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Model Predictive Control of a Swiss Office Building

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Abstract

The research project OptiControl (www.opticontrol.ethz.ch) deals with the development of novel, predictive control strategies for buildings. The strategies are tested on a fully occupied, well instrumented typical Swiss office building. This work presents our experience with the application of Model Predictive Control (MPC). The application of novel rule-based control (RBC) strategies on the same building is presented in a companion paper (Integrated Predictive Rule-Based Control of a Swiss Office Building).

Here we describe, first, the implementation and key aspects of model predictive building control. Second, we report on our experience with running the MPC controller on the building for three months. Third, we compare the controller's performance in terms of comfort compliance and energy use to the previously installed industry standard RBC strategy using whole-year simulations with the EnergyPlus software.

The experimental data show that the MPC operated reliably and successfully satisfied comfort constraints during a period of three months in summer. The simulation study suggests a superior control performance with respect to the original control strategy.

Keywords – building automation; model predictive control; experiment.

1. Introduction

Approximately 40% of the global energy consumption occurs in buildings [1], of which, in industrial countries, roughly half is used for Heating, Ventilation, and Air Conditioning (HVAC) [2]. In industrialized countries the main building stock is already in place and refurbishments of the building hull are expensive, while control systems can be improved at comparatively low costs. This makes it attractive to focus on building automation, at least for reasonably insulated buildings.

Model Predictive Control (MPC) is a promising alternative to standard strategies for building control. MPC uses a mathematical model of the building and predictions of disturbances (e.g., ambient temperature) over a given prediction horizon (e.g., two days) for defining an optimization problem that is solved such as to maintain thermal comfort for the occupants while minimizing some objective (e.g., energy use or monetary cost). See [3] for more detail on MPC. In contrast to most conventional building control approaches, MPC makes it possible to integrate all available actuators and their interactions as well as predictions of weather, internal gains and electricity prices into a coherent, mathematically founded control framework that can handle constraints on control inputs and room temperatures.

Several authors have proposed the application of MPC for buildings in a centralized control architecture [4],[5],[6]. For office buildings, this approach is particularly interesting since the control system is typically already organized in a centralized manner.

In the first phase of the OptiControl project, the potential for new predictive control strategies was assessed with the aid of computer simulations [4],[7]. In the second, ongoing, phase, some of the newly developed control strategies are applied to a fully occupied, well instrumented demonstrator building.

Here we present our experience with the application of MPC to this building in experiment and simulation. The application of novel Rule-Based Control (RBC) strategies is reported in a companion paper [8].

Fig. 1: View of the building from south.

2. Demonstrator Building

Fig. 1 shows the demonstrator building, which is a typical Swiss office building, located in Allschwil, close to Basel. The building was constructed in 2007 and aside from the ground floor, it has five office levels and a total conditioned floor area of ca. 6’000 m^2. The investigated control strategies were applied to the upper five floors, while the ground floor was seperately actuated. The measured average heat and electrical energy consumption of the whole building is 46 kWh/m^2 and 83 kWh/m^2 per year, respectively.

The main heating/cooling source is a thermally activated building system (TABS), which is a series of pipes buried in the concrete slabs of the floors carrying hot/cold water. See [9] for a comprehensive treatment of TABS. The building’s HVAC system further includes an air handling unit

(AHU) with a return air energy recovery system (ERC), an evaporative cooler and a heating coil. The blinds are the third centrally controlled actuator (local manual override possible). The cold water for the TABS is generated by a cooling tower (a heat exchanger to ambient air) while the hot water for the TABS and the AHU heating coil is generated by a gas boiler.

As outlined in Section 3.1, the control strategies evaluated in this work have been implemented as high-level algorithms that manipulate setpoints and operating modes which are subsequently realized by the (already existing) low-level control. The high-level control interface comprised: i) supply air temperature and flow rate setpoints for the AHU; ii) supply water temperature and operating mode for the TABS (heat/cool/off); iii) blinds commands for each of the facades (open/low shading position/high shading position/close).

Several additional sensors and meters (wireless room temperature sensors, electric load meters, TABS and AHU heating/cooling power meters) were installed to enable the thorough evaluation of the control experiments and validation of the building model as well as to support the high-level control strategies. Moreover, an industry PC for running the high-level control algorithms and an external database for monitoring the building's operation were set up.

3. MPC

3.1 MPC Implementation

We defined a clear interface between high-level (MPC) and (existing) low-level control, both on a conceptual and on a technical implementation level. The MPC algorithm was implemented on an industry PC in Matlab. Communication between control levels was accomplished through a BACnet-OPC server using Matlab as an OPC client. The read interface included all control relevant measurements, while the write interface comprised the actuator setpoints and operating modes as described in Section 2. The chosen hierarchical control approach allowed us to keep the original low-level control essentially unchanged.

Since the building was occupied throughout the experiments, a robust operation of the high-level control was of major importance. The implementation was such that switching back to the original control solution (that ran independently from the industry PC) was possible at all times. Conditions for triggering an automated switch back included communication failure between control levels or the failure of the high-level control (e.g., due to problems with the high-level control algorithm, the underlying software, or the input data acquisition). Error handling by the MPC algorithm is described in Section 3.2.

The algorithm was executed in the Matlab computing environment with a sampling time of 15 minutes. The Matlab software was restarted at the beginning of every control iteration by a periodic Windows task in order to be robust against previous execution errors and to avoid memory fragmentation. The execution time of the algorithm was less than 2 minutes on a 2.8 GHz dual core PC. The optimization problem was solved by the CPLEX optimization software.

3.2 MPC Control Algorithm

Every iteration consisted of a Matlab session comprising the following steps:

Step i) Reading of new measurements. The latest measurements are gathered via the OPC interface and measurement data quality checks are performed.
Step ii) Kalman filtering. The current state of the building model used for MPC is estimated given the latest measurements.
Step iii) Preparation of predictions. The latest available 72 hour prediction by the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss) for ambient temperature and global radiation is combined with local radiation and temperature measurements as described in [4]. The forecast is uploaded by MeteoSwiss three times a day. If unavailable, we calculate a persistence forecast. Internal gains by people and equipment are predicted by hourly and weekly schedules based on measurements.
Step iv) Preprocessing of costs and constraints. Maximum and minimum constraints for the future solar gains and TABS as well as the costs of the TABS operation are computed over the whole MPC horizon.
Step v) Computing of new control inputs. If the previous steps were correctly executed, the optimization is run. Otherwise, the second entry of the previously computed control trajectory is used. If the controller fails to produce a new control trajectory in several consecutive iterations, the fallback strategy is activated.
Step vi) Postprocessing of results & writing of setpoints and operating modes. The control vector is converted to setpoints and operating modes. They are checked and sent via the OPC interface to the low-level controller.

3.3 MPC Optimization Problem

The goal of the MPC was to minimize non renewable primary energy (NRPE) consumption while maintaining thermal, air quality and illumination comfort. Thermal comfort was defined by requiring during office hours the operative room temperatures (an average of the room air temperature and the mean radiant temperature) to be within a comfort band of 22°C to 25°C in cold and 22°C to 27°C in hot periods and constraining the minimum and maximum supply air temperature. Air quality was enforced by a minimum required supply air massflow rate during office hours and illumination comfort was considered by only setting three (morning, noon, evening) centrally-controlled blind movements per day while allowing only non-closed positions during working hours and requiring some minimum shading in the afternoon in case of high solar radiation at noon.

Equations (1a)-(1f) describe the MPC problem

$$\min_{\mathbf{u}} \sum_{k=0}^{N-1} c_k^T u_k \tag{1a}$$

$$\text{s.t.} \quad y_{\min,k} \le y_k \le y_{\max,k} \tag{1b}$$

$$x_{k+1} = Ax_k + B_u u_k + B_v v_k + \sum_{i=1}^{n_u} \left[\left(B_{vu,i} v_k + B_{xu,i} x_k \right) u_{k,i} \right] \tag{1c}$$

$$y_k = Cx_k + D_u u_k + D_v v_k + \sum_{i=1}^{n_u} \left[\left(D_{vu,i} v_k + D_{xu,i} x_k \right) u_{k,i} \right] \tag{1d}$$

$$Fx_k + Gu_k \le g_k \tag{1e}$$

$$\forall k = 0,1,\ldots,N-1$$

$$x_0 = \hat{x}_0 \tag{1f}$$

with states x, inputs u, predicted disturbances v and outputs y as listed in Table 1. The prediction horizon was 58h, which implied $N = 232$.

The aim of minimizing NRPE was formalized in expression (1a) which considered the costs as a linear function of the control inputs. The time-dependency of the cost vectors c_k was due to the cooling tower efficiency's dependency on the ambient air temperature. The room temperature comfort was enforced by the constraints (1b). The building model (1c)-(1d) was at the very core of the MPC algorithm. It is bilinear in inputs and states as well as in inputs and disturbances. We used a sequential linear programming approach as described in [4] to solve the nonlinear optimization problem. For the modeling, we used a physical first-principles based algorithm to derive from basic geometry and construction data a model of the building's thermal dynamics, which we then enhanced by submodels for the actuators and disturbances. For the details of this modeling method we refer to [10]. A difficulty encountered during the modeling was that the TABS and blinds could not be conveniently represented as a bilinear function of their corresponding setpoints and operating modes. Therefore, we had to model these actuators' influence as heat fluxes ($u_{\text{TABS heating}}$, $u_{\text{TABS cooling}}$, $u_{\text{transm solar, \{N,E,W,S\}}}$). Since the constraints on these heat fluxes can typically be expressed as (time-varying) lower and upper bounds and since their costs are (mostly linearly) proportional to their magnitude, this approach allowed us to express their costs and constraints in a convex way which made the resulting optimization problem tractable. Hence, the non-convexity of the actuator models was bypassed by (i) an appropriate preprocessing of costs and constraints (see Step iv) in Section 3.2) and (ii) a postprocessing step that computed actual setpoints and operating modes from the 'intermediate' heat fluxes used in the optimization. In (1e), aside from the physical limits on the actuators, the air quality comfort constraint as well as the limits on the ventilation supply air

Table 1: Overview of MPC optimization variables. {N,E,W,S} in the subscript of a variable denotes that there are individual variables per north/east/west/south orientation.

Variable	Unit	Description
$y_{\text{avg room T},\{N,E,W,S\}}$	°C	averaged room temperature
$u_{\text{TABS heating}}$	W	TABS heating heat flux
$u_{\text{TABS cooling}}$	W	TABS cooling heat flux
$u_{\text{transm solar},\,\{N,E,W,S\}}$	W/m^2	average transmitted solar heat flux
$u_{\text{AHU m ERC}}$	kg/s	air massflow through ERC
$u_{\text{AHU m noERC}}$	kg/s	air massflow bypassing ERC
$u_{\text{AHU m cooler}}$	kg/s	air massflow through air cooler
$u_{\text{AHU heater}}$	W	AHU heat coil heat flux
v_{IG}	W/m^2	internal gains
$v_{\text{T ambient}}$	°C	ambient air temperature
$v_{\text{solar},\,\{N,E,W,S\}}$	W/m^2	solar radiation on façade

temperatures are encoded. Equation (1f) finally expresses that the initial state is given by the current state estimate generated by a standard Kalman filter.

4. Experimental Results

The MPC was used to control the demonstrator building from May 1 until July 31, 2012. Fig. 2 shows the ambient temperature during this time. Although this was mainly a cooling period, temperatures dropped to 5°C around May 15 which required some heating action. Fig. 3 depicts for the second floor (which was the most thoroughly equipped) the measured individual office temperatures and their mean. The lower comfort bound was set to 22°C, while the upper bound (computed according to [11]) varied between 25°C and 27°. 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 that the cooling capability of the technical system was overwhelmed (the controller had operated the cooling for several days at maximum capacity up to this date). Individual room temperature trajectories exhibited several downward spikes. A closer analysis revealed, that these had been caused by open windows over night. Apart from these spikes and the very hot period around end of June, comfort was maintained at a satisfactory level for each single room.

A second, more qualitative, assessment of thermal comfort was possible thanks to the feedback from the facility manager, who is in direct contact with the occupants of the building. Apart from the need for a small adjustment of the maximum allowed supply air temperature, no complaints were issued.

Throughout the whole experiment, the controller was found to operate

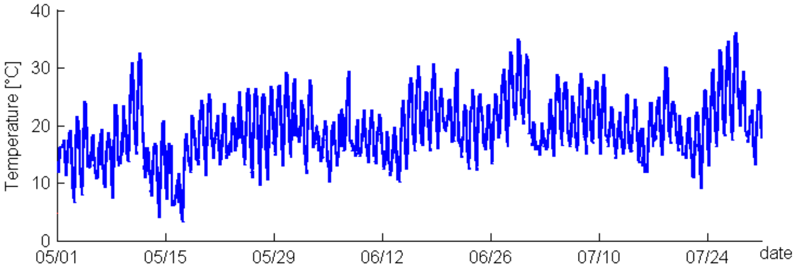

Fig. 2: Measured ambient air temperature.

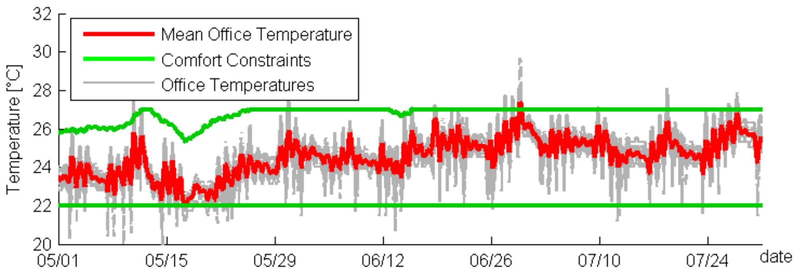

Fig. 3: Measured individual and mean office temperatures and comfort bounds.

smoothly and the fallback strategy was never activated. Also, the facility manager was very satisfied with the control system's overall performance.

5. Simulation Results

The sequential nature of on-site experiments and the varying operating conditions make the experimental comparison of different controllers very difficult. For comparative controller assessment we therefore resorted to whole-year simulations based on a detailed and validated model of the building's second floor. The model was built with the EnergyPlus software and was coupled to Matlab with the Building Controls Virtual Test Bed (BCVTB) middleware. Details on the simulation environment are given in [12]. Below we compare the simulated performances of MPC and the rule-based baseline strategy RBC-0 as originally implemented in the building.

We simulated one year with weather data recorded in Basel in 2010. The left and right bars of the bar pairs in Fig. 4 and 5 correspond to MPC and the RBC-0 strategy, respectively. Fig. 4 shows in the left plot the annual and in the right plot the monthly energy consumption by load type for the simulated second floor. MPC used 14% less energy (including lighting and equipment energy consumption) compared to RBC-0. These numbers correspond to annual NRPE savings[1] of 15.8 MWh NRPE/a or 21.8 kWh NRPE/(m^2·a).

[1] The corresponding numbers for net energy usage (not shown in the plots) were 23%, 13MWh/a, 18 kWh/(m^2·a), respectively.

Most of the savings were realized in the heating period. MPC used slightly more control energy during the Summer months but it provided during this time significantly improved thermal comfort. Interestingly, MPC relied for heating more on the AHU and used the TABS only when a very high heating demand was predicted.

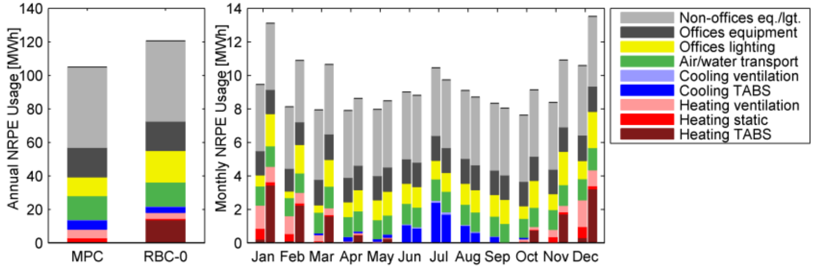

Fig. 4: Energy simulation results for the second floor. Simulated year: 2010. Left plot: whole-year energy comparisons. Right plot: monthly energy comparisons (left bar: MPC; right bar: rule-based baseline strategy RBC-0).

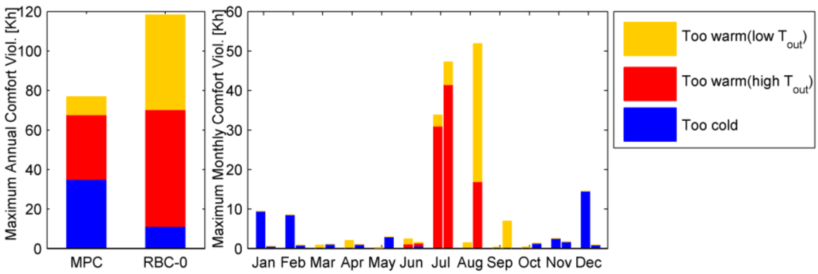

Fig. 5: Comfort simulation results for the second floor. Simulated year: 2010. Left: Maximum annual comfort violations (i.e. maximum over all zones of the annual sum of each of the three violation types) Right: Maximum monthly violations (left bar: MPC; right bar: rule-based baseline strategy RBC-0)

Fig. 5 shows the comfort violation in terms of Kelvin-hours (Kh) which is the time integral of the comfort bound violations. We distinguish violations of the lower bound ('Too cold') and of the upper bound during warm ('Too warm (high T_{out})') and cold periods ('Too warm (low T_{out})'). Fig. 5 visualizes the number of Kelvin-hours of the room with the most violations on an annual (left plot) and on a monthly (right plot) basis. The MPC control resulted in an increase in lower bound violations but achieved a significant reduction of the upper bound violations such that the overall comfort was improved. A closer analysis revealed that the lower bound violations mainly stemmed from the fact that MPC controlled the average temperatures of groups of rooms instead of individual room temperatures. In the summer months, in particular in August, the MPC control resulted in significantly less Kh violations as compared to RBC-0.

6. Discussion

The experimental results of Section 4 show that MPC successfully satisifed the thermal comfort in the demonstrator building. In addition, the results of Section 5 indicate, in accordance to previous results, that MPC has a significant energy savings potential compared to industry standard control. However, the efforts undertaken in this research project would be prohibitive in an industrial application of MPC. For the current MPC algorithm to be implemented on another building, it would be necessary to have, i) a PC running Matlab and an optimization solution; ii) an interface to the building automation system (BAS) that is capable of reading measurements and setting setpoints and operating modes; iii) measurements of temperatures on a per room basis and of the overall electricity consumption (for the estimation of internal gains) as well as of the TABS and AHU supply and return temperatures and massflow rates; iv) weather measurements and forecasts; v) a model in the form of (1c), (1d).

It can be expected that in an industrial application of MPC, custom (non-Matlab) software solutions would be developed, which, together with the fact that today's BAS include powerful automation stations or industry PCs would render i)&ii) uncritical. Regarding iii), temperature and electricity sensors are not expensive and – if not already in place – readily connected to the BAS. Moreover, although the current state estimation makes use of temperature sensors on a per room basis, it is possible that a subset of reference rooms would be sufficient. Many commercial buildings include weather stations and weather services increasingly offer quantitative forecasts via the web. Hence, while coping with points i-iv) required a lot of work in this project, they probably are not critical in an industrial application. However, the derivation of a good MPC applicable model is not expected to be easily standardized for commercial application, which makes v) the most critical, if not the currently prohibitive factor. For MPC as a product to be successful on the market, the modeling effort must be negligible and the model parametrization must be practicable for a typical building control expert. The modeling methodology of [10] that we applied aims in this direction by generating suitable models in a systematic way from basic construction data. There is still room and need for improvement but we believe that the methodology can eventually be used to efficiently develop models that are accurate enough to enable MPC controllers and which can be refined during operation (when long-term measurements become available) in order to further improve the MPC's performance.

We believe that the need for improved energy efficiency, the growing complexity of appliances and systems, the increasing propagation of time-varying electricity tariffs and peak-power penalties as well as benefits related to online visualization of cost-comfort tradeoffs will make MPC an even more attractive alternative in the near future.

7. Conclusions

In this work a representative, fully occupied Swiss office building was controlled by MPC. During a three month experimental period the controller ran smoothly and maintained the requested thermal comfort to the occupants' and facility manager's full satisfaction. Whole-year simulation comparisons against the originally implemented standard rule-based controller showed for MPC a significantly better control performance in terms of both, energy usage and comfort.

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References

[1] T. Barker. et al., Technical summary. In:Climate change 2007: mitigation. Contribution of working group III to the fourth assessment report of the intergovernmental panel on climate change. Technical report. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press; 2007.

[2] L. Pérez-Lombarda, J. Ortiz, C.Pout. A review on buildings energy consumption information. Energy and Buildings 2008;40(3):394–8.

[3] J. Rawlings and D. Mayne. Model Predictive Control: Theory and Design. Nob Hill Publishing, 2009.

[4] D. Gyalistras & M. Gwerder (Eds.) (2010). Use of weather and occupancy forecasts for optimal building climate control (OptiControl): Two years progress report. Terrestrial Systems Ecology ETH Zurich, Switzerland and Building Technologies Division, Siemens Switzerland Ltd., Zug, Switzerland, 158 pp, Appendices. ISBN 978-3-909386-37-6.

[5] Y. Ma, F. Borrelli, B. Hencey, B. Coffey, S. Bengea, and P. Haves.Model predictive control for the operation of building cooling systems.Control Systems Technology, IEEE Transactions on, 20(3):796–803, may 2012.

[6] J. Siroky, F. Oldewurtel, J. Cigler, and S. Prıvara. Experimental analysis of model predictive control for an energy efficient building heating system. Applied Energy, 88(9):3079 – 3087, 2011.

[7] F. Oldewurtel, D. Gyalistras, M. Gwerder. et al. (2010). Increasing Energy Efficiency in Building Climate Control using Weather Forecasts and Model Predictive Control. Paper presented at the 10th REHVA World Congress Clima 2010, Antalya, Turkey

[8] M.Gwerder, S. Boetschi, D. Gyalistras, C. Sagerschnig, D. Sturzenegger, R. Smith, B. Illi. Integrated Predictive Rule-Based Control of a Swiss Office Building. Submitted to Clima 2013.

[9] J. Tödtli, M. Gwerder, B. Lehman. et al (2009). TABS-control: Steuerung und Regelung von thermoaktiven Bauteilsystemen. Faktor Verlag Zurich, Switzerland; 2009. ISBN: 978-3-905711-05-9 [in German].

[10] D. Sturzenegger, D. Gyalistras., M. Morari., R.S. Smith, (2012) Semi-Automated Modular Modeling of Buildings for Model Predictive Control. Paper presented at BuildSys 2012, Toronto, Canada.

[11] EN 15251:2007: Indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics.

[12] C. Sagerschnig, D. Gyalistras, A. Seerig. et al. (2011). Co-Simulation for Building Controller Development: The Case Study of a Modern Office Building. Paper presented at CISBAT 2011, Lausanne, Switzerland.