experiments over three weeks, in which a centralized AHU supplying a 650-m^2 space of a research facility was controlled using a nonlinear model.

All the above studies report a successful operation of MPC and efficiency improvements when compared with baseline control. The experiment durations and the numbers of controlled zones varied significantly across the studies. However, all focused on the control of a single HVAC actuator. In general, all of the studies aimed at demonstrating MPCs benefits but lacked a discussion of the development and implementation costs.

This paper differs from the above studies in several respects. First, we considered the integrated simultaneous control of several actuators (TABS, ventilation, and blinds). Our choice was guided by the results of numerous simulation studies that had shown that the benefits of MPC increase with an increasing complexity of the control task at hand. Second, unlike a majority of the above studies (exceptions being [11], [12], [14], and [16]), we did not consider only test cells or individual rooms, but an entire, fully operational building. Third, we did not manipulate or replace the existing control hierarchy, but rather we introduced an additional level of supervisory control. Fourth, we performed long-term experiments in both, the heating and the cooling seasons (CSs). Finally, the goal of the project was from the beginning that the resulting control solutions can later be easily incorporated in commercial workflows and building automation systems (BASs).

III. Building

Fig. 1 shows the building used in the experiments. It is located in Allschwil, close to Basel, Switzerland. The building was constructed in 2007 and has a total conditioned floor area of ca. 6000 m^2. The ground floor hosts a kitchen and a restaurant, while the upper five floors are used as offices. The measured average heat (i.e., the heating value of the gas used in the building's boiler to produce hot water for heating) and electricity consumption of the whole building is 46 and 83 kWh/m^2 per year, respectively. The building is of a heavy construction type with a glazing fraction of approximately 50%. The overall heat transfer coefficients of the opaque parts and windows are 0.32 and 1.34 W/(m^{2}K), respectively. The usage, HVAC systems, insulation level, window fraction, and BAS are typical for a modern Swiss office building. The MPC strategy was applied to the upper five floors, while the ground floor was separately actuated.

A. Actuation

A TABS is the main heating and cooling actuator, supplied by a gas boiler and a cooling tower [Fig. 2(a) and (b)]. The entire building is served by a single TABS zone, i.e., the circulating water's mass flow rate and supply water temperature are determined globally for the entire building.

A central AHU supplies the offices with fresh air [Fig. 3]. It includes a heat exchanger for return air heat/cold recovery, a heating coil in the supply air, and an evaporative cooler[3] in

[3] An evaporative cooler cools the air flow through evaporation of water that is sprayed into the air. Due to the resulting undesired moisture in the air, it is placed in the return air duct and the cold is transferred to the supply air through the heat exchanger.

the return air. The supply air temperature and mass flow rate are again determined globally for the entire building. On each floor, the air is supplied to the offices on the outer parts of the floors and returned from the rooms in the center of the building. Natural ventilation by manual opening of windows is possible in all office rooms.

In addition, in the corner offices, radiators are available whose supply water temperature is controlled.

The gas boiler provides all heating energy for the TABS, the AHU heating coil, and the radiators. The cold water for the TABS is generated by a hybrid cooling tower.[4] However, to minimize maintenance effort, the tower was operated prior to and throughout the project in dry mode only.

The venetian blinds on a particular facade can only be set collectively and just to four distinct positions (open, low shading position, high shading position, and closed). Their position can be overridden by the occupants. Lighting in the offices is operated by the users and if turned ON, it is controlled locally to a luminance set point.

B. Sensing

Several wireless room temperature and window contact sensors, as well as electric load meters, TABS, and AHU heating/cooling power meters were installed at the beginning of the project to enable the thorough evaluation of the control experiments and the validation of building models as well as to support the newly developed RBC and MPC control strategies. Moreover, the blinds control was integrated into the BAS. A weather station was already in place on the building's roof prior to the project. It was complemented by additional temperature and radiation sensors on all four facade orientations. Finally, an industry PC was setup for running the RBC and MPC control algorithms and an external database was established to monitor and analyze the building's operation.

IV. Modeling

The choice of the modeling approach is fundamental to setting up an MPC and heavily influences the rest of the implementation. We settled for a bilinear model constructed from physical first principles. The motivation for a bilinear formulation was that the resulting MPC problem should be as close as possible to a linear program, while allowing bilinear airflow effects to be modeled which appear in ventilation models.[5] This approach has also been used by others [21]. Due to the mild nonlinearity, it usually results in MPC problems that can be reasonably well solved by a sequence of linear programs (Section V-C).

In this section, we outline the modeling on a high level (HL); for a detailed, equation-level description we refer to [6, Sec. 3.3]. Our approach is discussed in Section VIII.

We modeled the entire second floor (i.e., the floor above the first office floor), subdivided in 20 thermal zones. Supported by measurements, we assumed the second floor to be representative for the whole building. Recall that due to the building's HVAC system design, the identical control actions had to be applied to all of the office floors. The floors and ceilings were modeled to have adiabatic boundary conditions. The modeling follows the procedure proposed in [22].

First, geometry and construction data were extracted from an EnergyPlus model that had been developed to enable the simulation-based controller comparisons (Section VI-B). An algorithm was developed to derive from these data a linear, time-invariant model of the thermal dynamics based on a thermal resistance–capacitance (RC) approach. In this model, the states $x(t)$ represent temperatures of wall/floor/ceiling layers and room air volumes. The model was driven by *external heat fluxes* (solar gains, hull gains/losses, HVAC systems, and internal gains) $q(t)$

$$\dot{x}(t) = A_t x(t) + B_{q,t} q(t). \quad (1)$$

Next, the external heat fluxes were modeled as functions of the states x, control inputs u, and predicted disturbances v, i.e., $q(t) = q(x(t), u(t), v(t))$. Then, outputs y representing averaged zone temperature were defined, the model was discretized, and finally, the model order was reduced from around 300 to 35.

While linear modeling of the thermal dynamics usually provides a good approximation, choosing the form of $q(x(t), v(t), u(t))$ is more delicate and the best approach depends on the problem at hand. As mentioned before, we adopted a bilinear formulation resulting in the control model

$$\begin{aligned} x_{k+1} &= Ax_k + B_u u_k + B_v v_k \\ &\quad + \cdots \sum_{i=1}^{n_u} (B_{vu,i} v_k + B_{xu,i} x_k) u_{k,i} \\ y_k &= C x_k. \end{aligned} \quad (2)$$

Here, n_u denotes the number of inputs and $u_{k,i}$ the ith element of u_k. The inputs and outputs of model (2) are listed in Table II. Note that ideally one would want to formulate the optimization problem in terms of set points and operating modes that can be communicated directly to the BAS. However, by limiting the model to a bilinear form, this was not possible. Hence, the control inputs in Table II are intermediate quantities that had to be postprocessed after the optimization.

As a part of the project, this modeling procedure was implemented in a MATLAB toolbox named the BRCM Toolbox[6] [23]. It provides functions for the fast physics-based generation of bilinear RC type models from basic building geometry, construction, and systems data. Moreover, it supports the generation of a large part of the model from EnergyPlus model description files. Model (2) (without the u_{lighting} and $u_{\text{radiator},\{N,E,W,S\}}$ inputs of Table II) can be generated from the demonstration file made available in the BRCM Toolbox installation.

[4] Hybrid cooling towers pass the fluid to be cooled through a tube bundle typically on the roof of a building, upon which clean water is sprayed and a fan-induced draft applied.

[5] The net heat flux to a room resulting from a forced ventilation is in the simplest case (without any conditioning of the supply air) proportional to the air mass flow rate (control input) and to the difference between the ambient and the room's air temperature (predictable disturbance and state, respectively).

[6] www.brcm.ethz.ch

TABLE II

MODEL INPUTS AND OUTPUTS. {N, E, W, S, (C)} IN THE SUBSCRIPT OF A VARIABLE DENOTES THAT THERE ARE INDIVIDUAL VARIABLES PER ZONE LOCATION NORTH/EAST/WEST/SOUTH/(CENTER)

Variable	**Description**	**Unit**
$y_{\text{avg room T},\{N,E,W,S,C\}}$	Averaged room temperatures	°C
$u_{\text{TABS,heating}}$	Total TABS heating heat flux	W
$u_{\text{TABS,cooling}}$	Total TABS cooling heat flux	W
$u_{\text{radiator},\{N,E,W,S\}}$	Radiator heat flux in the corner offices	W
$u_{\text{transm solar},\{N,E,W,S\}}$	Transmitted solar heat flux into room	W/m^2
$u_{\text{lighting},\{N,E,W,S\}}$	Electrical lighting power per m^2	W/m^2
$u_{\text{AHU},\dot{m}\text{ ERC}}$	Air mass flow through ERC	kg/s
$u_{\text{AHU},\dot{m}\text{ noERC}}$	Air mass flow bypassing ERC	kg/s
$u_{\text{AHU},\dot{m}\text{ cooler}}$	Air mass flow through air cooler	kg/s
$u_{\text{AHU,heater}}$	AHU heater heat flux	W
v_{IGoff}	Internal gains in the offices	W/m^2
v_{IGnonoff}	Internal gains in non-office zones	W/m^2
$v_{\text{T ambient}}$	Ambient air temperature	°C
$v_{\text{solar, }\{N,E,W,S\}}$	Solar radiation on facade	W/m^2

TABLE III

COSTS COEFFICIENTS. HIGH-TARIFF PERIOD: MONDAY–FRIDAY 06:00–21:00 AND SATURDAY 06:00–12:00. LOW-TARIFF PERIOD: OTHERWISE

Objective	**Costs type**	**Value**	**Unit**
Money	Natural gas	0.075	CHF/kWh
	Electricity (low tariff)	0.097	CHF/kWh
	Electricity (high tariff)	0.145	CHF/kWh
NRPE[7]	Natural gas	1.2	kWh/kWh
	Electricity	3.32	kWh/kWh

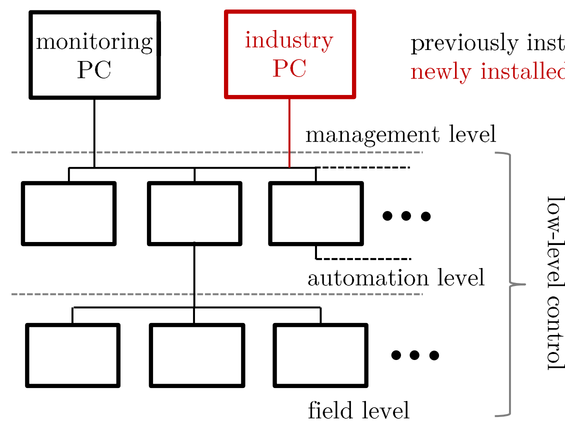


Fig. 4. Schematic of the control topology.

V. IMPLEMENTATION

The implementation is described in a top-down fashion. First, the control task is defined in Section V-A. Then, the control system topology of the BAS and the placement of the MPC supervisory control is described in Section V-B. In Section V-C, the MPC control algorithm is detailed.

A. Control Task

The main goal of the control system is to ensure the comfort of the occupants while minimizing operating costs. In this section, we define comfort and operating costs for our particular case.

1) Comfort Specification: In coordination with the facility management, four quantitative comfort criteria that had to be met during working hours (defined as 08:00–19:00 on workdays) were specified as follows.

a) Thermal comfort: The comfort range for winter and summer was 22 °C–25 °C and 22 °C–27 °C, respectively. In midseason, the comfort range was shifted depending on the running mean of the outside air temperature calculated according to EN 15251 [24]. To prevent air draught, the supply air temperature set point was limited to 16 °C–28 °C in summer and 22 °C–28 °C in winter.

b) Air quality: To satisfy air demand in the offices, the same minimum ventilation mass flow rate as in the previously installed control strategy was enforced. Prior to our project, this mass flow rate had been shown to ensure a good air quality.

c) Blinds movements: To keep disturbance for the occupants at a minimum level, the controller was allowed the execution of one blinds control action at 13:00. During nights and weekends no restrictions were applied.

d) Visual comfort: To avoid glare, the 13:00 blinds control action for facades with higher than 200 W/m^2 irradiation (indicating direct sunlight) was restricted to positions that ensured the complete blocking of direct sunlight. Moreover, completely closed blinds positions were not allowed during working hours.

2) Operating Costs: Operating costs arise from operating the boiler (gas) and the electricity costs of the cooling tower fans, the ventilation fans, the evaporative cooler, the lighting, and the pumps of the TABS system. They were considered either in terms of money or nonrenewable primary energy[7] (NRPE) via the coefficients shown in Table III.

B. Control System Topology

The building is equipped with the Siemens BAS DESIGO [25]. It is partitioned hierarchically into field, automation, and management level [Fig. 4]. The field level includes all sensors, actuators, and their local controllers. The automation level executes primary plant control (e.g., control of AHUs and heat/cold generation and distribution). The default RBC strategy RBC-0 that previously controlled the building had been implemented in the automation level. MPC was implemented on a newly installed industry PC in the management level. Prior to the project, the management level was mainly used for monitoring and manual set-point adjustments. In the following, we use the term HL control for the MPC on

[7]That amount of an unprocessed (nonrenewable) fuel's energy (gas, coal, and so on) that is necessary to produce a particular amount of *final* (i.e., consumed) energy (including conversion and transport losses). Hence, 1 J of electricity results in significantly higher NRPE costs than 1 J of gas.

the industry PC and low-level (LL) control for the automation and field-level controllers.

The HL control received measurements from and sent set points and operating modes to the LL control via the building automation and control networks (BACnets) protocol using a BACnet Object linking and embedding for Process Control (OPC) server running on the industry PC. Moreover, it downloaded weather forecasts from MeteoSwiss [26] over an Internet connection that was also used to remotely access the industry PC. For a description of the read/write interfaces and the LL control, we refer to [6, Secs. 4.1.3 and 4.1.4].

The HL control algorithms were executed in MATLAB using the OPC client toolbox to connect to the BACnet OPC server. Control was done at a sampling time of 15 min. The control algorithm took about 3 min to complete, of which the solution of the optimization problem used about 30 s. MATLAB was restarted at the beginning of every control time step by a periodic operating system task to be robust against previous execution errors and to avoid memory fragmentation. HL control was monitored and in the event of failure control reverted to the default RBC-0.

C. Control Algorithm

In this section, we give an overview of the control algorithm, for details we refer to [6, Sec. 4.3.3].

At the beginning of its execution, the current measurements were gathered via the OPC interface and the latest (three updates per day) available 72-h MeteoSwiss forecast for outside air temperature and global solar radiation (i.e., direct plus diffuse radiation on a horizontal surface) was downloaded, if not already locally available. Next, two different Kalman filters were applied as follows.

1) A standard extended Kalman filter [27] was used to update the current state estimate $\hat{x}$. Its process and measurement noise covariance matrices as well as the initial estimation error covariance matrix were chosen based on physically motivated initial values and turned out to perform well for a large range of values.
2) A second Kalman filter was used to improve the weather forecast using local temperature and radiation measurements from the weather station on the roof of the building. The filter was based on an autoregressive model for the correction coefficients. It is described in more detail in [28].

The MPC problem was set up to minimize total operating costs over the next N time steps while maintaining the occupants' comfort as defined in Section V-A. We used a discretization/control time step of 15 min. This value was found to be a good compromise between a sufficiently fast-reacting control and the complexity of the resulting optimization problem.[8] We used a prediction horizon of 58 h, limited by the length of the weather forecast's prediction horizon just before the next update. An analysis in [29] showed in simulations that for a building similar to the one in this paper, a prediction horizon of at least 38 h is necessary to achieve a closed-loop cost which is no more than 5% above the optimal. Motivated by this and the fact that we were able to solve the problem easily also for a horizon of 58 h, we chose the latter horizon length, resulting in $N = 232$.

Using (2), the resulting optimization problem was bilinear in u and x as well as in u and v

$$\min_{u_0 \dots u_{N-1}} \sum_{k=0}^{N-1} c_k^T u_k \tag{3a}$$

$$\text{s.t. } x_{k+1} = Ax_k + B_u u_k + B_v v_k + \cdots \sum_{i=1}^{n_u} (B_{vu,i} v_k + B_{xu,i} x_k) u_{k,i} \tag{3b}$$

$$y_k = Cx_k \tag{3c}$$

$$y_{\min,k} \le y_k \le y_{\max,k} \tag{3d}$$

$$F_{x,k} x_k + F_{u,k} u_k + F_{v,k} v_k \le f_k \quad \forall k = 0, 1, \dots, N-1 \tag{3e}$$

$$x_0 = \hat{x}. \tag{3f}$$

The total operating costs were represented as a cost function (3a) linear in u_k with potentially time-varying coefficients $\{c_k\}_{k=0,1,\dots,N-1}$. The room temperature constraints were reflected as time-varying lower and upper bounds on the outputs (3d). To avoid infeasibilities, we used soft constraints, i.e., we did not enforce the room temperature constraints strictly but heavily penalized their violation in the cost function.[9] The other comfort constraints as well as the constraints on the actuators were represented[10] in (3e).

The disturbance predictions, $\{v_k\}_{k=0,1,\dots,N-1}$, were parameters to the problem that were computed in every step as follows. The predictions for $v_{T\text{ambient}}$ (Table II) were obtained by simply resampling the Kalman-filtered temperature forecast. The internal gains from people and equipment, v_{IGoff} and v_{IGnonoff}, were predicted using standard schedules which had been adjusted to measurements. Computing the predictions of $v_{\text{solar},\{N,E,W,S\}}$ required the disaggregation of the Kalman-filtered global solar radiation forecast into direct and diffuse components and their projection taking into account the shadowing of neighboring buildings.

To solve the bilinear optimization problem without having to rely on nonlinear solvers, we used a sequential linear programming approach. The problem was solved by iteratively linearizing around the state trajectory computed in the last iteration until convergence was achieved. The linear programs were solved with CPLEX [30].

Finally, the first element of the newly computed optimal input trajectory was converted into the set points and operating

[8]Given the algorithm execution time, the fastest possible sampling time would have been 5 min. However, we believe that due to the slow building dynamics this would not have resulted in an improved control quality.

[9]More precisely, the hard comfort constraints (3d) were replaced with $y_{\min,k} - z \le y_k \le y_{\max,k} + z$ and $z \ge 0$. The penalization term $\gamma^T z$ was added to the cost function with $\gamma > 0$ sufficiently large to enforce $z = 0$ if possible.

[10]Note that since only four distinct blinds position could be set, handling the constraints on the blinds required a heuristic to avoid integer programming. We relaxed the problem by allowing a continuous variation of the heat gains $u_{\text{transm solar},\{N,E,W,S\}}$ which represent the solar heat flux into the zones modified by the blinds position. For details we refer to [6, Sec. 4.3.3].

modes that were subsequently communicated to the building via the OPC interface.

VI. Experimental and Simulation Results

To assess the performance of the MPC strategy two approaches were taken. Long-term experiments were used to demonstrate the feasibility, comfort satisfaction, and soundness of the control actions. This is described in Section VI-A. However, the sequential nature of on-site experiments and the varying operating conditions make the experimental comparison of controllers difficult. Therefore, for more rigorous comparative controller assessment, we also employed whole-year simulations based on an EnergyPlus model of the building's second floor. These results are reported in Section VI-B.

A. Experiments

The experimental setup was operational from October 7, 2011 to April 2, 2013. Before and after, the preinstalled control strategy was active. Most of the time was used to test different controllers. In between open-loop experiments were performed [6, Sec. 5.2]. Here, we report on the MPC experiments only.

The MPC controlled the building during three intervals: i) a 14-week CS period from May 1 to August 7, 2012; ii) a six-week heating season (HS-1) period from November 10 to December 22, 2012; and iii) a nine-week HS-2 period from December 27, 2012 to March 1, 2013. During all of the experiments shown here, the MPC was optimizing NRPE[7] usage except from February 5 to 14, 2013 during which a load shifting experiment with time-varying costs took place. This experiment is reported in more detail in [6, Sec. 6.1.2] and [31].

Thermal comfort was assessed in terms of the time-integral of room temperature comfort range violations, measured in kelvin hours (Kh). Measured supply air temperatures and mass flow rates (not shown here) indicated that the respective constraints were satisfied. The blinds movement restrictions were satisfied by design. Visual comfort could not be assessed via measurements, however, the occupants were at all times able to set the blinds in their office to any desired position.

Fig. 5(a)–(c) shows for each of the periods the ambient temperature, the average and individual room temperatures of the second floor (which was the most thoroughly equipped with sensors and meters) together with the room temperature comfort constraints, and the cumulative comfort violations, respectively. Recall that the room temperature comfort constraints were only enforced during working hours. Lower bound comfort violations were only counted when the window contacts indicated closed windows. For detailed energy consumption data during the MPC experiments we refer to [6, Sec. 5.2.2]. In the CS period, the controller managed to keep the mean room temperature within the prescribed comfort range except for one day around the end of June when temperatures were high enough to overwhelm the cooling capability of the system (MPC had operated the cooling for several days at maximum capacity up to this date). Several downward spikes due to the opening of windows

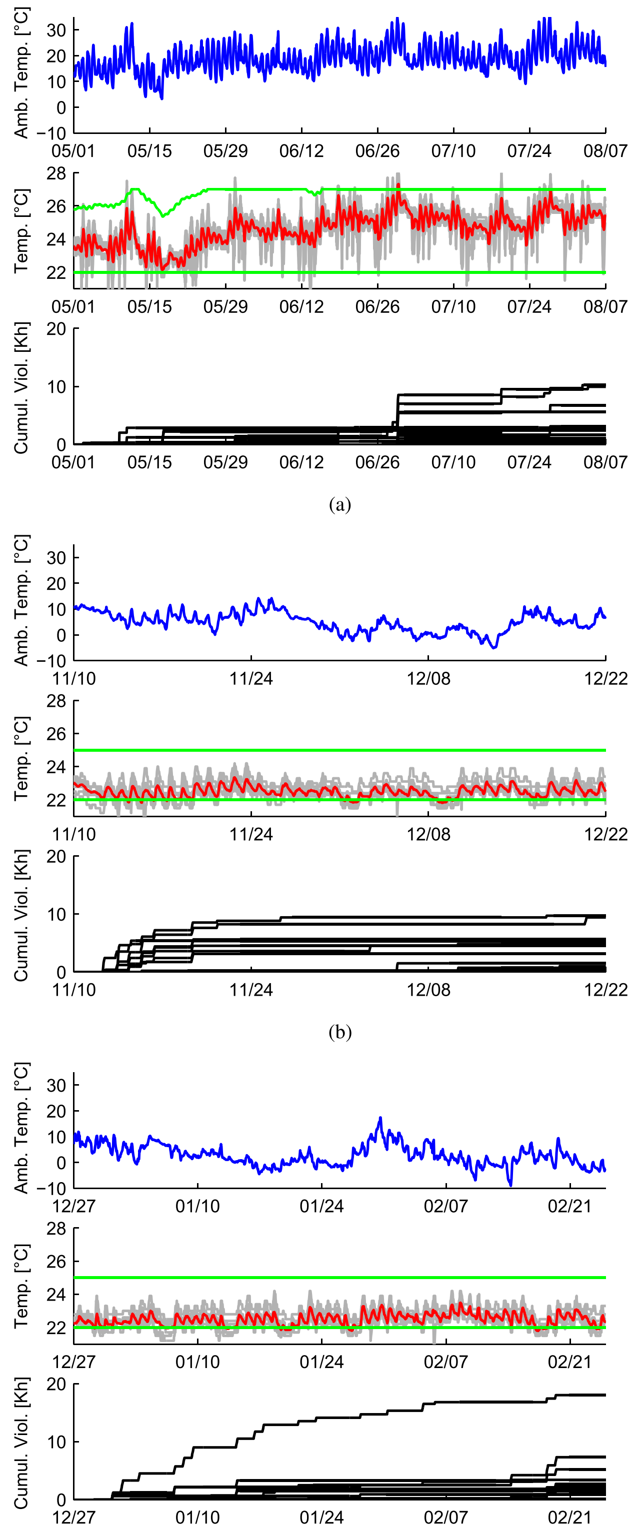
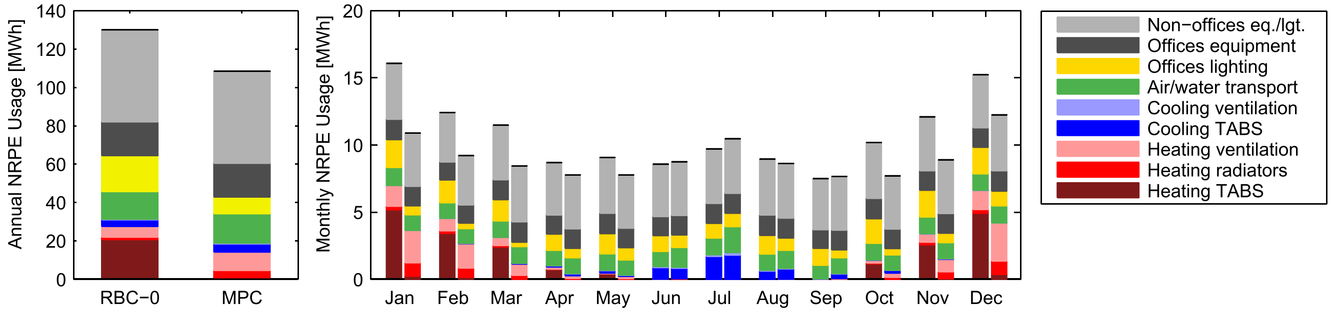
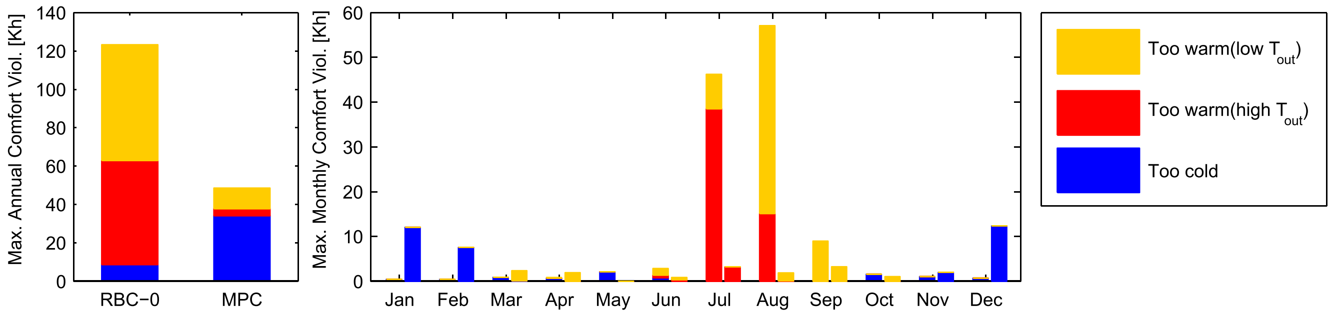


Fig. 5. Experimental MPC results during three periods. Top plots: ambient temperature. Middle plots: average (red) and individual (gray) room temperatures and comfort bounds enforced from 07:00–19:00 during workdays (green). Bottom plots: cumulative comfort violations for each room. (a) May 1 to August 7, 2012. (b) November 10 to December 22, 2012. (c) December 27, 2012 to March 1, 2013.



(a)



(b)

Fig. 6. Simulation results for the second floor. Comparisons of RBC-0 (left bar of the bar pairs) and MPC (right bar). (a) Simulation results: NRPE[7]. Left plot: whole year. Right plot: monthly. (b) Simulation results: comfort. Violations of the upper bound during warm [too warm (high out T)] and cold periods [too warm (low out T)] are distinguished to indicate when the violation could have been alleviated by opening the windows. Left plot: maximum annual comfort violations (i.e., maximum over all zones of the annual sum of each of the three violation types). Right plot: maximum monthly violations.

can be observed. Maximum cumulative violations amounted to an acceptable[11] level of 10 Kh in 14 weeks or 37 Kh/a (kelvin hours per year).

In the HS-1 and HS-2 periods, the MPC controlled the building as expected at the lower constraint. The daily peaks above 22 °C were due to internal and solar gains. Maximum cumulative violations amounted to an again reasonable level of 10 and 17 Kh or 86 and 98 Kh/a, respectively.

A more qualitative assessment of thermal comfort was possible due to the feedback from the facility manager who was in direct contact with the occupants. Apart from the need for an adjustment of the minimum allowed supply air temperature, no complaints were issued. Throughout all experiments, the controller was found to operate smoothly and the fallback strategy was never activated. The facility manager's response to a questionnaire showed that he was also very satisfied with the control system's overall performance.

B. Simulation

To assess the MPCs energy savings compared with the baseline control strategy RBC-0, we performed whole-year simulations for both, RBC-0 and MPC using a detailed and validated EnergyPlus model developed by the building simulation experts from Gruner–Roschi AG as simulation model. MATLAB (used for control calculations) and EnergyPlus (used for building simulation) were coupled with the aid of the building controls virtual test bed middleware [33]. Details on the EnergyPlus model and the simulation environment are reported in [6, Sec. 3.2] and [34]. In the simulations, MPC minimized NRPE[7]. We used weather data recorded in Basel in 2010.

Fig. 6(a) and (b) shows the simulation results. The left and right bars of the bar pairs correspond to RBC-0 and the MPC strategy, respectively. Fig. 6(a) shows in the left plot the annual and in the right plot the monthly NRPE energy consumption by load type for the simulated second floor. MPC used 17% less NRPE energy (including lighting and equipment energy consumption) compared with RBC-0. These numbers correspond to annual NRPE savings[12] of 21.6 MWh NRPE/a or 40.4 kWh NRPE/(m^2a). The corresponding numbers for monetary cost savings (not shown in the plots) were 16.9%, 1118 CHF/a, and 2.1 CHF/(m^2a), respectively. Most of the MPCs savings come from reduced lighting and substituting TABS with ventilation heating. The former is achieved when setting the blinds by considering the lighting costs that are necessary to satisfy the minimum illumination constraint. Using primarily the ventilation instead of the TABS heating allows a delayed start of the heating in the morning. Moreover, the MPC strategy allows an operation closer to the temperature constraints which is difficult in the case of the nonpredictive RBC-0 strategy due to the slow building dynamics. MPC has somewhat higher cooling costs which are necessary to satisfy comfort in the cooling season. RBC-0 often fails to do so since it is not predictive but the main cooling has to take place during the night (cooling tower).

[11] In [32], acceptable annual violations were defined to be around 70 Kh/a.

[12] The corresponding numbers for delivered energy (i.e., the unweighted sum of the total gas heating energy and total electrical energy) usage (not shown in the plots) were 25%, 14 MWh/a, 26 kWh/(m^2a), respectively.

Fig. 6(b) shows the number of kelvin hours of the room with the most violations on an annual (left plot) and on a monthly (right plot) basis. We distinguish violations of the lower bound (too cold) and of the upper bound during warm [too warm (high out T)] and cold periods [too warm (low out T)] to indicate when the violation could have been alleviated by opening the windows.

Most of the savings were realized in the heating period. During the summer months, MPC used slightly more control energy but provided significantly improved thermal comfort. Even though the MPC control resulted in an increase in lower bound violations, overall comfort was improved.

VII. Cost/Benefit Analysis

In midsized to large residential buildings, typically custom control systems are set up. Their application consists of several steps: i) the definition of the requirements; ii) the choice and design of the control system; iii) its implementation and commissioning; and iv) its possible adaptation to changing requirements throughout the building's life cycle. From this, it is clear that although good control performance in terms of energy usage and occupant comfort is essential, the value of a new control strategy also depends on the inherent effort for these steps. This is often neglected in the academic literature. This section gives a condensed version of the cost/benefit analysis reported in [6, Sec. 7], which is backed by the practical experience of the Siemens team. Here, we comment solely on cost/benefit *differences* of MPC when compared with an industry-standard control strategy such as the RBC-0. The main goal is to point out which according to our experience we think are the current major obstacles for a wide-spread adoption of building MPC.

This section will show that MPC can be expected to have an improved performance (Section VII-A) at the expense of higher installation costs (Section VII-C). Since the technology still has to be developed to a product level, significant development costs also arise (Section VII-B). Maintenance and data costs are somewhat higher as well (Section VII-D).

A. Control Performance

The assessment of the achievable control performance in terms of energy and monetary costs is based on the simulation results of Section VI-B, while comfort-wise the assessment is also based on the experimental evidence.

The simulated savings reported in Section VI-B for the second floor translate into 5590 CHF/a for all five upper (office) floors. These values have been obtained using 2012 energy prices.

The MPC strategy achieved a high thermal comfort level in simulation and experiments. Air quality comfort was considered by enforcing a minimum supply airflow rate according to standards. Blinds movements were for both control strategies restricted by design to the desired behavior. A simple analysis (not shown) that evaluated undershading and overshading hours suggested comparable visual comfort levels between the baseline strategy RBC-0 and MPC.

B. Development Costs

Here, we define the development costs for a new control strategy as the effort required by a building automation company to develop a product and the engineering expertise required to routinely apply the control strategy. To develop building MPC to this point, a significant effort is necessary that can mainly be attributed to the following points.

1) Control Framework: A product level MPC software framework needs to be developed from scratch, including a solver for the (moderately sized) linear programs. However, given an HL/LL control abstraction as used in this paper, the development of such a framework and its integration into existing BASs appears quite straightforward.

2) Model Generation Framework: The building model lies at the core of the MPC algorithm and hence of the control framework. Without appropriate tools, the necessary modeling effort most likely could not be justified by cost savings on the order of the ones reported in Section VII-A. Therefore, we believe that a framework allowing the fast generation of MPC suitable models is a key factor to the widespread adoption of MPC in building control.

3) Training: Since experience with MPC is currently very limited within the building industry, significant costs are related to the training of the engineering, commissioning and service personnel if it were to be included in the portfolio of an existing building automation company.

C. Installation Costs

Here, we consider the installation costs that would arise per building if a completely developed MPC control system as defined in Section VII-B was available. Installation costs arise during the engineering (design of the control) and commissioning (tuning of the control) phases. Here, we consider the case of a typically (i.e., sparsely) instrumented building such as the OptiControl-II target building. In particular, we assume that: i) the control of the HVAC system is completely integrated, i.e., all HVAC actuators can be centrally accessed; ii) blinds control is *not* integrated; and iii) ambient temperature but no solar radiation sensors are available. In the following, we distinguish costs for hardware installation and for software configuration.

1) Hardware Installation: The proposed setup with MPC as an HL control requires at least the installation of: i) a dedicated HL control device (e.g., industry PC)[13]; ii) blinds control integration; iii) one room temperature sensor per facade and core facilities; and iv) solar radiation sensors. Optional additional installations include presence detectors and electricity meters that can be used to improve internal gains predictions, TABS heat/cold meters to improve heat flux estimates and window contact measurements.

For cases similar to the building studied here, we estimated the following additional hardware installation costs.[14]

[13] Alternatively, the computation could also be performed in the cloud, i.e., on a server hosted by a building automation company. Given a sufficient number of buildings having such a setup, this likely would lower the hardware costs compared to the here proposed local configuration.

[14] These include costs for sensors, wiring, and input/output modules as well as labor costs and depend to a large extent on the project size.

Industry PC	600–2500 CHF
Blinds control integration	3000 CHF
Room temperature sensors	1200 CHF
Solar radiation sensors	400 CHF

These numbers reflect explicitly the estimated lower limit of the investment costs required to implement MPC. In particular, the costs of optional measurements are not taken into account.

2) Software Configuration: When setting up a building MPC, the two main software related tasks are the modeling of the building and the setting up of the HL control. Given the model and a control framework that only needs to be parameterized (model, interface, and settings) to a certain building, the engineering and commissioning effort for the latter can be expected to be moderate and potentially even lower than for industry-standard control systems that may require delicate tuning.

Even given a modeling framework, the necessary engineering effort for constructing a model still remains the largest unknown factor on the cost side because it heavily depends on the realization of the framework and the model accuracy required by the MPC.

Clearly, without such control and modeling frameworks, the resulting per-case engineering effort will likely be prohibitive for a widespread commercial application.

D. Maintenance and Data Costs

Maintenance and data costs arise due to the need for equipment servicing, troubleshooting, and the procurement of weather forecast data from a meteorological service. According to our experience, servicing and troubleshooting costs for MPC should be comparable with the ones for industry-standard control systems. Our MPC controller requires two types of weather data, outside air temperature and global radiation on a horizontal surface. Today, typical fees for state-of-the-art weather forecasts by a meteorological service (e.g., MeteoSwiss [26]) amount to 100–600 CHF per site, per year, and per meteorological variable. It can be expected that in future, fees will be lower.

VIII. Discussion

In the following, we first discuss choices related to the setup of the MPC and second the economic aspects based on the cost/benefit analysis.

A. Technical Aspects

Two key design choices regarding the setup of the MPC have been made: i) implementing MPC as an HL supervisory control and ii) modeling the building using a physics-based approach.

An alternative to i) would be to implement MPC in the LL control to save the expenses for a dedicated HL control PC. However, this comes with several disadvantages such as individual programming, need for communication to achieve integrated control, a lack of computational power and usually no access to weather forecasts. We believe that for the case of integrated model predictive HVAC control, the additional expense for a dedicated HL control device is greatly outweighed by its advantages.

The standard alternative to ii) is to model the building using black-box or gray-box identification. The most prominent downside of these approaches is the fact that due to time and building usage constraints the effort of identifying multi-input multi-output building models necessary for integrated control may well be prohibitive or, due to limited excitation, even impossible in practice. In particular for the building studied here, identification experiments were usually only possible on weekends. Since the time constant of the TABS is on the order of days, the identification of this aspect alone would have been difficult. The major downside with physics-based modeling is that materials data is often not easily available and guesses have to be made which requires expert know how. However, this is in our opinion heavily offset by the advantages.

B. Economic Aspects

MPC is expected to have an improved performance (i.e., lower operating costs) but higher investment costs (i.e., engineering and commissioning of the software and installation of additional hardware). Central to the success of MPC as a commercial product is the question whether customers are willing to pay for the higher investment costs of the control solution in return for lower operating costs. Unfortunately, investment and operating costs are usually paid by a different entities, namely, by the owner or the general contractor and the tenant, respectively. Other factors influencing the customer's decision are the user acceptance of MPC on the facility management side but also its innovativeness and greenness as a selling argument.

For cases similar to ours, net operating cost savings likely are on the order of 5000 CHF/a. This number was computed by subtracting the additional maintenance and data costs from the simulated energy savings. Under the assumption of a low-instrumented building, minimum additional installation costs are in the range of 3000–6,000 CHF, the lower range corresponding to a case in which the blinds control is already integrated. The largest uncertainty on the cost side lies in the engineering effort. The availability of an efficient modeling framework may well become the decisive factor whether building MPC makes economic sense as a product. Note that even with a good modeling framework, expert knowledge will still be required to handle issues such as missing construction data. Commissioning effort can be expected to be similar or lower than for industry-standard control strategies due to less parameter tuning.

The BRCM Toolbox [23] was developed as a first step toward the needed modeling framework. Given the experience from the present project, we believe that the toolbox is suitable to generate sufficiently accurate initial models for MPC controllers.

For several reasons, we expect the operating costs savings to increase with time. First, energy prices will likely increase in the future. Second, due the expected increase in the use of renewable energy sources, future energy prices are likely to show larger time-variations which can be exploited by MPC. Third, weather forecasts are expected to become cheaper; and finally, advanced building climate control can improve the monitoring of the building system due to a usually increased number of sensors. This facilitates the detection of misconfigurations, which are commonly regarded as a reason for significant energy-efficiency reductions. Also, note that in this paper, the number of actuators was very small. The savings can be expected to be larger when room temperatures can be influenced on a more individual basis.

IX. Conclusion

Our experiments have shown that an MPC strategy can successfully control the TABS, ventilation, and blinds of a typical Swiss office building to the complete satisfaction of the building owner, the facility manager, and the occupants. The implementation of MPC as an HL supervisory control was demonstrated to be a most promising approach for integrated HVAC control.

Simulations using the EnergyPlus software showed that the MPCs simulated energy savings for HVAC, lighting, and equipment were around 17% of the simulated energy use under industry-standard RBC while providing an improved level of comfort. Subtracting annual costs for weather data, this corresponded to monetary savings of around 5000 CHF per year for all floors.

Nevertheless, for similar buildings as ours, given present-day energy prices, and with the tools currently available, the required effort for model development and engineering appears to be too high to justify the deployment of MPC in everyday building projects on the basis of operating costs savings alone. However, significant development investments in a model predictive building automation framework, a modeling tool, and the training of engineers together with the increasing importance of demand response and rising energy prices may push the technology into the net benefit range.

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