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Embedding Predictive Control in Hierarchical Integrated Room Automation Systems (Part 2/2)

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Abstract

Aiming at an increase in energy efficiency of buildings the research project OptiControl deals with the development of new predictive control strategies for building climate control by using weather and occupancy forecasts. A current challenge within the project is to adapt these strategies such that they fit into the hierarchical structure of current building automation and control systems, which consists of high-level and low-level controllers communicating by operating modes.

In this semester project a new MPC-strategy addressing the above requirements and thus delivering operating modes was developed, which is based on a HYSDEL-model accounting for both the building dynamics and the low-level controller. Its implementation is done in BACLab, the MATLAB-based modeling and simulation environment developed within OptiControl. Different versions of implementations and approximations were investigated in order to improve the performance and reduce the computational complexity. The comparison with other previously developed control strategies shows that the new strategy is beneficial.

Contents

1	Introduction	1
2	Fundamentals	3
2.1	Control Problem	3
2.1.1	Control Task	3
2.1.2	Building Model	4
2.1.3	Weather Data	4
2.1.4	Hierarchical Control Structure	4
2.2	Control Strategies	6
2.2.1	Rule-Based Control Strategies	6
2.2.2	Model Predictive Control Strategies	6
2.2.3	Model Predictive Control Interpreted by Rules	8
2.3	BACLab Software	8
3	Controller Design	9
3.1	High-level Controller for Building Climate Control	9
3.2	Hybrid Systems	9
3.3	Modeling and Implementation	10
3.3.1	Overview	10
3.3.2	HYSDEL-Model	10
3.3.3	MPC-Formulation	12
3.3.4	Challenges and Approximations	13
4	Simulations	15
4.1	Introduction	15
4.2	Simulation Setup	15
4.3	Simulation Results	17
4.3.1	Assessment 1 - HMPC variants	17
4.3.2	Assessment 2 - Benchmarks	20
4.3.3	Assessment 3 - MMPC	23
4.4	Discussion	23
4.4.1	Assessment 1 - HMPC variants	23
4.4.2	Assessment 2 - Benchmarks	25

4.4.3	Assessment 3 - MMPC	26
4.5	Conclusions	26
5	Remodeling of Low-level Controller	29
6	Conclusion and Outlook	31
6.1	Conclusion	31
6.2	Outlook	31
A	Abbreviations	33
	References	35

1 Introduction

Buildings cause ca. 40% of the worldwide energy consumption and the major part of this is consumed during their use. Aiming at an increase in energy efficiency the research project OptiControl¹ deals with the development of new predictive strategies for building climate control. The considered application is the Integrated Room Automation (IRA), which operates on blinds, artificial light and typical HVAC setups. In this context model predictive control strategies which make use of weather and occupancy forecast have been designed.

A current challenge within the project is to adapt these strategies such that they account for the hierarchical structure of current building automation and control systems, which consists of high-level and low-level control. In particular, new designed algorithms should replace the high-level part, while keeping low-level control and their interface unchanged.

The task of this semester project is to design, implement and test a new MPC controller which (i) delivers the needed input signals for the low-level controller in form of operating modes, and (ii) is based on a new hybrid model that accounts for both the building and the low-level controller. To obtain a reasonable computational performance, possible controller simplifications should be considered. As an extension to that work, the so far assumed ideal low-level controller should be remodeled.

This report is structured as follows:

- Chapter 2 describes the work done so far within OptiControl which is the basis of this semester project
- Chapter 3 addresses the design and implementation of the new controller
- Chapter 4 reports the conducted simulations and results to assess the new controller
- Chapter 5 deals with the remodeling of the low-level controller
- Chapter 6 gives the conclusion and outlook

¹<http://www.opticontrol.ethz.ch>

2 Fundamentals

This chapter deals with the work done so far in OptiControl which is the basis for this semester project. In Section 2.1 the control problem is described. Section 2.2 introduces the investigated control strategies. Section 2.3 presents the developed software. More details about the work in the OptiControl project can be found in [10].

2.1 Control Problem

Section 2.1.1 describes the problem setup and the control objective. Section 2.1.2 deals with the building model and in Section 2.1.3 the used weather data is introduced. Section 2.1.4 addresses the implementation in current building automation systems.

2.1.1 Control Task

In Integrated Room Automation (IRA), the control object is an individual building zone or room in an office building equipped with a building system. A building system consists of a combination of automated subsystems for Heating, Ventilation, Air Conditioning (HVAC); electrical lighting, and blinds. In Table 2.1, the five considered typical variants of building systems are listed.

The control task is to use a minimum amount of energetic or monetary cost for maintaining occupant comfort and rejecting disturbances. The occupant comfort is defined by standard comfort ranges for the room temperature, illuminance level and CO_2 concentration. The considered disturbances are internal gains of occupants and equipment as well as the weather described by outside air temperature, wet bulb temperature, and solar radiation.

The comfort range for the room temperature is a function of the running mean of the past measured outside temperature. For the minimum illuminance level, a standard value for offices of 500 lux is used during working hours. For maintaining the air quality, the minimal air change rate is determined depending on the occupancy.

To account for different building types, the following attributes can be varied: facade

Automated Subsystems	Building System				
	S1	S2	S3	S4	S5
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 ventilation heating/cooling (night-time only)	-	-	-	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 systems for heating/cooling	-	-	-	-	x

Table 2.1: Building systems variants. Reproduced from [1].

orientation, construction type, building standard with respect to insulation level, and window area fraction of the facade. The most common configurations are: Swiss average insulation level with low window area fraction, and passive house with high window area fraction; both combined with a heavyweight construction.

2.1.2 Building Model

For simulating the behavior of the building, and for the controller design, a building model was needed. For this purpose, a new bilinear model of both the building's thermal dynamics and its various automated subsystems was developed in [4]. This model is based on a multi-node resistance-capacitance network. This network and the system equations are presented in detail in [8]. The discretized version of the equations is summarized in [3] as follows:

$$x_{k+1} = Ax_k + B_u u_k + B_v v_k + \sum_{i=1}^{n_u} [(B_{vu,i} v_k + B_{xu,i} x_k) u_i] \quad (2.1a)$$

$$y_k = Cx_k + D_u u_k + D_v v_k + \sum_{i=1}^{n_u} [(D_{vu,i} v_k) u_i] \quad (2.1b)$$

The states x are the twelve temperatures of the room and of different layers in the slab and walls. The inputs u are the control inputs to the building subsystems. The disturbances v are the input variables related to weather or occupancy. The outputs y are the variables considered for comfort and other bounds. Note the bilinearities between inputs, and states or disturbances.

2.1.3 Weather Data

This section addresses the weather data available in OptiControl and described in [5].

Two sorts of weather data are used as simulation input: hourly *measurements* of the real weather for driving the simulation model, and corresponding COSMO-7 *forecasts* needed by the predictive controllers. These data have been provided and prepared by MeteoSwiss for different years. To account for different climatical conditions, ten European sites are available.

MeteoSwiss uses the numerical weather prediction model COSMO-7 to operationally compute weather forecasts for large parts of Europe. Every day at 00UTC and 12UTC a new COSMO-7 prediction for the following 72 hours is available. The direct model output is post-processed to remove systematic model biases.

2.1.4 Hierarchical Control Structure

In this section the hierarchical structure, interfaces and tasks of current building automation systems are described. More details are in [1] and [2].

Current Building Automation and Control (BAC) systems use a hierarchical control structure consisting of high-level (HLC) and low-level controllers (LLC). Figure 2.1 shows, how this looks like for the IRA application.

The communication between high-level controller and low-level controller is done as follows: The high-level controller sends the so-called operating modes and associated signals to the

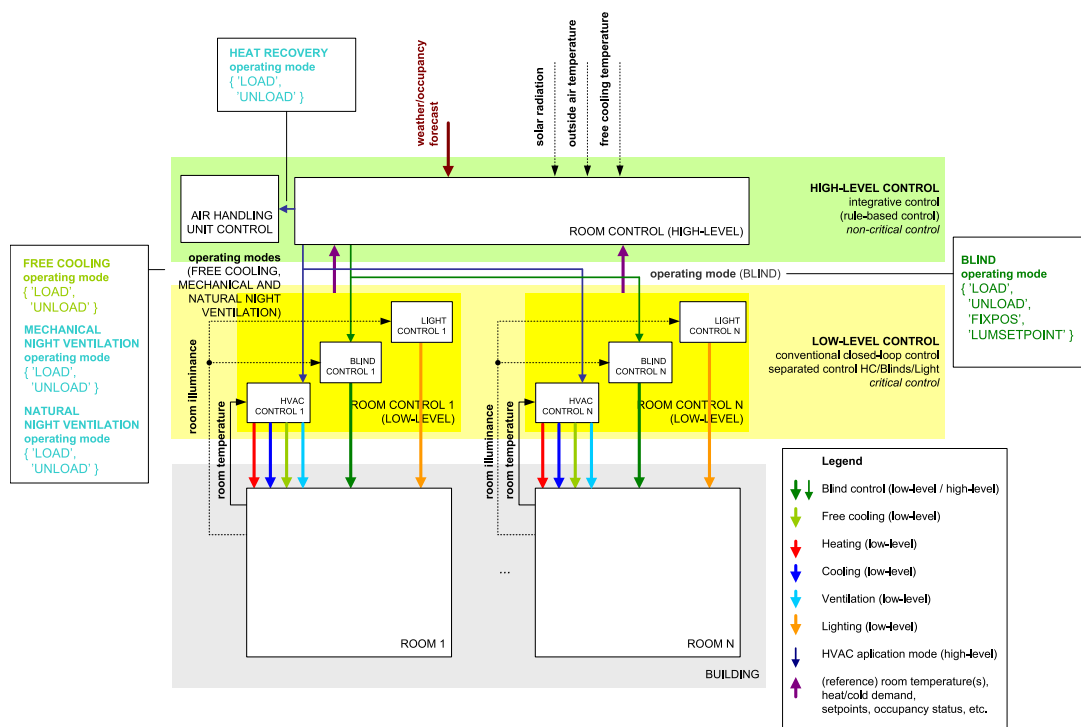


Figure 2.1: Schematic representation of present-day IRA solution. Reproduced from [1].

low-level controller. The low-level controller delivers measurements (in particular the room temperature), heat/cold demand, etc. to the high level controller. Operating modes are defined for the following so-called low-cost control actions:

- Blind positioning
- Free cooling operation
- Mechanical night-time ventilation operation
- Natural night-time ventilation operation
- Energy recovery (ERC) operation

The corresponding aggregates make use of cheap energy such as solar radiation or cool outside air, these together with an exploitation of the thermal mass of the building. The two basic options for an operating mode are LOAD or UNLOAD. This refers to the influence of the control action on the thermal energy stored in the building mass. So LOAD loads the building mass with more energy and UNLOAD unloads it from some energy.

The tasks of the high-level and low-level controller can be summarized as follows: The high-level controller optimizes the usage of the low-cost actions and thus determines the operating modes. The low-level controller has to keep the output variables within the comfort range. Based on the operating modes and measurements it determines the control inputs for all building subsystems. Beside the low-cost aggregates, this includes also the high-cost aggregates such as active heating or cooling, and ventilation.

2.2 Control Strategies

This section describes control strategies developed in OptiControl which are used in this semester project. These can be divided into Rule-Based Control strategies (RBC; Section 2.2.1) and Model Predictive Control strategies (MPC; Section 2.2.2). Finally the strategy developed in the parallel semester project [9] is introduced in Section 2.2.3.

2.2.1 Rule-Based Control Strategies

The four rule-based control strategies (RBC1-RBC4) developed within OptiControl are described in detail in [2]. These strategies use 'if *condition* then *action*'-rules to determine the control actions. They are designed according to the hierarchical control structure and the interface with the operating modes, described in Section 2.1.4. They all works with the same mode-driven low-level controller, called MSTOC.

RBC1 represents a state-of-the-art strategy.

RBC2 is as RBC1, but has more freedom in blind positions. It was designed solely for comparison with PB and is not applied in practice.

RBC3 is a novel very advanced strategy working with historical data of room temperature and heat and cold demand. It allows the LLC to do continuous blind control *during* a time step. In real buildings this is typically not feasible, because that would disturb the occupants.

RBC4 is as RBC3, but the blind movement is restricted to one movement at the beginning of each time step, thus to once per hour. This fix blind position is determined based on the solar gains from the *previous* time step and then sent to the low-level controller with the operating mode FIXPOS.

MSTOC stands for Short Term Optimal Control driven by modes. The control inputs are determined by solving an MPC-problem with optimization horizon of one step and perfect disturbance knowledge, according to the following procedure:

Depending on the operating modes received from the high-level controller and some conditions on measured room and outside air temperature, it is first decided whether the corresponding low-cost actions should be forced or not. Then, these decisions are implemented by new cost weights and/or new bounds for the corresponding inputs in the MPC-formulation. This is later referred to as *cost- and bound-adjusting*. Thereafter the MPC-problem is solved. Finally the electric light is adjusted such that the minimum required illuminance level is reached. This ideal illuminance control is called EL control and can also be applied separately, as seen below. It is done because the occupants would also do that.

This procedure approximates an ideal closed-loop low-level control over the next time step for all control actions not fixed to a certain value by the cost- and bound-adjusting.

2.2.2 Model Predictive Control Strategies

In this section the OptiControl PB- and CE-MPC strategies described in [3] are introduced.

The elements of Model Predictive Control (MPC) are: a model of the system dynamics to predict the system's future behavior starting with the measured current state; a cost function describing the performance; a prediction horizon over which the optimization is done, and additional constraints on involved variables. With these ingredients in each time step a constraint finite time optimal control problem is formulated and solved. From the obtained control input plan over the prediction horizon, only the first control action is applied to the building. Then one time step later the optimization is redone with the new measured state as initialization and a shifted horizon. With this receding horizon approach feedback is introduced.

For the PB/CE-MPC the elements are as follows: The cost function considers either the accumulated Non-Renewable Primary Energy usage (NRPE) or monetary cost of energy over the prediction horizon. Additionally the below introduced slack variables are penalized with a quadratic cost. The constraints are the input bounds such as power limits, as well as the output bounds such as comfort ranges. The output bounds are softened by heavily penalized slack variables, which allows for violations of the bounds on the drawback of high costs if it is not possible to fulfill all constraints.

For the model, the building model described in Section 2.1.2 is used, and therein the predictions are used as disturbance inputs. But because this model is bilinear the optimal solution is determined with an iterative procedure. In each iteration the bilinear building model is linearized around the problem solution of the previous iteration. In detail: To calculate the state-bilinearities, the future states are fixed to the initial state vector in case of the first iteration, and in the subsequent iterations the corresponding optimal state vectors of the previous iteration are used. Then the optimization problem is solved again. This is repeated until the convergence criterion is fulfilled.

CE-MPC Certainty equivalence MPC uses the uncertain weather predictions and determines the control action as if the predictions were equal to certain.

PB-MPC In performance bound MPC, the controller has perfect knowledge of the system dynamic and all future disturbances. In particular it uses the real future weather measurements instead of the predictions to compute the control action. With this perfect information the optimal performance is obtained, which is an absolute benchmark and therefore called performance bound. This controller uses a prediction horizon of 144 hours and then applies the first 48 hours to the building before doing the next optimization.

Together with these MPC-controllers the EL low-level controller, which was previously introduced as also embedded in MSTOC, is used. EL does ideal illuminance control by adjusting the electric lighting such that the minimum required illuminance level is reached.

For CE, the following simple low-level controllers can instead be used to act against the often occurring temperature bound violations:

L2STOC First it is checked whether bounds will be violated when using the control sequence received from the high-level controller. If this is the case, this control sequence is rejected and a new one is calculated by means of an MPC-algorithm with prediction horizon of one time step. Finally, in all cases EL is applied.

RL2STOC is the same as L2STOC, but the blinds are not controlled by the low-level controller. Their position is always taken directly from the high-level controller.

2.2.3 Model Predictive Control Interpreted by Rules

The control strategy designed in the parallel semester work consists of the high-level part MMPC and the low-level part MMSTOC.

MMPC calls an MPC algorithm to get the optimal control sequence and translates the low-cost control actions into operating modes which are sent to MMSTOC. When using the RBM option (Restricted blind movement, MMPC_RBM), the blind position is fixed to the MPC value and not controlled by the low-level controller.

MMSTOC is a modification of MSTOC. Some conditions including threshold values are not needed anymore and therefore removed.

More details can be found in [9].

2.3 BACLab Software

The Building Automation and Control Laboratory (BACLab) software is the modeling and simulation environment developed within OptiControl and written in Matlab code. In this software all the developed models, control algorithms and data sets are integrated, and with this software the simulation studies are done. The data sets are stored in two databases: 'OptiControl Weather and occupancy Data Base' (OCWDB) and 'Buildings and building Systems DataBase (BuSyDB)'. More details about BACLab can be found [4].

In this semester project version 1.2 of BACLab is used, and into this version the new control strategies are implemented.

3 Controller Design

In this chapter the new high-level controller for building climate control is presented. It is based on a hybrid model and called HMPC. Section 3.1 describes the setting, in Section 3.2 an introduction to hybrid models is given, and Section 3.3 deals with the actual modeling and implementation.

3.1 High-level Controller for Building Climate Control

The goal is to design a model predictive control procedure which fits into the hierarchical structure of building automation systems described in Section 2.1.4. Therein, the task of the high-level controller is to derive the operating modes for the low-cost actions, which are the needed input signals for the low-level controller. Based on these signals the low-level controller has then to provide the control inputs for all building subsystems. This setup has already been used in the RBC strategies, and for these strategies there was derived such a mode-based low-level controller called MSTOC, as described in Section 2.2.1. The new control strategy is now designed based on this low-level controller. In particular:

- MSTOC is used as LLC in the simulations, and
- the model in the HLC-MPC-formulation accounts for both the dynamics of the building and the LLC MSTOC

The new controller is to be designed for a realistic setting as it is done in RBC4. Therefore the same modes as in RBC4 are made available and RBC4 is used as benchmark. In particular the blind movement is restricted to once per hour, because continuous blind control is typically not possible in real buildings. Therefore the blind mode is fixed to FIXPOS and the high-level controller determines the position which is applied by the low-level controller for the entire following hour. The other modes can be either LOAD or UNLOAD.

3.2 Hybrid Systems

A hybrid system contains continuous dynamics and discrete components and depends on the interaction between the two. To model such a system there exist several frameworks. Two of them are the *discrete hybrid automata* (DHA) and the *mixed logical dynamical* (MLD) model, [16].

The DHA consists of the interconnection between a switched affine system (SAS), which represents the continuous part of the hybrid system, and a finite state machine (FSM), which is the discrete part of the system. Their interconnection is based on an event generator (EG) and a mode selector (MS). The SAS consists of several dynamics, where the dynamic mode chooses which one to use. The EG generates logical signals depending on the fulfillment of some constraints on the continuous variables. The FSM has Boolean states and is driven by these events and external Boolean inputs. The MS selects based on all Boolean variables the dynamic mode for the SAS. Summarizing, the DHA-framework consists of linear dynamic systems, automata, logic, if-then-else rules, and constraints.

To describe such DHA models on a textual basis, there exists the HYbrid System DEscription Language (HYSDEL). For details on the modeling in HYSDEL, it is referred to

the HYSDEL-manuals [16] and [13]. With the HYSDEL-compiler this description is then translated into an MLD system, which is described by the following equations:

$$x^+ = Ax + B_u u + B_{aux} w + B_{aff} \quad (3.1a)$$

$$y = Cx + D_u u + D_{aux} w + D_{aff} \quad (3.1b)$$

$$E_x x + E_u u + E_{aux} w \leq E_{aff} \quad (3.1c)$$

where $x \in \mathbb{R}^{n_x} \times \{0, 1\}^{n_{xb}}$ is a vector of continuous and binary states, $u \in \mathbb{R}^{n_u} \times \{0, 1\}^{n_{ub}}$ are the inputs, $y \in \mathbb{R}^{n_y} \times \{0, 1\}^{n_{yb}}$ the outputs, $w \in \mathbb{R}^{n_w} \times \{0, 1\}^{n_{wb}}$ represents auxiliary variables, and $A, B_u, B_{aux}, B_{aff}, C, D_u, D_{aux}, D_{aff}, E_x, E_u, E_{aux}$ are matrices with appropriate dimensions.

Based on this MLD model, Hybrid MPC can now be done. The general formulation is: Minimize some cost function depending on the above variables and based on linear or quadratic norms over a certain horizon with respect to the above dynamics and constraints. The resulting online-optimization problem is then a mixed-integer quadratic program (MIQP), which can be solved for example with CPLEX [12].

3.3 Modeling and Implementation

This section deals with the modeling and implementation of the new high-level controller (HMPC). In Section 3.3.1 an overview of the implementation is given. Section 3.3.2 addresses the HYSDEL-model which is used in the MPC-formulation described in Section 3.3.3. In Section 3.3.4 three challenges and their solutions are discussed.

3.3.1 Overview

In the HMPC-preparation-task the HYSDEL-model corresponding to the considered building system is chosen and compiled. The result of this is an m-file which describes the MLD-matrices. Therein, parameters which will change during the simulation are symbolic.

During the simulation when HMPC is called, the following is done: For each iteration due to the bilinearities, the MPC-formulation is created with the help of YALMIP time step by time step based on the MLD-matrices. For each time step the current parameters are determined, what includes the system-matrices for the linearized building model. This linearization and the iterative approach is done identically to the other MPC-strategies, as described in 2.2.2. With these parameters the current MLD-matrices are derived by executing the above mentioned m-file. The obtained optimization problem is then solved with CPLEX.

When the states have converged, i.e. when the difference between the states of the current optimization and the previous one is less than a threshold, or when the maximal number of iterations is reached, then the iteration is stopped. Out of the optimal values of the first time step of the current optimization, the operating modes are extracted and sent to the low-level controller.

3.3.2 HYSDEL-Model

The purpose of this section is to describe the HYSDEL-model (HM) needed in the MPC-formulation. As described earlier this model accounts for the dynamics of the building as well as the underlying low-level controller MSTOC. It is written in HYSDEL 3.0.

As in the other MPC-strategies, the building dynamics are described by the linearized bilinear building model. This linearization is done outside of the model and the system-matrices derived for the current time step enter the model as parameters. As seen in Section 2.2.1, MSTOC setups and solves an MPC-problem with a horizon of one step, based on the *cost- and bound-adjusting*, which depends on the operating modes and other conditions. The idea is now to incorporate exactly this condition depending *cost- and bound adjusting* into the HM. Altogether, the HM is then used as prediction model of the building dynamics as well as for calculating the condition depending costs needed in the MPC-objective function, both for one time step.

Interface The interface of the HM is therefore defined as follows:

Inputs are the building model inputs (u) and the operating modes (m). Depending on the building system these numbers vary. The modes are binary variables, where one represents LOAD and zero represents UNLOAD. Note that because the blindmode is fixed to FIXPOS no variable is needed for the blindmode. As blind position input signal for the low-level controller, the optimized blind position value of the building model input is used. Finally this results in two binary inputs (or one in case of system S1).

States are the 12 states (x) of the building model.

Outputs are the outputs of the building model (y) as well as the costs of the current time step for the MPC-objective function (cost). This cost depends on the particular combination of the inputs, modes, state and disturbances.

Parameters are the predicted disturbances (v), the matrices for the building system, the original bounds on the inputs, the original input-cost-weights and some parameters needed in the MSTOC conditions. Most of them are time dependent.

Building Implementation The implementation of the building part in the HM looks as follows: The continuous dynamics of the HM are the linearized system update equations of the bilinear building model. The first outputpart of the HM is described by the linearized building model output equation. The original input bounds are implemented as constraints.

MSTOC Implementation Next, the implementation of the MSTOC in the HM is described. Each building system has one low-cost cooling action and most system has ERC. The generic formulation of the cost- and bound-adjustment in MSTOC for such a low-cost cooling action can be described as follows:

```
Switch Mmode
  Case UNLOAD
    If roomTemperature <= outsideTemperature - Mthreshold
      // force Musage
      Mucostnew=-1e-3;
      MuboundmaxNew=MNewMax1;
      MuboundminNew=MNewMin1;
    Else
      // stop forcing Musage
```

```

Mucostnew=MucostNormal;
MumaxNew=MNewMax2;
MuminNew=MNewMin2;
Case LOAD
// do not force Musage
Mucostnew=MucostNormal;
MumaxNew=MNewMax2;
MuminNew=MNewMin2;

```

Note that new bounds are not for all low-cost cooling actions needed, and that for ERC the description is similar.

Therein the elements of a DHA can be identified. The condition on the room temperature generates an event. The operating mode $Mmode$ works as binary input. The selector selects depending on this input and the event, one of two situations: *force usage* or *not force usage*. With if-then-else rules the new costs and bounds are finally assigned.

The new input bounds can be directly implemented as additional input constraints. Implementing the new costs is more involved. Note that because in HYSDEL it is not allowed to use nonlinear terms, it is not possible to first assign -depending on conditions- a new input-cost-weight to a variable and then later multiply this variable with the corresponding input. But instead of this one can directly assign -depending on conditions- the value resulting from the multiplication of the new input-cost-weight and the corresponding input to a new variable.

The second outputpart of the HM, the cost, can now be calculated as the sum of two parts. The first part is the sum of the above new assigned input-costs for the low-cost-actions; the second part is the cost of the other inputs, which is calculated as usually as the multiplication of the input with the input-cost-weight.

Because each building system has different low-cost actions, a different HYSDEL-model for each building system was derived, which accounts only for the actions available in the considered case.

3.3.3 MPC-Formulation

With the MLD-model derived from the HYSDEL-model, the MPC-formulation can be stated as follows:

$$\min_u \sum_{k=0}^{N-1} (c_k + s_k^T S s_k)$$

such that $\forall k = 1 \dots N - 1$

$$\begin{aligned} x_{k+1} &= A_k x_k + B_{u,k} U_k + B_{aux,k} w_k + B_{aff,k} \\ Y_k &= C_k x_k + D_{u,k} U_k + D_{aux,k} w_k + D_{aff,k} \\ E_x x_k + E_u U_k + E_{aux,k} w_k &\leq E_{aff,k} \\ y_k &\leq y_{max,k} + s_k \\ y_k &\geq y_{min,k} - s_k \\ s_k &\geq 0 \\ m_k &\in \{0, 1\}^{n_m} \end{aligned}$$

where

$$\begin{aligned} Y_k &= [y_k^T \quad c_k^T]^T \\ U_k &= [u_k^T \quad m_k^T]^T \end{aligned}$$

The optimization variables are the MLD-inputs U , the MLD-outputs Y , the states x , the auxiliary variables w and the slackvariables s . Some of these variables are constraint to be binary. The MLD-input consists of the building inputs u and the binary operating modes m .

The MLD-output is partitioned into (i) the vector of the building output (y), which is constraint by y_{min} and y_{max} , and (ii) the scalar value of the current input costs (c), which is needed in the objective function. As in the CE-MPC strategy the constraints on the outputs are softened by slackvariables and input power is considered to be limited.

The cost function is composed of two parts. The first part is the summation of the input costs of all time steps as obtained from the model. This considers the input energy usage and the cost-adjustment for forcing the low-cost action. The second part penalizes the usage of the slack variables. So the main idea behind this cost function is the same as in the CE-MPC strategy.

The implementation of the above MPC-formulation is done with YALMIP [14], a modeling language for defining optimization problems. To solve this problem CPLEX 10.0 [12] is used.

3.3.4 Challenges and Approximations

This section describes three challenges and their solutions.

Backup-Strategy For the very rare cases when the solver cannot find a solution within a reasonable time limit, a backup-strategy has been implemented. In such a case the corresponding solution from the previous optimization will be used.

Free cooling The simulation results in Section 4.3.1 shows that there are some problems with too often free cooling. Until now the free cooling subsystem input in the HLC was allowed to have a value between zero and one. The hypothesis is now that by restricting this input further to be either zero or one the results should be better. This controller is called HMPC1.

Complexity Because of all these binary variables the original problem needs much computational time. But in principal it is not necessary to consider the modes in later parts of the horizon because we are only interested in a good approximation of the cost-to-go. Therefore the following well known approximation was implemented: The original model with the modes is only used in the first six time steps (six hours) and for the remainder of the horizon the much simpler model of the CE-MPC strategy is used. This controller is referred to as HMPC2.

4 Simulations

4.1 Introduction

This chapter reports the simulations done to explore the control performance of the new controller (HMPC).

Assessment 1 - HMPC variants The three different versions of HMPC as described in the previous chapter and summarized below are compared in order to examine the proposed approximations. This gives the reasoning for the choice of version used in the below investigations.

HMPC0 original formulation with prediction horizon of 24 hours

HMPC1 as HMPC1, but plant input for free cooling in HLC restricted to be Boolean

HMPC2 uses the HYSDEL model and the free cooling input restriction only for the first six hours, and for the remainder of the horizon the CE-MPC model

Assessment 2 - Benchmarks HMPC is assessed with control strategies developed within OptiControl. HMPC with realistic weather predictions was compared to the two benchmarks RBC4 and PB, and additionally to CE. RBC4 was chosen because it has exactly the same setting in terms of blind movement restriction as HMPC. PB, because it has the best possible performance. CE, because it has the simplest MPC-setup for realistic weather predictions. The following questions are addressed: *What is the benefit of HMPC with respect to RBC4 and CE? And how far away from the optimum is it?*

To explore the influence of the imperfect weather predictions, HMPC was additionally simulated with perfect predictions. This allows partitioning the performance loss into loss through design and loss through uncertain disturbances. The following questions are addressed: *How close to the optimum does the new strategy get in case of perfect weather predictions? And what is the influence of imperfect weather predictions?*

Assessment 3 - MMPC HMPC is compared to the control strategy MMPC developed in the second semester project. To explore how much the result depends on the low-level controller, HMPC2 was additionally simulated with MMSTOC.

This chapter is organized as follows. Section 4.2 describes the simulation settings in more detail. The results are presented in Section 4.3 and discussed in Section 4.4. In Section 4.5 the conclusions follow.

4.2 Simulation Setup

In Table 4.1 the overview of the simulation experiments is given. The parts refer to the above described structure.

For each controller the entire year 2007 was simulated. The discrete time step was one hour. The used optimization criterion was Non-Renewable Primary Energy (NRPE) usage. The optimizations were done with a prediction horizon of 24 hours, except for the performance bound which has 144 hours. In HMPC, 5 iterations for the bilinearities are done, in the other MPC strategies 10. The input power was limited.

Part	HLC	WP	LLC	Cases
1a	HMPC0	pp, c7	MSTOC	01, 02, 05, 06
	HMPC1	pp, c7	MSTOC	01, 02, 05, 06
1b	HMPC1	pp, c7	MSTOC	01 - 06
	HMPC2	pp, c7	MSTOC	01 - 06
2	HMPC2	c7	MSTOC	01 - 06
	PB	pp	EL	01 - 06
	RBC4	pe	MSTOC	01 - 06
	HMPC2	pp	MSTOC	01 - 06
	CE	c7	RL2STOC	01 - 06
3	HMPC2	c7	MSTOC	01 - 06
	MMPC_RBM	c7	MMSTOC	01 - 06
	HMPC2	c7	MMSTOC	01 - 06

Table 4.1: Overview of simulation experiments. WP: weather prediction method, see Table 4.2; Cases: see Table 4.3

WP	Description
pp	perfect prediction (prediction is equal to future disturbance realizations)
pe	persistent prediction (prediction for the following hour is equal to disturbance realization of previous hour)
c7	COSMO-7 prediction, Kalman-filtered by MeteoSwiss

Table 4.2: Used weather prediction (WP) methods

Weather data The used weather data are the hourly measurements and corresponding predictions of the year 2007 for the sites Zurich-Fluntern (SMA) and Marseille-Marignane (MSM). The weather prediction methods are summarized in Table 4.2.

Case Set For the investigations the six building cases summarized in Table 4.3 have been selected. This selection is based on the selection for the in-depth analysis [6], which consists of very common cases. It was completed by two cases for building system variant one, because that is the simplest one and a simpler setup might be helpful for interpreting the results. It contains the two standard building types which are passive house with high window area fraction (pa-h-wh) and swiss average insulation level with low window area fraction (sa-h-wl), both combined with a heavy-weight construction. Each building system is at least in one case present. The list contains only a few cases because the simulations for the initial controller design with no approximation were very time expensive. It is the same set as defined in [9].

Performance Assessment To assess the performance of a certain controller in an experiment, the same method as in [7] is used, that means, both the NRPE usage and the total amount of violations of the thermal comfort range (measured in Kelvin hours) are considered and a total amount of 70Kh/a is tolerable. To compare two control strategies, the difference in NRPE usage and the difference in amount of violations of each individual case are shown in a plot. This is referred to as delta-plots as in [7]. If a strategy needs less in both attributes, then it performs better; if it needs more in both, then it performs worse; if it needs more in one and less in the other, then it is undetermined.

Case	Site	BSV	BT
01	SMA	S2	pa-h-wh
02	MSM	S2	sa-h-wl
03	SMA	S3	sa-h-wl
04	SMA	S4	pa-h-wh
05	SMA	S1	pa-h-wh
06	SMA	S1	sa-h-wl

Table 4.3: Selected building cases. BSV: building system variant, see Table 2.1; BT: building type; pa-h-wh: passive house with high window area fraction; sa-h-wl: swiss average house with low window area fraction.

4.3 Simulation Results

4.3.1 Assessment 1 - HMPC variants

Comparison of HMPC1 and HMPC0 In Figure 4.1 selected signals during January for Case 01 are depicted. On the left side are the results with HMPC0, on the right side with HMPC1, both with C7-predictions. From top to bottom the following signals are shown: resulting room temperature (1); result of optimization in the HLC for free cooling plant input (2) and free cooling operating mode (3); control inputs determined by the LLC for free cooling (4) and room heating (5). Recall, that the plant inputs in the HLC are only needed for optimization, and only operating modes such as (3) are sent to the LLC. Nevertheless these HLC plant inputs are now used for diagnosis of controller behavior.

For HMPC0 the result of the optimization in the HLC is to use mostly no free cooling but sometimes a little bit. The optimal mode is also mostly LOAD, represented in the figure as value one, and sometimes UNLOAD. In the LLC mostly no free cooling action is applied, but sometimes free cooling is used half to fully. This is very different to the signal resulting from the optimization in the HLC. Additionally, room heating is occasionally needed. Furthermore the room temperature is often close to the lower temperature comfort bound.

In HMPC1 the HLC-optimization resulted in never using free cooling and always sending operating mode LOAD. The LLC never applied free cooling except in two cases. This is very similar to the HLC-Signal. Furthermore room heating was never used, and the room temperature was more in the middle of the comfort bound.

Figure 4.2 shows the difference HMPC1-HMPC0 in NRPE usage and violations. Depicted are all cases with free cooling, both for perfect weather predictions and C7-predictions. It can be seen that HMPC1 needs for all cases less NRPE and has in seven of eight cases also less violations. In these seven cases HMPC1 has clearly the better performance. In the single other case, HMPC1 has 0.85 Kh more violations, and it is undetermined which strategy is better.

Comparison of HMPC2 and HMPC1 Figure 4.3 shows the difference HMPC2-HMPC1 in NRPE usage and violations, both for perfect weather predictions and C7-predictions. Both controllers have in all twelve cases almost the same NRPE usage (± 0.25 kWh/m²/a). In ten of twelve cases, HMPC2 has less or less than 1.1 Kh more violations than HMPC1. Then there are two outliers, the results of Case 04, where HMPC2 has 11 Kh and 14 Kh more violations, respectively.

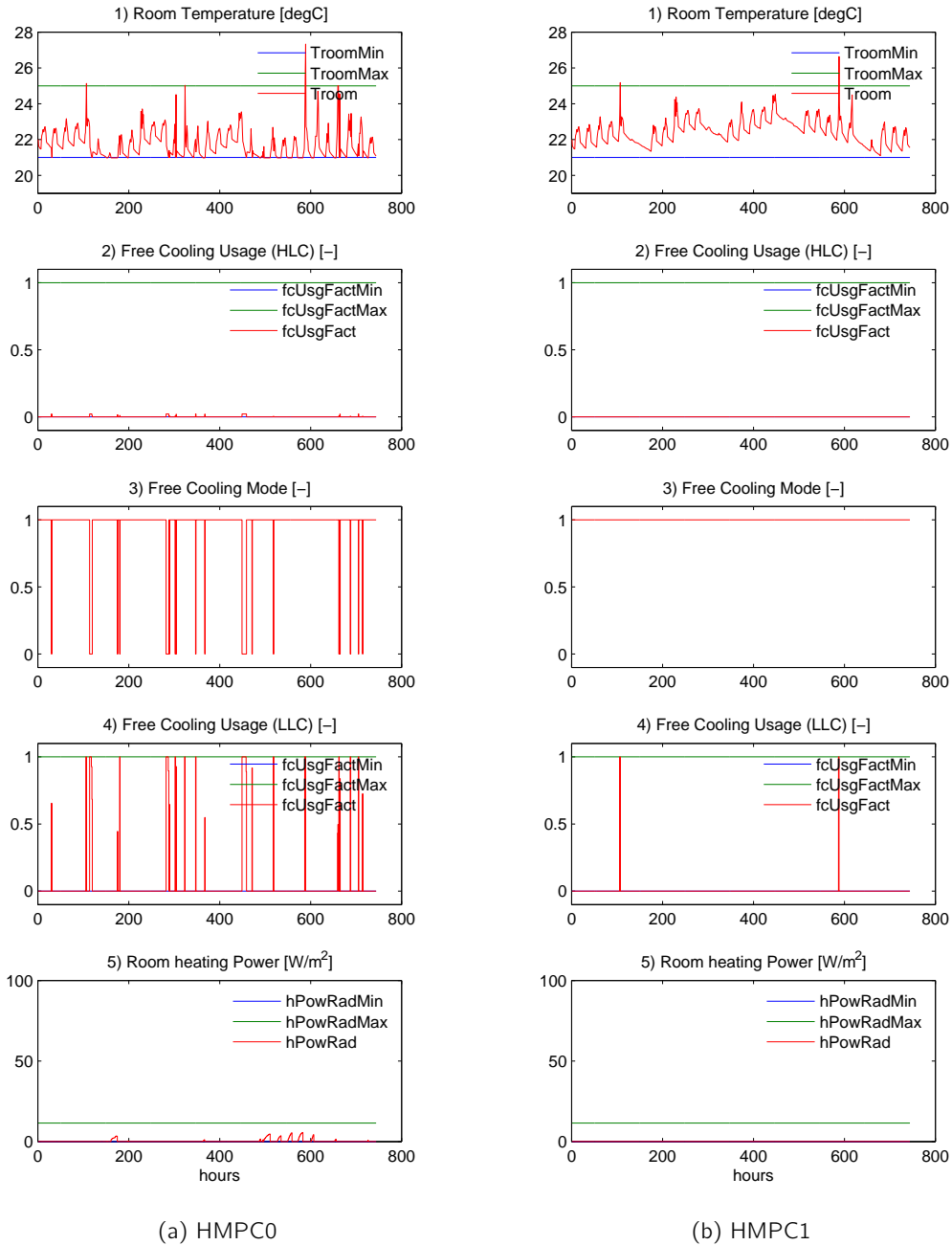


Figure 4.1: Selected signals of HMPC0 (left) and HMPC1 (right) of Case 01 with C7-predictions for January. (2) and (3) are results of the optimization done in the high-level controller. The free cooling mode (3) can be either 0=UNLOAD or 1=LOAD. (4) and (5) are control inputs determined by the low-level controller and applied to the building.

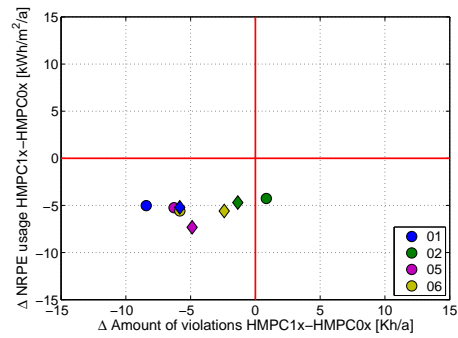


Figure 4.2: Comparison of H MPC1 and H MPC0 in terms of differences in NRPE usage versus differences in amount of violations, for all cases with free cooling, both for perfect (◇) and C7 (○) weather predictions.

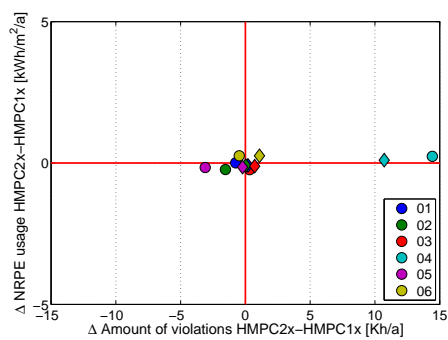


Figure 4.3: Comparison of H MPC2 and H MPC1 in terms of differences in NRPE usage versus differences in amount of violations, both for perfect (◇) and C7 (○) weather predictions.

Case	Simulation-Time (hr)	
	HMPC1	HMPC2
01	56	7
02	44	7
03	62	7
04	36	6
05	17	5
06	9	4

Table 4.4: Times to simulate one year for HMPC1 and HMPC2 with C7-predictions.

Table 4.4 shows how long it took to simulate one year for each case with HMPC1 and HMPC2. It can be seen that HMPC2 needs much less time.

4.3.2 Assessment 2 - Benchmarks

Figure 4.4 gives an overview of the results of HMPCc7 together with PB, RBC4 and CE, in terms of NRPE usage and violations.

Comparison to RBC4 and PB Figure 4.5 compares HMPC2 with C7-predictions (HMPC2c7) with the two benchmarks RBC4 and PB. The circles depicts the differences HMPC2c7-RBC4 in NRPE usage and violations, the diamonds, the ones between HMPC2c7 and PB.

First RBC4 is considered. In five of six cases HMPC2 needs less NRPE and has fewer violations than HMPC2c7 and has therefore the better performance. In the four Cases 01, 02, 05, 06, which are the cases with free cooling, the NRPE savings are about 13-20% PB usage. Case 04 needs almost the same amount of NRPE but has much less violations (-338). In Case 03, HMPC2 has almost the same amount of violations but has a higher NRPE usage by 6.5% PB usage. This case is undetermined.

Second PB is considered. It can be seen that PB needs always less NRPE and has always less violations, therefore its performance is clearly better than HMPC2c7. In the Cases 01, 04, 05, which are the passive houses, HMPC2 has an increased NPPE usage by 60-90% PB usage. In the other cases, the NPPE usage is higher by about 35% PB usage.

Influence of Weather Forecast Figure 4.6 compares the results of HMPC2 with C7-predictions (HMPC2c7), HMPC2 with perfect weather predictions (HMPC2pp), and PB. The circles depict for the six cases the differences in NRPE usage and violations between HMPC2c7 and PB, which was shown before in Figure 4.5.

The diamonds depict the differences between HMPC2pp and PB. It can be seen that in all cases HMPC2pp is nearer to PB than HMPC2c7. In the three cases 01, 02, 05, HMPC2pp gets very close to PB. Cases 01 and 05 have even less violations than PB, but need a bit more NRPE. The other three cases produce 20-40 Kh more violations and have an increase in NRPE usage by up to 39% PB usage. The furthest from PB is Case 03.

Now the position of HMPC2pp with respect to HMPC2c7 is considered. In Case 05 or Case 01, HMPC2pp loses almost nothing with respect to PB, but then HMPC2c7 loses much through the imperfect weather prediction with respect to HMPC2pp. The other extreme is Case 03, where HMPC2pp performs much worse than PB, but then the imperfect weather

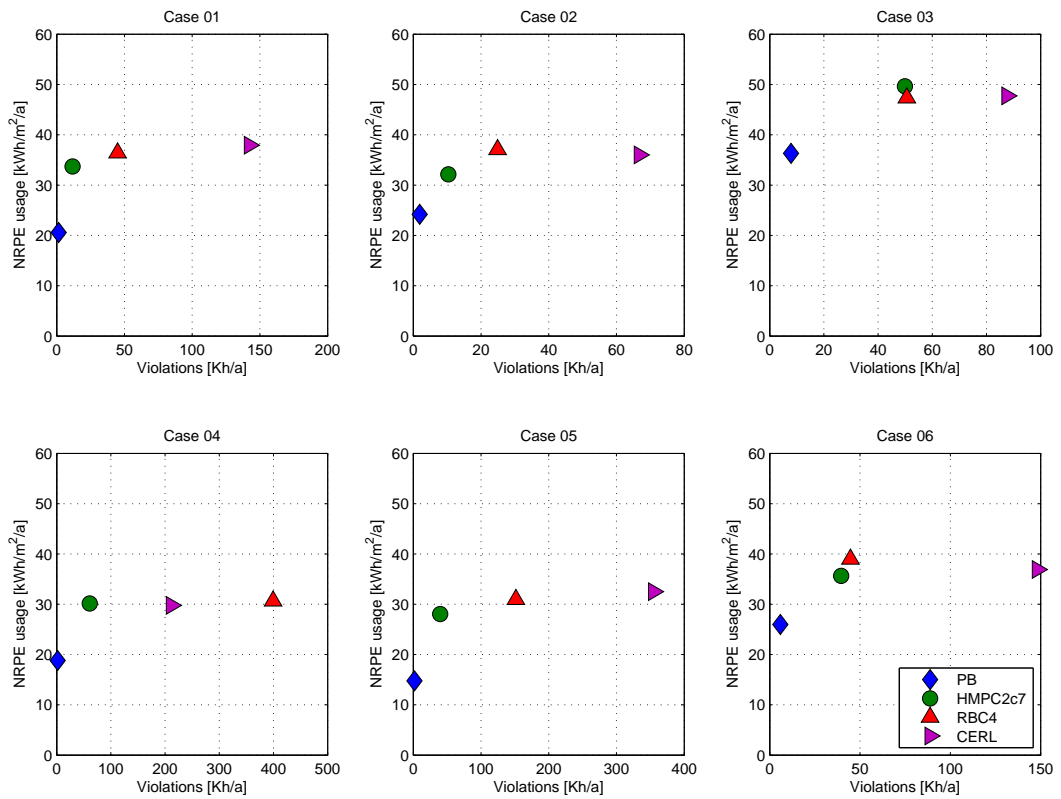


Figure 4.4: Case wise comparison of PB, HMPC2c7, RBC4 and CE in terms of NRPE usage versus amount of violations.

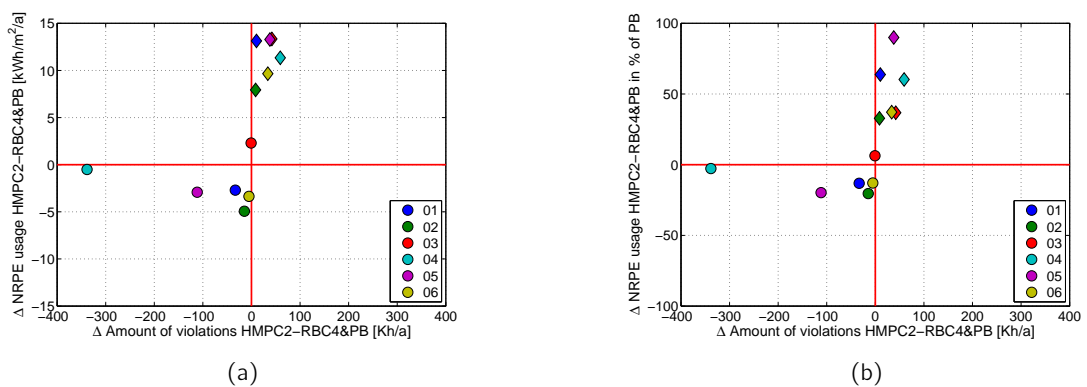


Figure 4.5: Comparison of HMPC2 with C7-predictions and RBC4 (o) as well as PB (◇), in terms of differences in NRPE usage, absolute (left) and relative to PB (right), versus differences in amount of violations.

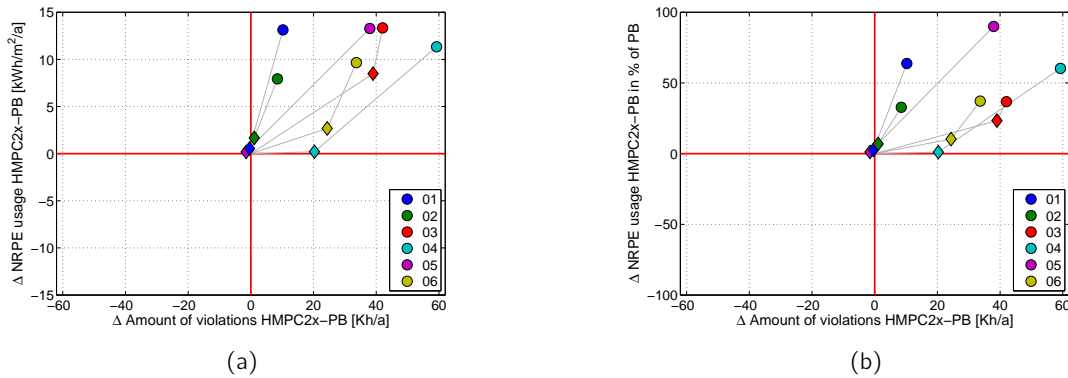


Figure 4.6: Comparison of HMPC2 with perfect weather predictions and PB (\circ), and HMPC2 with C7-predictions and PB (\diamond), in terms of differences in NRPE usage, absolute (left) and relative to PB (right), versus differences in amount of violations.

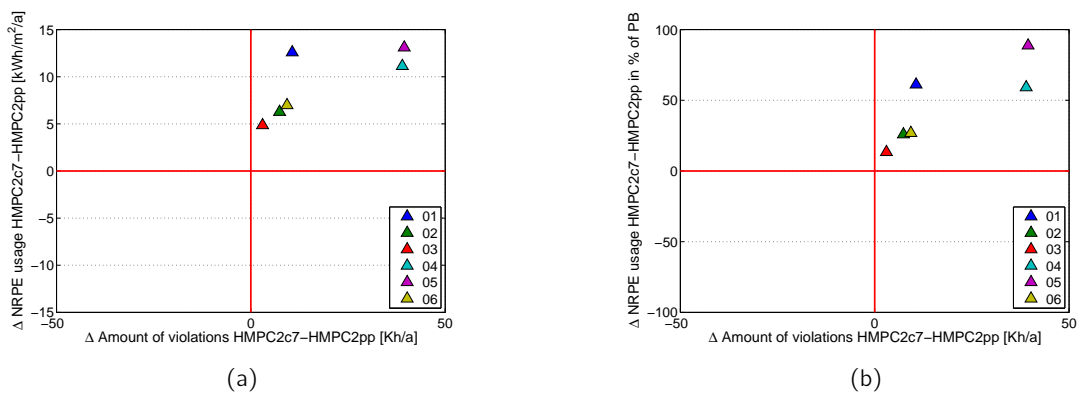


Figure 4.7: Comparison of HMPC2 with perfect weather predictions and HMPC2 with C7-predictions, in terms of differences in NRPE usage, absolute (left) and relative to PB (right), versus differences in amount of violations.

prediction does not change much.

The difference between HMPC2pp and HMPC2c7, i.e. the influence of imperfect weather predictions, is additionally separately shown in Figure 4.7. It can be seen, that the difference in NRPE usage is for the Cases 01, 04, 05, which are the passive houses, much higher than for the other three cases. For the former it is 60-90% PB usage, for the latter less than 30%. For four cases the difference in violations is less than 11 Kh, for the other two cases around 40 Kh.

Comparison to CE In Figure 4.8 the difference between HMPC2 and CE with RL2STOC (CERL) is shown in NRPE usage and violations. HMPC2 has for all cases less violations. For the Cases 01, 02, 05, 06, HMPC2 uses also less NRPE and performs therefore better. For the other two cases HMP2 needs a bit more NRPE and thus it is undetermined.

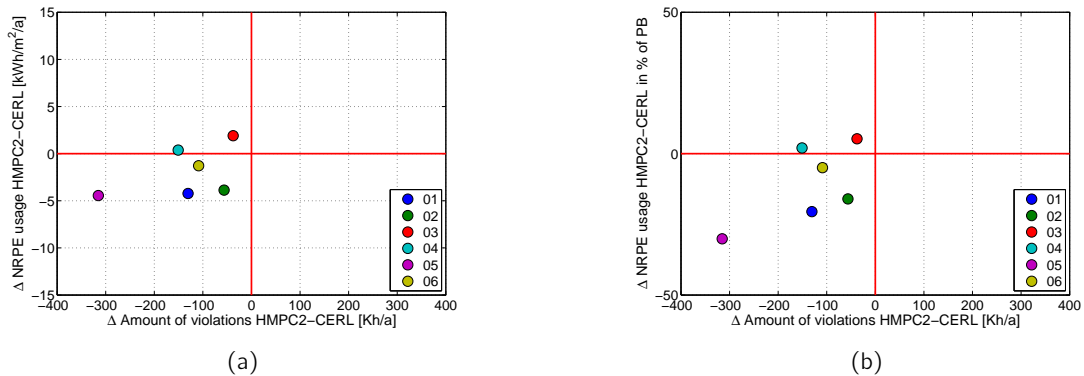


Figure 4.8: Comparison of HMPC2 with C7-predictions and CE with LLC RL2STOC (CERL), in terms of differences in NRPE usage, absolute (left) and relative to PB (right), versus differences in amount of violations.

4.3.3 Assessment 3 - MMPC

In Figure 4.9 the results of HMPC2 and MMPC and the two benchmarks PB and RBC4 are shown case wise in terms of NRPE usage and violations. Figure 4.10 shows the difference HMPC2-MMPC in NRPE usage and violations. In five of six cases, HMPC needs less NRPE and has less violations than MMPC, thus its performance is better. The NRPE usage is lower between 4 and 40% PB usage. In the Cases 01, 04, 05, which are the passive houses, the violations are much lower by 150-350 Kh. In Case 03, HMPC has an increase in PB usage by 5% PB usage, but has 14 Kh less violations. Here it is undermined.

In the initial setup HMPC2 is used with LLC MSTOC and MMPC with LLC MMSTOC. In order to check how much the result of HMPC2 depends on the LLC, HMPC2 was additionally simulated with LLC MMSTOC (HMPC2mm) and then NRPE usage and violations between HMPC2 and HMPC2mm were compared. In four of six cases, the result does not depend on the LLC. In Case 02, HMPC2mm has a higher NRPE usage of 0.6% PB usage, but has 0.6 Kh less violations. In Case 03, HMPC2mm has an increase in NRPE usage by 7% PB usage and has 0.7 Kh less violations.

4.4 Discussion

4.4.1 Assessment 1 - HMPC variants

Figure 4.2 shows that HMPC1 performs mostly better than HMPC0, or in one case at least comparable. In this latter case NRPE was saved and only a little bit more violations were caused. The reason for the better performance of HMPC1 is discussed in the following by means of the example for January for Case 01 in Figure 4.1.

In Figure 4.1a it can be seen that with HMPC0 whenever the optimal value for free cooling was greater than zero, the optimal setting for the free cooling mode was UNLOAD. If the free cooling mode is UNLOAD, this forces the use of free cooling in the LLC, what means that free cooling is likely be applied unless bounds are violated. This leads to the fact that free cooling is much more applied to the plant than originally planned in the optimization of

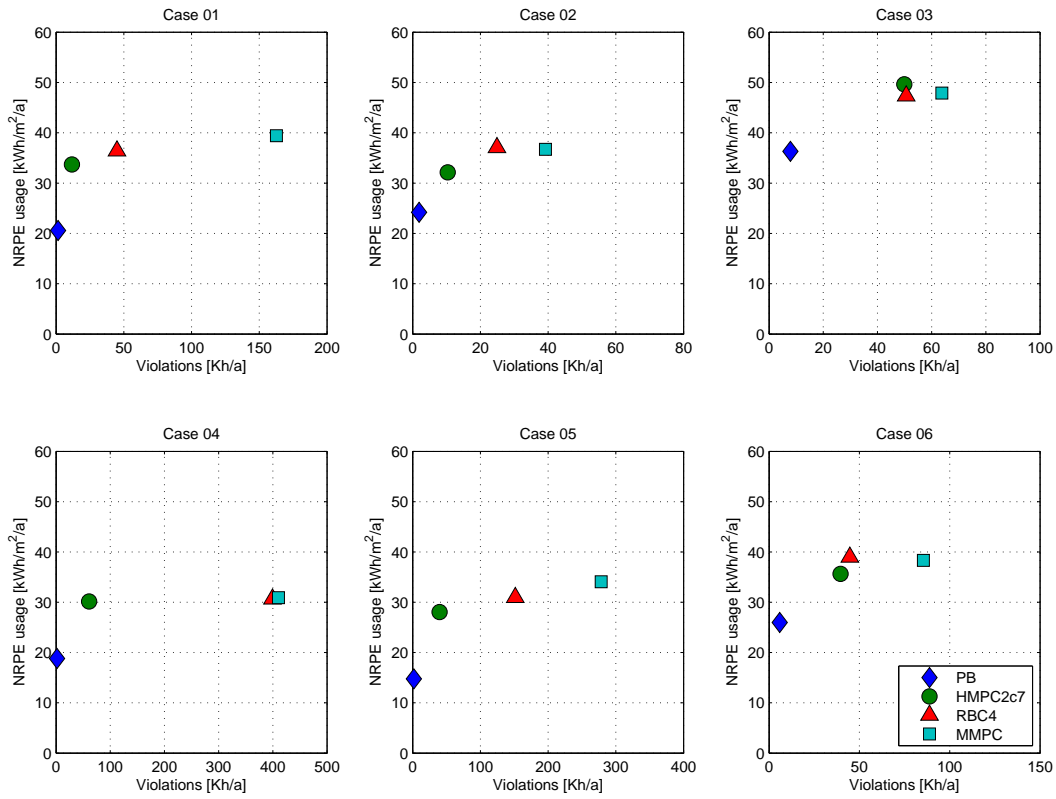


Figure 4.9: Case wise comparison of HMPC2c7 and MMPC in terms of NRPE usage versus amount of violation. As reference also PB and RBC4 is shown.

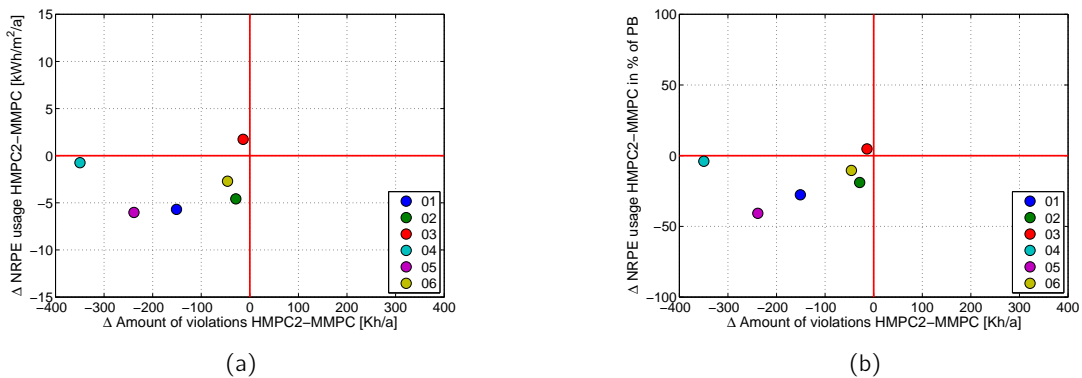


Figure 4.10: Comparison of HMPC2 and MMPC, both with C7-predictions, in terms of differences in NRPE usage, absolute (left) and relative to PB (right), versus differences in amount of violations.

HLC, and is thus too often done. The consequence is, that the room temperature is often next to the lower comfort bound and that sometimes even room heating becomes necessary.

The situation for HMPC1 seen in Figure 4.1b is different. Recall that here, the HLC free cooling plant input is restricted to be Boolean. Therefore, applying free cooling by only a small amount as in Figure 4.1a cannot happen. Now the optimal decision is always to do no free cooling and to set the free cooling mode to LOAD. With LOAD, free cooling is not forced, but it can be applied if otherwise bounds would be violated. Exactly that can be seen here. The LLC never applies free cooling except in the two cases when the room temperature exceeds the upper bound. As a consequence the room temperature is more around the middle of the comfort bound and room heating is not needed.

The advantage of HMPC1 compared to HMPC0 is thus that HMPC1 approximates the behavior of the LLC much better and can thus provide a better solution. Also the temperature profile is more favorable, because the diurnal variations are smaller.

Figure 4.3 shows that the performance of HMPC2 is in ten of twelve cases comparable or even better to those of HMPC1. At the same time, in Table 4.4 it can be seen that the time required to simulate a year is much reduced. So HMPC2 is really favorable. The exception is Case 04, where HMPC2 produces much more violations than HMPC1. This case is the only case with building system S4. In this system natural night cooling can be done, but only at night. Perhaps because of this additional schedule, the horizon of six hours for the complexer model with modes is too small. This should be further investigated. However as seen in Figure 4.5, RBC4 has for this case 338 Kh more violations than HMPC2. Compared with that, the loss due to the approximation is very small.

4.4.2 Assessment 2 - Benchmarks

Figure 4.5 shows that HMPC2c7 outperforms RBC4 in five of six cases, with the exception of the undetermined Case 03, which seems to be special as described below. Recall that HMPC2 and RBC4 use exactly the same LLC, whereby the HLCs can directly be compared. That means that in these cases the modes produced by HMPC are better than the modes produced by RBC4. That shows using weather predictions combined with considering the LLC in the HLC is beneficial.

In the half of the cases HMPCpp gets very close to PB. This is remarkable because HMPC2 has only a horizon of 24 hours whereas PB optimizes over 144 hours.

In Figure 4.7 it can be seen, that with HMPC2 the passive houses are much more sensitive to uncertainties in weather predictions than the swiss average houses. A possible reason could be the fact that the passive houses have high window area fraction. With large windows the difference between open and closed blinds is much bigger. A non ideal blind positioning due to bad solar gain prediction has then much more influence.

From Figures 4.6 and 4.7 it can be seen, that better weather predictions would likely improve the performance of HMPC2 significantly. Therefore, improved weather prediction methods, such as the local Kalman filter proposed in [7], should be investigated in the future.

HMPC2 for Case 03 behaves very different compared to the other cases: (i) For this case it is not determined whether HMPC2c7 performs better with respect to RBC4 (Fig. 4.5) or CE (Fig. 4.8) or MMPC (Fig. 4.10); (ii) here HMPC2pp is only a bit better than HMPC2c7 (Fig.4.7) and the difference to PB remains large (Fig. 4.6); (iii) it is the case with the biggest

difference when changing the LLC from MSTOC to MMSTOC (Sec. 4.3.3). Maybe this is caused by the setup of Case 03. This is the only case with building system S3. In this system heating and cooling can only be provided by ventilation. The other building systems have a separate aggregate for the low-cost cooling. Here, the aggregate which does this only at night, has another job during daytime. In addition, it is coupled to ERC, the other mode-based aggregate of this system, what leads to the complexest HYSDEL-Model. To explore this situation in detail, further investigations are needed.

In Figure 4.8 it can be seen that CE has often much more violations than HMPC2c7, and from Figure 4.4, that in five of six cases CE has two times till five times more violations than allowed. This is probably due to the fact, that CE has a very simple LLC, which only acts when violations will occur, and which in such a case completely discard the HLC input. In this context the tuning aspect described in [7] should be considered. That allows to reduce the violations on the price of higher NRPE usage. Therewith it will be possible to decide which controller performs better in situations as in Figure 4.8 where for two cases it is not determined a priori.

4.4.3 Assessment 3 - MMPC

The results of Section 4.3.3 shows, that the combinations HMPC2c7 with MSTOC or MMSTOC, perform and behave in five of six cases identical or very similar. That suggests that in these cases the thresholds in MSTOC do not get active or only a little bit, and that therefore these thresholds are already sufficient considered in the HLC despite the fact that the predictions are uncertain. But what cannot be said with this result is whether this considering of such thresholds in the HLC is necessary or not. The single exception is Case 03 as already mentioned before. Here the disturbances seem to have a bigger influence. Finally with this result it can be said that it is fair to compare HMPC2c7 with MSTOC against MMPC with MMSTOC.

In Figure 4.10 it can be seen, that MMPC has in each case more violations and especially for passive houses much more. This could indicate a non ideal blind positioning. Recall that here the RBM version of MMPC is used, in which the blind position is directly taken from the underlying CE-MPC controller. In contrast to HMPC, CE-MPC does not know about the LLC. Also it takes the weather prediction to be certain. Furthermore it seems to be that the blind position in HMPC is more conservative what could make it more robust against solar gain uncertainties. To come up with that solution HMPC has to solve a complexer problem and needs more computational effort than MMPC, on the other hand no rule-tuning is necessary.

4.5 Conclusions

With HMPC1 the performance for the building systems with free cooling is improved with respect to HMPC0. The main advantage is, that the behavior of the low-level controller is much better approximated in the HLC.

HMPC2 provides a good approximation of HMPC1. The computational complexity is much reduced, the simulations need much less time and the obtained performance is in most cases comparable or even better than HMPC1. For these reasons this controller is favorable and therefore it is used in the remaining comparisons.

In most investigated cases, HMPC2c7 performs better than RBC4, MMPC and CE. This implies that the potential of weather forecasts can be beneficially used when the HLC formulation accounts for the LLC.

An improvement of the weather predictions could significantly improve the performance of HMPC2c7 towards PB, because with perfect predictions the half of the cases get very close to PB.

To enhance the discussion, more cases should be examined. In particular building system 3 should be further investigated, because Case 03 behaved different from the others.

5 Remodeling of Low-level Controller

In reality, the low-level room temperature control is typically done with sequenced PI controllers [15]. If the upper thermal comfort bound is violated, cooling aggregates are used in a predefined sequence to bring the temperature again down to this bound. If the lower bound is violated, heating aggregates are used in a predefined sequence to bring the temperature again up to this bound.

The idea was now to implement such a PI-controller cascade into BACLab, and then to compare in future investigations the achieved performance of this controller with the one of the ideal low-level controller MSTOC used so far within OptiControl.

To start with, the simplest building system S1 is considered. This system is equipped with radiators for active heating, with a cooled ceiling for active cooling, and with free cooling; furthermore blinds and electric light are present (see Table 2.1). Because in reality continuous blind control is not applicable, the blind movement is restricted to once at the beginning of each hour, exactly as done in RBC4 and HMPC.

Together with experts from Siemens the following design for the new low-level controller was specified: The blind position is taken from the high-level controller and directly applied to the plant. For electric light correction the EL controller from the other strategies is used. Active heating is controlled by a single PI-controller for the radiator. This controller is always active. Cooling is controlled by a sequence of two PI-controllers. The first one is the one for the free cooling. It is always active but has two different temperature setpoints depending on the operating mode. If the free cooling operating mode is LOAD, the setpoint is the upper temperature comfort range bound; if the free cooling operating mode is UNLOAD, the setpoint is one Kelvin above the lower temperature comfort range bound. The second PI-controller is the one for the active cooling with cooled ceilings. Its setpoint is the upper temperature comfort bound. It is only active if free cooling is fully used and more cooling power is needed. The outputsignals of the PI-Controllers are saturated by the input bounds and then applied to the plant. The PI constants for active heating and cooling are chosen according to the common values in [11]. For the free cooling PI-controller the same values as for active cooling are chosen.

In a first step the controller was implemented as a continuous version in SIMULINK. BACLab works with a discrete time system. It provides the possibility to use different sampling times for HLC and LLC, where the plant has the same one as the LLC. Weather data is in different forms available and is then complex prepared to fit into the discrete model with the chosen time step. Cost and performance evaluation is also based on discrete time steps. To fit into that given framework and to allow meaningful comparisons, it was necessary to implement a discretized version of the controller. This controller is referred to as MPIC, which stands for modebased PI-Cascade.

In future works the following should be investigated:

- Validation of the discrete model with the continuous SIMULINK model
- Comparison of MPIC and MSTOC
- Comparison of HLC strategies when using the two different LLCs

6 Conclusion and Outlook

6.1 Conclusion

A new MPC-controller, providing directly the operating modes needed as input to the LLC of a current hierarchical BAC system, and based on a new HYSDEL model which accounts both for the building and for the LLC, was successfully designed, implemented and tested.

In the investigated cases, the new controller performs mostly better than RBC4, MMPC and CE. This implies that weather forecast together with accounting for the LLC in the HLC has an added value.

For the systems with free cooling the performance was improved by considering in the HLC a better approximation of the LLC behavior.

The conducted approximation of the MPC-formulation reduced the computational effort significantly while keeping the performance, which makes the controller applicable and allows to do large-scale studies in the future.

For one building system, the ideal low-level controller was remodeled according to real implementations. Therewith the ideal low-level controller can be assessed in the future.

6.2 Outlook

In future work the following could be investigated:

- To get in-depth informations about the influence of several parameters or especially about building system S3, more cases should be considered
- A similar reformulation as for free cooling could perhaps also be beneficial for the other low-cost cooling subsystems
- To improve the weather predictions and to possibly improve the performance, the local Kalman filter should be implemented
- The influence of varying the prediction horizon for the HYSDEL-model, or also of varying the overall prediction horizon could be investigated
- The remodeled low-level controller needs to be verified and to be compared to the ideal controller used so far; then this remodeling should also be done for the other building systems

A Abbreviations

Abbreviations	Description
BAC	Building Automation and Control
C7	COSMO-7
CE	Certainty Equivalence
ERC	Energy Recovery
HLC	High-level Controller
HVAC	Heating, Ventilation, Air Conditioning
IRA	Integrated Room Automation
LLC	Low-level Controller
MPC	Model Predictive Control
NRPE	Non-Renewable Primary Energy
PB	Performance Bound
RBC	Rule-Based Control

Table A.1: Abbreviations

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