# Increasing Energy Efficiency in Building Climate Control using Weather Forecasts and Model Predictive Control

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## SUMMARY

This paper presents an investigation of how *Model Predictive Control (*MPC) and weather predictions can increase the energy efficiency in *Integrated Room Automation* (IRA) while respecting occupant comfort. IRA deals with the simultaneous control of heating, ventilation and air conditioning as well as blind positioning and electric lighting such that the room temperature as well as $CO_2$ and luminance levels stay within given comfort ranges. MPC is an advanced control technique which, when applied to buildings, employs a model of the building dynamics and solves an optimization problem to determine the optimal control inputs. The result is an optimal plan in the sense that it takes into account the future weather and internal gains and controls the HVAC, light and blind units to minimize energy costs while respecting comfort constraints.
Through a large-scale factorial simulation study we show that MPC coupled with weather predictions is beneficial in terms of energy efficiency and occupant comfort. In particular, we investigate the control performance, the impact of the accuracy of weather predictions as well as the robustness and tunability of the control strategy.

## INTRODUCTION

In this paper we aim to determine whether the use of model predictive control (MPC) and weather predictions for building climate control is beneficial. Experimental analyses of MPC for particular building setups can be found for example in [1,2]. Here, we focus on a large-scale simulation study and as building automation application we consider the integrated control of the HVAC system, blind positioning, and electric lighting (Integrated Room Automation, IRA) in office buildings. In particular, our investigations address the following questions:
Q1 – MPC performance: What is the added value of MPC in building climate control?
Q2 – Weather predictions: What impact do weather forecasts and their quality have?
Q3 – Robustness analysis: How accurate does the building model have to be?
Q4 – Tunability: How can MPC help to increase comfort?
An overview of the overall control problem is given in Figure 1. The building is affected by the weather, but several measurements of the building state and weather conditions can be taken both inside and outside. These measurements are sent to the MPC controller alongside weather predictions that are corrected with local measurements (by a Kalman filter) as well as information about energy costs and comfort criteria. Based on a building model describing the

building dynamics MPC solves an optimization problem to determine the optimal control inputs that are then sent to the HVAC-, lighting- and blind-systems.
In the following sections, we first describe the building model, second, we comment on the weather predictions and the Kalman filter, and third we explain the control procedure with MPC in detail.

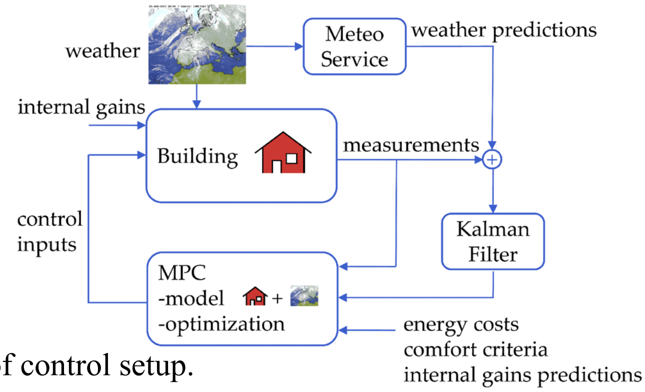



Figure 1. Overview of control setup.

**Building Model**

The integrated control of the HVAC system, blind positioning, and electric lighting of a room is the focus of our investigations, which is currently a common scheme in office buildings. As discussed in [3] it is reasonable to estimate the building-wide energy use by the weighted average of individual zones and so we focus here on single zone dynamics.
Investigations in [4] indicated that the developed 12 state bilinear model captures the majority of the relevant dynamic behaviors sufficiently well for our purposes. The discrete-time bilinear building model with a sampling time of one hour can be written in the following form

$$x_{k+1} = Ax_k + Bu_k + B_v v_k + \sum_{i=1}^{m} \left[ \left( B_{vu,i} v_k + B_{xu,i} x_k \right) u_i \right]$$

where $x_k$ is the state representing the temperatures in the room, wall, floor, and ceiling, $u_k$ are the control inputs representing the HVAC, blind positioning and lighting, and $v_k$ is the disturbance representing the weather and occupancy input at time step $k$. There are $m$ different control inputs available and the matrices $A$, $B$, $B_v$, $B_{vu,i}$ and $B_{xu,i}$ are of appropriate sizes. The building model was validated by comparing its dynamic response to simulations with TRNSYS [5], a well-known simulation software for buildings and HVAC systems. This building model was used twofold: as a simulation model indicated in Figure 1 within the box “Building” and as a controller model indicated in the box “MPC”. This corresponds to the assumption that the controller had a perfect model of the building dynamics, which will not hold in reality and we therefore also investigated the sensitivity to model-parameter mismatch. Further details about the building model and the HVAC systems can be found in [4]. The reader is referred to e.g. [7] for a detailed introduction to MPC.

**Weather predictions:**

The weather predictions were given by the numerical weather prediction model COSMO-7 operated by MeteoSwiss. The data comprised the outside air temperature, the wetbulb temperature and the incoming solar radiation. COSMO-7 delivers hourly predictions for the next three days with an update cycle of 12 hours [6].
The major challenge from a control point of view with using numerical weather predictions lies in their inherent uncertainty due to the stochastic nature of atmospheric processes, the imperfect knowledge of the weather model’s initial conditions as well as modeling errors. The weather predictions were thus filtered with a standard linear Kalman filter to correct for location-specific effects at the building site as well as to take into account the newest on-site weather measurements in between the 12-hourly updates.

**Model predictive control:**
MPC is a very simple and intuitive approach to constrained control [7]. During each sampling interval, a finite horizon optimal control problem is formulated and solved over a finite future window. The result is a trajectory of inputs and states into the future that satisfy the dynamics and constraints of the system while optimizing some given criteria.
At the current point in time, a heating/cooling etc. plan is formulated for the next several hours to days, based on predictions of the upcoming weather conditions. Predictions of any other disturbances (e.g., internal gains), time-dependencies of the control costs (e.g., dynamic electricity prices), or of the constraints (e.g., thermal comfort range) can be readily included in the optimization.
The first step of the control plan is applied to the building, setting all the HVAC components, before moving one step forward and repeating the process at the next sampling time. This *receding horizon* approach is what introduces feedback into the system, since the new optimal control problem solved at the next time interval will be a function of the new state at that point in time and hence of any disturbances that have meanwhile acted on the building.
The main challenge of the overall control problem lies in the uncertainty due to the use of weather predictions. We accounted for this in the MPC formulation in two ways:

- Motivated by Swiss building standards, e.g. [8], we do not require constraints to be satisfied at all times, but only with a predefined probability, which is formulated with so-called chance constraints: $P(x \in \mathcal{X}) \geq 1 - \alpha$ , where $\mathcal{X}$ denotes the set of constraints and $\alpha$ denotes the predefined probability level of constraint violation. As will be seen later, this probability level of constraint violation can be used for tuning purposes in a very intuitive and simple way.
- We explicitly account for the uncertainty in the controller by formulating the future control inputs as functions of future past disturbances, i.e. each predicted control input is a function of the disturbances that will have happened up to that point in time.

With this formulation we were able to take the stochastic nature of the problem into account without being overly conservative. The detailed mathematical formulation and background can be found in [9].

## METHODS

A large-scale factorial simulation study has been carried out with BACLab, a MATLAB-based modeling and simulation environment for building climate control developed within the project OptiControl (www.opticontrol.ethz.ch). We employed the bilinear model of the building dynamics described in [4] and assumed perfect state measurement as well as a perfect prediction of the internal gains. We compared MPC with two other control strategies:
*Rule-based Control (RBC):* This is current best practice; RBC determines all control actions based on a series of rules of the kind "if *condition* then *action*". Here we used the "RBC-5", which is either "RBC-1" or "RBC-4" in [10] depending which one is better. This is the currently best RBC controller known to us that assumes hourly blind movement as the other control strategies considered in this study.
*Performance Bound (PB):* This is not a controller, but rather a concept; PB is defined as the ultimate, theoretical bound on the control performance, which is given by the optimal control action with perfect knowledge of all future disturbances including weather, and can be used as a benchmark.

### Controller Assessment Concept

The controller assessment was done in different steps as shown in Figure 2.
1) *Theoretical potential*: First we compared the performance of RBC and PB, which yielded the theoretical energy savings potential. This was done because there is only hope to improve

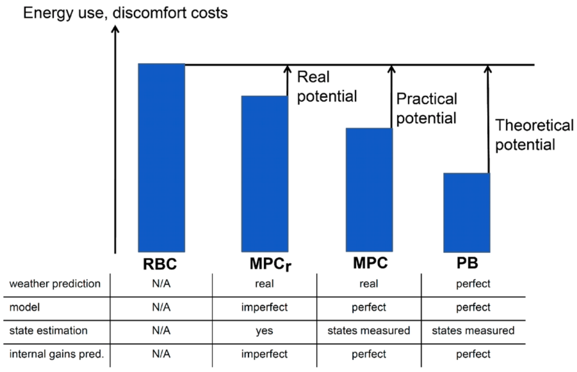


Figure 2. Controller assessment concept.

on current best practice significantly if the gap between RBC and PB is large. This investigation was done in a large-scale factorial study for a broad range of cases representing different buildings and different weather conditions as described below.
2) *Practical potential*: The practical potential was defined as the difference in energy usage of RBC and MPC with real weather predictions. Model-parameter mismatch is being investigated This investigation was done only for selected cases taken from the theoretical potential study, for which Questions Q1, Q2, Q3, and Q4 were answered.
3) *Real potential:* The real potential is given when considering MPC with all realistic assumptions. We expect real weather predictions and their uncertainty to have the largest impact on the control performance compared to the other factors in Figure 2. We therefore focused on this in the present study, so the real potential is outside of the scope of this paper. A similar study was done in [12], but with an idealized RBC controller "RBC-3" for the theoretical potential and "RBC-4" for the practical potential. Here instead, we wanted to focus on all controllers having the same blind movement assumption, i.e. once per hour.
Controllers were assessed in terms of annual Non Renewable Primary Energy (NRPE) use [kW/m$^2$/a] and in terms of amount of comfort violations [Kh/a]. It was necessary to compare controllers in terms of both criteria since there is a tradeoff between NRPE use and comfort violations, i.e. the NRPE use can be reduced by allowing more comfort violations. Based on building standards we defined a reasonable comfort violation level of 70Kh/a [9].

## Factorial Study

For the potential assessment a factorial study with the following variants of HVAC system, building envelope and comfort criteria, as well as the weather conditions was undertaken, which is described in [11]. In order to be self-contained we provide a brief summary here.

Table 1. Overview of building system variants and their automated subsystems. [11]

| *Automated subsystems* | *Sys1* | *Sys2* | *Sys3* | *Sys4* | *Sys5* |
|---|---|---|---|---|---|
| Blinds | x | x | x | x | x |
| Electric lighting | x | x | x | x | x |
| Mechanical ventilation flow, heating, cooling | - | x | x | x | x |
| Mechanical ventilation energy recovery | - | x | x | x | x |
| Natural night-time ventilation | - | - | - | x | - |
| Cooled ceiling (capillary tube system) | x | x | - | - | - |
| Free cooling with wet cooling tower | x | x | - | - | x |
| Radiator heating | x | x | - | - | - |
| Floor heating | - | - | - | x | - |
| Thermally activated building system (TABS) | - | - | - | - | x |

• *HVAC system*: Five different building system combinations were considered, see Table 1. Each system variant employed a different combination of HVAC subsystems.

• *Building*: Variants differed in building standard (swiss average/passive house), construction type (heavy/light), window area fraction (high/low), internal gains level (high/low), façade orientation (north/south etc.), ventilation strategy (fixed variable air volume with/without indoor air quality (IAQ) control) and thermal comfort range width (narrow/wide).
• *Weather*: We used weather data from four locations (Lugano, Marseille, Zurich, Vienna) being representative for different climatic regions within Europe. All weather predictions and observations were historical data of 2007.

**Q1 - MPC Performance**
Based on the results of the factorial study, six example cases were chosen which are common in the European building stock and have a large theoretical potential (see Table 3). For these cases the performance of MPC was compared with RBC.

**Q2 – Quality of Weather Predictions**
This question was treated by comparing the MPC performance using COSMO-7 weather predictions, i.e. provided by a weather service, versus using 24h persistence predictions, i.e. continuous recycling of the data from the last 24h. Again, the same six example cases listed in Table 3 were analyzed. In both cases the predictions were Kalman filtered.

**Q3 - Robustness Analysis**
The robustness analysis was carried out for Building case 1 in Table 3 by changing the parameters in the MPC controller model as listed in Table 2. The choice of parameters and their range of variation were specified by experts of the Building Technologies Laboratory, EMPA Dübendorf, Switzerland.

Table 2. Applied changes in controller model for robustness analysis.

| *Experiment* | *Mismatch* | *Change* |
|---|---|---|
| BPvar1/ BPvar2 | U-values windows | +10% / -10% |
| BPvar3/ BPvar4 | Heat transmission coefficients | +15% / -15% |
| BPvar5/ PBvar6 | Energy recovery efficiency ventilation | +15%/ -15% |
| BPvar7/ PBvar8 | Building mass | +10%/ -10% |
| BPvar9/ PBvar10 | g-value and visual transmission windows | +10%/ -10% |

**Q4 - Tunability**
We investigated for Building case 1 in Table 3 how the desired comfort level can be achieved with MPC considering the tradeoff between energy use and comfort violations by varying the parameter $\alpha$ denoting the probability level of comfort violations.

## RESULTS

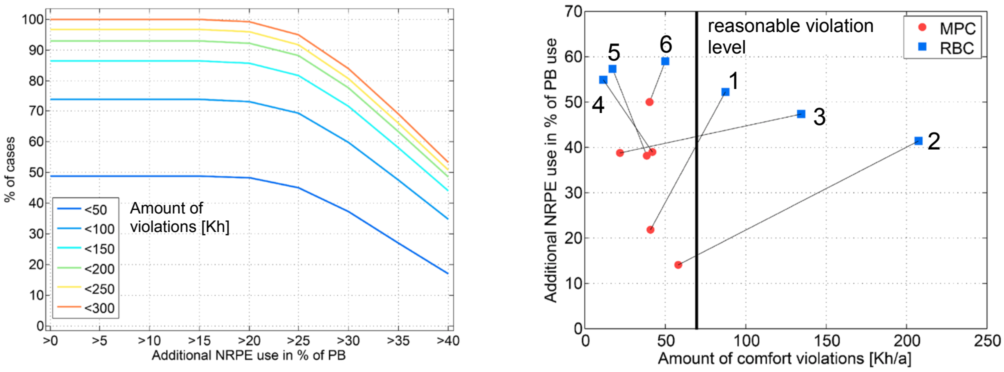
**Q1 – MPC Performance**
In Figure 3a the theoretical NRPE savings potential for 1228 common building cases is depicted.[1] Shown is the found joint cumulative distribution function of theoretical NRPE savings potentials (as additional NRPE use in % of PB)[2] and the amount of comfort violations in Kh/a. It can be seen that more than a half of the considered cases showed an additional

[1] In total 1472 cases investigated. Cases where amounts of violations with RBC > 300Kh/a are not considered, because they are unrealistically large, i.e. RBC would need to be tuned for these cases.
[2] Additional NRPE use is computed as (RBC-PB)/PB to have the same baseline (PB) also when only MPC cases are compared (e.g. Figure 5a), whereas in [12] the theoretical savings are based on RBC, i.e. (RBC-PB)/RBC.

NRPE use of more than 40% and comfort violation less than 300Kh/a. Thus, for many cases there was a significant savings potential, which can potentially be exploited by MPC. The selection of cases for the practical potential analysis was based both on common building setups and large theoretical savings potentials as well as results from [12]. We investigated six common building cases, which are depicted in Table 3.

Table 3. Investigated cases for practical potential.

| *Building case* | *Location* | *Building standard* | *Building system variant* | *Window area fraction* | *Ventilation IAQ controlled* |
|---|---|---|---|---|---|
| 1 | Lugano | swiss average | 2 | low | yes |
| 2 | Lugano | swiss average | 2 | low | no |
| 3 | Marseille | swiss average | 2 | low | yes |
| 4 | Zurich | passive house | 2 | high | yes |
| 5 | Zurich | passive house | 5 | high | yes |
| 6 | Vienna | passive house | 5 | high | yes |

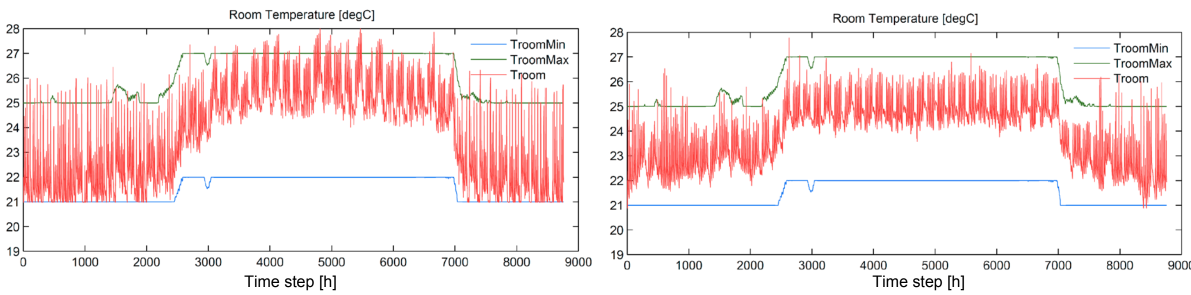



a) b)

Figure 3. Controller assessment. a) Theoretical savings potential: Joint cumulative distribution function of a particular additional NRPE use with RBC in % of PB and a particular amount of violations in Kh/a, b) Practical savings potential: Comparison of MPC and RBC, number denotes building case in Table 3.

The results of the practical potential analysis for the six selected cases is depicted in Figure 3b which shows that MPC has always clearly less NRPE use than RBC and in four of six cases smaller amounts of violations (below the violation limit). This indicated that the additional NRPE use with RBC can be reduced significantly with MPC.

Figure 4 shows the resulting room temperature profiles throughout the whole year for Building case 3 with RBC (a) and MPC (b). It can be seen that MPC showed smaller and less frequent thermal comfort violations than RBC. Furthermore, the diurnal temperature variations were much smaller with MPC.

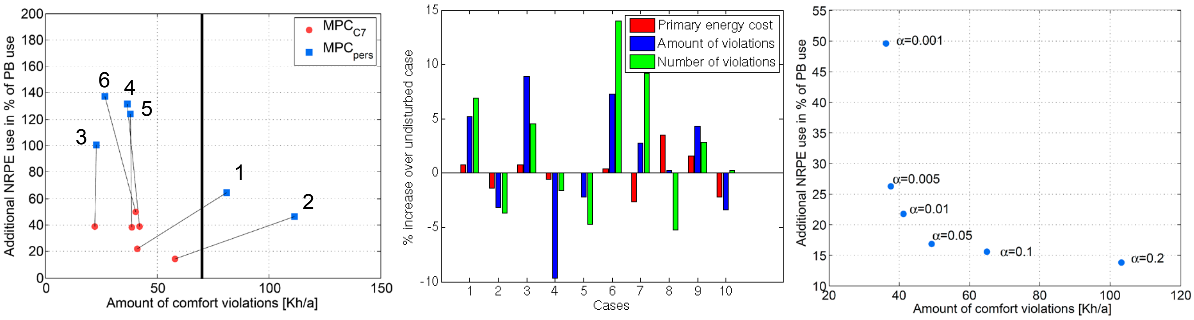



a) b)

Figure 4. Yearly room temperature profiles. a) RBC, b) MPC. The thermal comfort band width is a function of the 24h running mean of the outside air temperature.

**Q2 – Importance of Weather Predictions**

Figure 5a depicts the performance of MPC with persistence predictions ($MPC_{pers}$) versus COSMO-7 weather predictions ($MPC_{C7}$). $MPC_{pers}$ had in all cases clearly more NRPE use. In two cases each it showed slightly less violations, equal amounts of violations, and clearly larger violations than $MPC_{C7}$.




a) b) c)

Figure 5. a) Comparison of performance with persistence versus COSMO-7 weather predictions, b) Robustness analysis: Relative deviations from the reference case, c) Tradeoff curve: Performance of MPC for different probability levels of constraint violation $\alpha$.

**Q3 – Robustness Analysis**

In Figure 5b the result of the robustness analysis is depicted. For the 10 variations of the control parameters described in Table 2 it shows the percent increase in primary energy costs, as well as amount and number of violations compared to the undisturbed reference case. The energy costs among all investigated cases of model parameter mismatch were within a few percent, the amount of comfort violations differed by no more than 9% and the numbers of comfort violations did not differ by more than 14%[3].

**Q4 – Tunability**

First investigations show that the tradeoff curves between NRPE use and comfort violations obtained by changing the probability level of comfort violations $\alpha$ result in Pareto frontiers. For the Building case 1 (Table 3) the obtained Pareto frontier for the annual NRPE use and annual amount of comfort violations is shown in Figure 5c. The curve shows a smooth behavior and it can be seen that a decrease in the amount of violations from 70 to 40 Kh/a goes along with an additional NRPE use of 10% above PB.

**DISCUSSION**

Our potential analysis (Figure 3a) showed that there is indeed a large number of cases with a substantial potential for improvement over present-day RBC. This improvement could in principle be achieved in several ways, for instance with the aid of predictive RBC algorithms [13], although MPC is a particularly general, intuitive and effective approach to capturing this potential.

Here we focused on the MPC approach and our results demonstrate that when MPC is combined with real weather predictions it outperforms non-predictive RBC (Figure 3b). Furthermore, it yields more favorable room temperature dynamics, because it results in much smaller diurnal temperature variations within the predefined thermal comfort range (Figure 4). Comparisons of MPC with simple persistence weather predictions versus real weather predictions indicate a high importance of good quality weather predictions in the investigated

[3] Results obtained with a standard MPC controller not taking into account uncertainty as discussed in the section on MPC. With advanced MPC as used in all other investigations fewer violations are expected.

cases (Figure 8a). Additional investigations are needed to assess the role of the often very uncertain internal gains that were assumed to be perfectly known in all our simulations.
The sensitivity study with MPC and disturbed building model parameters showed that NRPE use does not differ by more than 4% and amount of violations by more than 9% in the cases considered indicating that the controller is robust to model parameter mismatch (Figure 8b). The considered stochastic MPC algorithm also enables specification of the desired energy use–comfort tradeoff by manipulation of a single tuning parameter, the probability of comfort violation $\alpha$ (Figure 8c).
Overall, our results suggest that MPC presents a promising approach to building climate control. Future work should further investigate the dependence of MPC performance on the quality of the used models and data (e.g., building state estimation, internal gains) and how MPC could be embedded in commercial Building Automation and Control systems.

## ACKNOWLEDGEMENT

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