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Embedding Predictive Control in Hierarchical Integrated Room Automation Systems (Part 1/2)

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Semester Thesis
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Abstract

This thesis was written in the framework of the OptiControl project[1], whose main goal is to assess the benefit of using weather and occupancy forecasts for building climate control.

The tasks of this thesis were to (i) further develop the existing model predictive control (MPC) strategies for the integrated room automation (IRA) such that they are suitable for the use in practical application, (ii) to design new predictive rule-based control (P-RBC) strategies for the IRA and (iii) to assess these strategies by comparison, e. g., to the performance bound (PB) or reference strategies.

Present-day building automation and control (BAC) systems are realized by a hierarchical control structure with so-called high-level (HLC) and low-level controllers (LLC). Communication between the controllers is based on operation modes (OMs). For that reason an interface was designed which translates the output of a MPC algorithm by rules into OMs. Ideal OM-based low-level control was assumed.

The design of the translation rules was done in an iterative procedure: An initial set of rules was defined and then assessed by simulations. The performance of the new OM-based controller (MMPC) could be measured by comparing it to the original algorithm (CE-MPC). The additional comparison to a rule-based control (RBC) algorithm gave a measure for the potential loss. The main result of the iterative procedure was a set of translation rules as part of the new (high-level) controller MMPC.

Simulations showed that for cases without restrictions on blind movement and with unlimited power for "high-cost" actions the presented set of rules translates the output of MPC to OMs with little cost increase compared to the performance bound (PB). The potential loss of MMPC compared to PB resulting from the translation is negligible. This result allows MPC to fit into a conventional BAC setup.

Further investigations were executed in order to assess the robustness of these rules. The translation rules proved to be robust against perturbed weather predictions. However, the performance of the rules depends on how the building parameters are chosen: It was found that in some cases MMPC performs even better with perturbed parameters than with perfect knowledge, whereas in some cases the performance is worse.

In case of power limitations for "high-cost" actions and restrictions on blind movement MMPC performs better than CE-MPC in terms of violations but worse in terms of costs. This is because the translation to OMs avoids a part of the violations caused by the MPC algorithm. This aligns with the above results: The translation to OMs adds robustness to the system, however, it also increases the costs.

Approaches for the design of P-RBC strategies are discussed. The presented ideas can easily be assessed with the existing resources.

While tasks (i) and (iii) were treated in-depth in this thesis, task (ii) needs to be further explored in order to provide significant results and conclusions.

[1] www.opticontrol.ethz.ch

Contents

1 Introduction

1.1 Motivation & Tasks

This thesis was written in the framework of the OptiControl project[2], whose main goal is to assess the benefit of using weather and occupancy forecasts for building climate control. The current status of the project can be seen in the Two-Years Report [10].

The aim of this thesis is to (i) further develop the model predictive control (MPC) strategies for the integrated room automation (IRA) such that they are suitable for the use in practical application, (ii) to design new predictive, rule-based control (P-RBC) strategies for the IRA and (iii) to assess these strategies by comparison, e. g., to the performance bound (PB) or reference strategies.

Both control approaches (i) and (ii) are worth to be explored out of the following reasons: Control approach (ii) has the advantage, that rule-based strategies are well known in practice. If predictions are added, nothing changes in principle for the service engineers and facility managers who have to deal with these systems every day. The developed strategies could therefore easily be brought to market. Control approach (i) has the potential of outperforming every other control strategy. However, first the development of such a strategy is much more involved and second the market has to be prepared to cope with this new approach.

The control strategies designed in this thesis should fit into a conventional building automation and control (BAC) system (e. g., [12]). Hence, it is important that they (a) fulfill the requirements for building automation control strategies (see [1]) and (b) have a hierarchical control structure. The communication among the different hierarchies shall be organized by operating modes (OMs).

This thesis is settled between phase II. and phase III. The enhancement of the control strategies developed in phase I. and II. , such that they can be included into existing building automation control, is a prerequisite for phase III. , where the goal is to demonstrate control strategies on a real object. The treated control applications were proposed by Siemens Building Technologies (BT). They do many investigations in developing and designing new IRA control systems.

1.2 Alignment of OptiControl and Building Automation Control System Development of Siemens

Siemens BT is constantly developing their building automation (BA) systems to further improve them and in order to comply with new market requirements. In recent years, a market trend started in BA towards flexible and integrated (instead of autonomous) control of HVAC, lighting and blinds. Integrated control can mean that the same hardware is used for multiple control tasks, however, the different control tasks can still be separated. While integration

[2] www.opticontrol.ethz.ch, The OptiControl project involves ETH Zurich, Building Technologies Laboratory, Empa Dübendorf, the Federal Office of Meteorology and Climatology, MeteoSwiss, Zurich and Building Technologies Division, Siemens Switzerland Ltd, Zug.

into a common can already be beneficial, the coupling of the control tasks can provide even more benefit: E. g., by coordinating the HVAC and blind control for heating/cooling purposes.

To meet this market trend and future market requirements, Siemens BT is currently focusing its automation system development on the integrated room control. Besides the "technical" integration (hardware, communication, etc.), new intelligent (control) applications for the integrated control are looked for.

1.3 Structure of the Thesis

The thesis is structured as follows:

- Chapter 2 presents the achievements of the OptiControl project which provide a basis for this thesis.
- Chapter 3 deals with the design procedure of the new controllers.
- Chapter 4 provides all information about the used weather data set and experiments sets and contains explanations about the simulation setups chosen for the assessment in this thesis.
- In Chapter 5 all results of this thesis are presented.
- In Chapter 6 all achieved results are discussed.
- Chapter 7 and 8 conclude the thesis and give an outlook on unsolved tasks.

2 Fundamentals

2.1 Integrated Room Automation

"The Integrated Room Automation (IRA) application deals with the automated control of blinds, electric lighting, heating, cooling, and ventilation of an individual building zone or room."[1] Today, BAC systems for IRA are typically realized by a hierarchical control structure with so-called high-level (HLC) and low-level controllers (LLC).

Each LLC is designed such that it is able to solve its control task autonomously. Optionally, it is able to receive certain parameters, set points or OMs from a HLC, such that it can be embedded into an IRA. In return it delivers measurements (e. g. room temperatures), heat/cold demand etc. to the HLC.

The task of the HLC is to coordinate LLC actions. This is typically done with a rule-based approach. The HLC determines a set of OMs that are sent to the LLC. The potential of

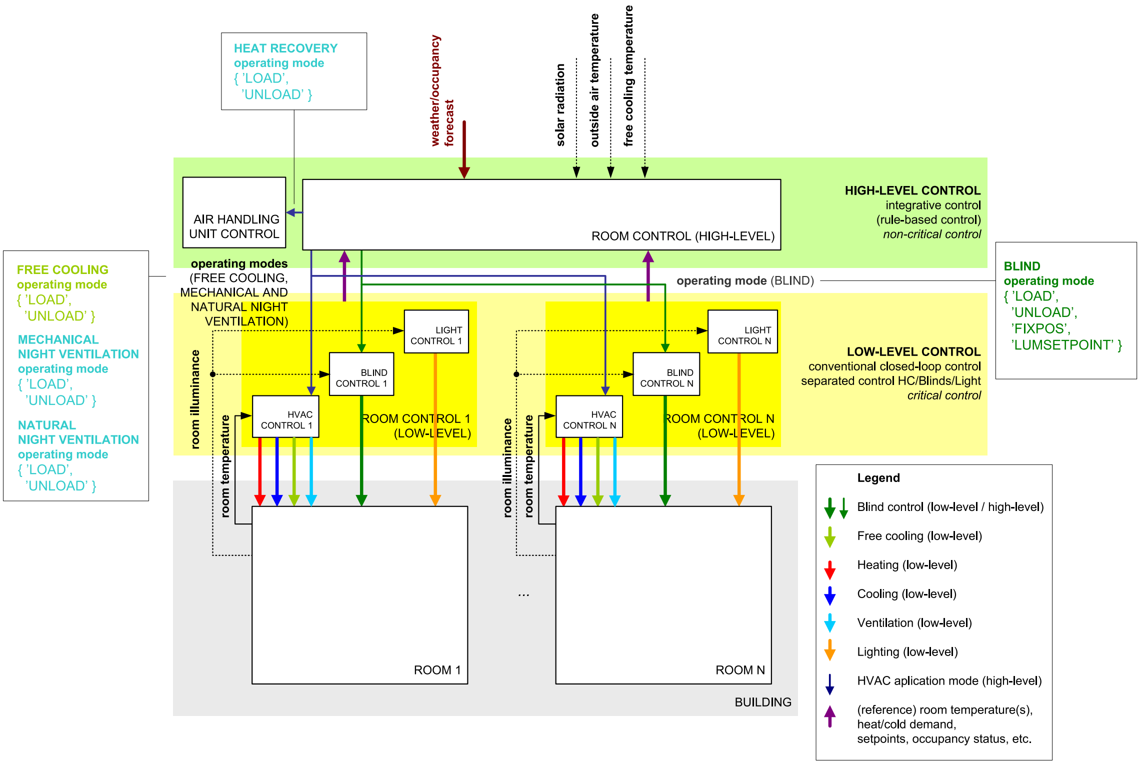

Figure 1: Reproduced from [2]. Schematic representation of present-day IRA control solutions. Note, only a subset of all signals is displayed. Typically the control for light, blinds and HVAC is seperated. Hence, three LLC are installed for each room. HLC is done centralized and typically controls tasks like ventilation and free cooling.

controlling IRA systems lies in coordinating the LLC actions such that occupant comfort is maintained at minimum energetic or monetary cost while at the same time disturbances related to, e. g., weather, internal gains, and occupant behavior are rejected. To exploit the potential a good management of the so-called "low-cost" actions (blind movement, free cooling usage, mechanical night-time ventilation, natural night-time ventilation and energy recovery operation) is mandatory. (The remaining control inputs such as heating and cooling are referred to as "high-cost" actions.)

The model-predictive HLCs developed within OptiControl cope exactly with the task above. Given, that the entire system is known to the controller (this includes, that all LLCs are accessible for the HLC), MPC allows for computing of the minimum energetic or monetary cost and the associated control signal. (For further descriptions on MPC see [4].)

However, some basic difficulties occur in practice: (i) LLC devices can be delivered from different companies which complicates integration, (ii) in most of today's buildings only a subset of all LLCs are integrated into one HLC,i. e., there exist multiple HLC in one building which do not communicate, (iii) each building has different properties and BAC systems which calls for individual control solutions, etc.

Furthermore, some difficulties concerning MPC arise: (i) The outputs computed by the MPC algorithm have to be manipulated variables in the real system. The strategies implemented so far have some outputs which cannot be directly regulated (e. g., power as output), (ii) the outputs of MPC should be in form which existing LLCs can deal with, e. g., OMs.

2.2 Control Strategies Designed in Phase I. and II. of the OptiControl Project

In the OptiControl project a series of control strategies have been implemented. The implemented controllers which are relevant in this thesis are introduced and their purposes discussed.

2.2.1 High Level Control

High-level controllers (HLCs) fall into the two classes of rule based controllers (RBC) and model predictive controllers (MPC). To estimate the potential of these controllers, the performance bound (PB) can be taken as a benchmark.

Rule Based Strategies Table 1 gives an overview of investigated rule-based control strategies. All RBC strategies output OMs.

Strategy	*Description*
RBC-1	Typical, broadly applied strategy
RBC-2	As RBC-1, but more freedom in blind movement
RBC-3	Novel strategy, newly elaborated within the OptiControl project
RBC-4	As RBC-3, but with restricted blind movement

Table 1: Reproduced from [3]: Overview of investigated rule-based control strategies.

RBC-1 is a broadly applied control strategy. It determines OMs for all "low-cost" actions, the other actions are determined directly by the LLC.

RBC-2 "This strategy deviates from the first only in one case: When the room is occupied and high solar gains are present, [...]the blinds are used to control the (lower) luminance set point. In practice, this strategy is not applied, it was considered only for comparison with the MPC controllers which were allowed to control the room luminance by the blinds."[3]

RBC-3 presents one of the most advanced RBC approaches with the greatest performance among all RBC strategies implemented in OptiControl (see [7]). One of its major qualities is, that it needs only very few control parameters, which is crucial when implementing a strategy in a real-world application. However, in practice, this strategy is not applied out of the same reason as RBC-2: instantaneous blind movement would not be accepted by the end user and therefore is not possible in reality.

RBC-4 is identical to RBC-3 except in one point: The blind movement is restricted. At the beginning of each time step the (constant) blind position during the next time step is determined. To determine the optimal blind position, the weather would have to be known for the next time step. However, RBC-4 uses data from the last hour as an approximation. Due to the restrictions the performance of RBC-4 compared to RBC-3 is worse. In return, the strategy is applicable in practice which, however, is not the case to date.

Strategy	*Description*
PB	Performance Bound: Ideal MPC with perfect information (including weather predictions)
CE	Certainty Equivalence MPC: MPC with realistic weather predictions

Table 2: Reproduced from [4]. Overview of investigated model-predictive strategies.

Model Predictive Strategies

Certainty Equivalence MPC (CE-MPC) calculates a control sequence which minimizes an energetic or monetary cost function with respect to a model of the building dynamics and user constraints. The horizon T_H of the optimization problem and assumptions on disturbances (e. g., weather, internal gains) during T_H have to be specified. The output of CE-MPC is called the optimal output for a given control problem. The full description of CE-MPC can be found in [4].

CE-MPC24, CE-MPC48 are CE-MPCs with a specific horizon T_H. In CE-MPC24 $T_H = 24h$ was chosen, in CE-MPC48 $T_H = 48h$ was chosen.

Performance Bound For the determination of the performance bound (PB) the CE-MPC routine was used with a special configuration: All disturbances and model parameters were assumed to be exactly known (perfect information case), i. e., instead of using weather forecasts, the real weather measurements were used; instead of using assumptions of the building parameters, the real building parameters were used, etc. As a consequence, "the plan must not be computed in a receding horizon fashion, since no feedback is required, but the optimal sequence for the entire interval considered (e. g., one year) can in principle be computed in one shot. However, due to the presence of a bilinear model this was actually found to be impracticable"[4], such that a modified procedure was employed with an open-loop computation interval $T_{OL} = 48h$ and horizon $T_H = 144h$ (see [7]).

PB24, PB48 are modifications of the PB calculation: $T_{OL} = 1h$ and $T_H = 24h$ and $48h$, respectively, were chosen.

2.2.2 Low Level Control

Low Level Controllers (LLCs) fall into the two classes of OM-based controllers and non OM-based controllers. OM-based LLCs receive OMs from the HLC, which are interpreted based on the current state of the system, the disturbances etc. Non OM-based LLCs receive a set of numerical control values which are in principle bypassed to the room automation. These LLCs only intervene if constraints are violated.

OM-based Low-Level Control

L2STOC STOC stands for Short Term Optimal Control, L2 stands for the second version of the artificial light correction (ALC; see [7]). This controller receives numerical control values from the HLC. It reproduces the behavior of an ideal low-level room controller. However, to achieve this ideality, it does not approximate the behavior of a real PI-sequence controller or a combination of hysteresis controllers (which is how present-day LLCs work, see, e. g., [12]), but is implemented as follows:

1. It first checks if the output of the HLC violates the constraints during the next hour.
2. If no violations take place, this step is skipped.
   If there are violations present, L2STOC drops output suggested by the HLC completely and calculates a new one. This is done by running a one step optimizer (PB with $T_H = T_S$ (sampling time, generally $1h$)). Unlike the HLC, the model parameters and the disturbances of the next hour are exactly known by the L2STOC. This ensures that the new signal does not violate the constraints.
3. At last, artificial light is corrected.

RL2STOC behaves the same way as L2STOC does, except that the blinds movement is restricted to the beginning of every time step.

Non OM-based Low-Level Control

MSTOC stands for Short Term Optimal Control based on OMs. This LLC receives OMs for all "low-cost" actions from the HLC. A one step optimizer (PB with $T_H = T_S$) calculates numerical values for both, "high-cost" and "low-cost" actions, which are applied to the BA. To bias the output according to the information provided by the OMs, first the weighting costs of the low cost actions are adjusted or their constraints narrowed. Thereby the information provided by the HLC is integrated to the behavior of the LLC.

Like the L2STOC, the MSTOC knows the model parameters and the disturbances of the next hour perfectly. This ensures that the new signal does not violate the constraints.

At last the artificial light is corrected.

2.2.3 Possible Combinations of High-Level and Low-Level Controllers at the End of Phase II.

At the end of phase II. the following combinations of HLCs and LLCs were possible: (i) All model-predictive HLCs could be combined non OM-based LLCs and (ii) all rule-based HLCs could be combined with OM-based LLCs.

It was not possible to combine model-predictive HLCs with OM-based LLCs, because an interface was missing which translates output signals of the MPC into OMs.

2.3 Building Model

In this section the model of the building is introduced. The model is a bilinear thermal Resistance-Capacitance (RC) network and was used for all simulations. Figures 2 and 3 give an overview of the model's components and introduce the abbreviations used.

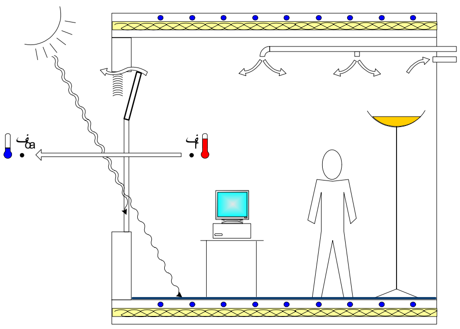

Figure 2: Reproduced from [5]. Overview and abbreviations of subsystems considered for modeling.

- Floor heating (hPowSlab)
- TABS: Thermally activated building system for heating (hPowSlab) and cooling (cPowSlab)
- Slow ceiling for cooling (cPowSlab)
- Free cooling with wet cooling tower (fcUsgFact) acting through cooled ceiling or TABS
- Radiator (hPowRad)
- Mechanical ventilation with energy recovery (nMevE, nMev0), heating (hPowMev) and cooling (cPowMev)
- Hybrid ventilation: working hours (nMevE, nMev0) - non working hours (nNav)
- Blinds (bPos)
- Artificial lighting (eLighting)
- Indoor air quality (CO_2)

"Note, for illustration both Figures contain all subsystems that occur in Building System variants S1 to S5. A separate representation for each of the 5 subsystem variants considered

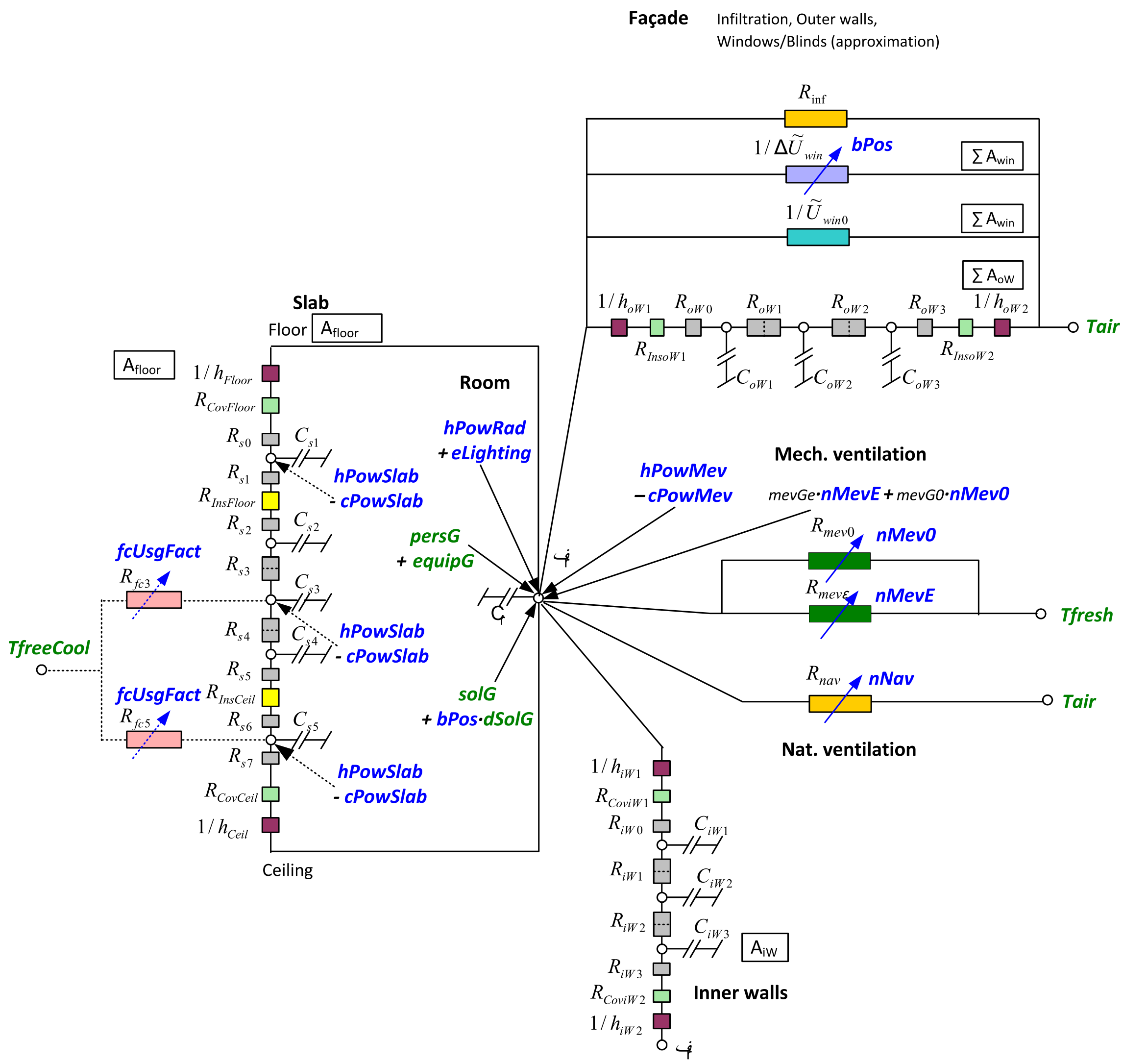

Figure 3: Reproduced from [5]. Thermal Resistance-Capacitance (RC) network model. Note, for illustration all supported subsystems are shown simultaneously.

within OptiControl can be found in [9]"[5]. Note, that in such a model power flows are added and subtracted at each node and that the state of each node is proportional to the energy accumulated over time.

2.4 Simulation Environment BACLab

All simulations were done on the basis of BACLab software version 1.2. This software includes the model of the building described in 2.3 and a hierarchical control structure with 2 levels. For ruther details on BACLab see [6].

The LLCs L2STOC and RL2STOC (see below) were developed and added to this version.

The weather and occupancy data were those from the OptiControl occupancy and weather database OCWDB v1.7. The building and building systems parameters were downloaded from the database BuSyDB v2.4. It was necessary to limit the upper bound of $nMev0$ while leaving everything else unchanged (see 4.2.2). Because this is not a standard case, the simulations had to be run offline.

3 Controller Design

In this chapter the controllers designed in this thesis are introduced. All abbreviations and function names used in the following are listed in A.1.

3.1 Design of an Model Predictive Controller which Outputs Operating Modes

The designed controller is referred to as MMPC. It consists of two functions: The first function, *bac_DoMPC*, is identical to the CE-MPC formulation. It calls the MPC algorithm which calculates the optimal control signal with respect to the actual state and the constraints. Instead of returning the control signal to the main program, it is sent to the function called *bac_CreateModes*, which translates the "low-cost" control actions into OMs. The high-cost control actions remain unchanged. Finally the OMs for the "low-cost" actions are sent to the LLC. The numerical values for the high-cost actions are rejected.

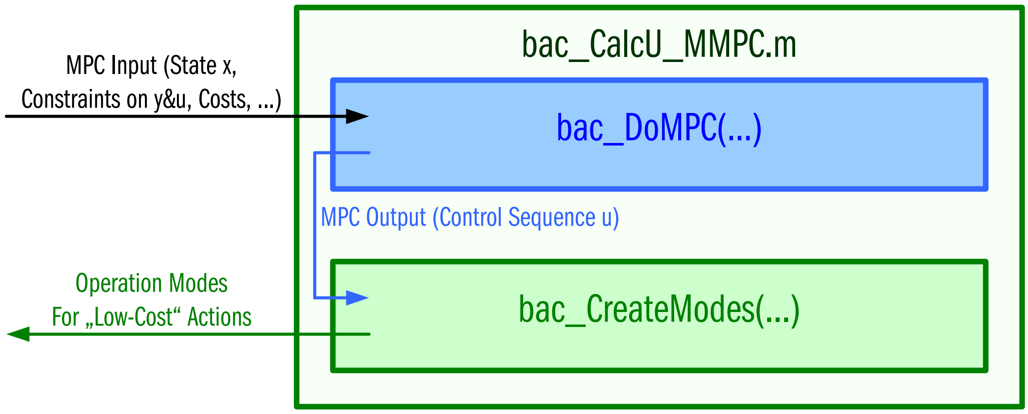

Figure 4: Structure of the MMPC

3.1.1 General Design Procedure

Overview First a simple set of threshold rules was proposed for the translation. Second, a dataset was chosen and simulation runs were done using these rules. In a third step, the yearly cost of the MMPC was compared to other strategies. Cost is defined here as usage of non-renewable primary energy (NRPE) per square meter. Also, the cost of each device was analyzed. From these investigations conclusions were drawn and the translation rules were adjusted. This procedure was iterated until the cost of the new controller was satisfyingly low. The design procedure is explained in detail below.

Experiment Set For the experiments set used for the design there were three main requirements: (i) the set should contain only a few cases,(ii) these cases should be very common cases and (iii) the cases should potentially have a big difference in cost for rule-based and model-predictive control. These conditions should ensure, that (i) the simulation time is limited, (ii) if the tuned rules would turn out to be biased, they would be biased for a great percentage of the real world buildings and were therefore still applicable very broadly, (iii) the analyzed cases are potentially interesting to control with a model-predictive based control algorithm. Out of these reasons the experiment set E1 was used.

Simulation Setup Goal of the simulation runs is to compute the costs of each control strategy such that a fair comparison is possible. Therefore SS1 was chosen.

Analysis Procedure The cost is a measure for the performance of a control strategy. For that reason the yearly costs of the system as a whole and for each device were compared amongst the simulated controllers for each case in set E1.

The translation of the output signal of bac_DoMPC to OMs in $bac\_CreateModes$ and the reverse translation in the MMSTOC should only increase the yearly costs little compared to the PB48. Little was defined as Δc, the difference of the yearly costs of RBC-3 and PB48. Δc specifies the saving potential of a model-predictive controller compared to a rule-based controller.

PB48 and RBC-3 were used as benchmarks. As long as the translation rules of the MMPC lead to higher energy consumption than RBC-3 in more than 20% of all cases the rules were further improved.

3.1.2 The Design of the Rules for the Energy Recovery Operation

The design of rules for the energy recovery operation turned out to be more involved. The following section leads through the development of the final set of rules, which can be found in the results section. All abbreviations and variables used here are identical to the ones used in BACLab and can be found in A.1 and A.2.

Note, that MMSTOC interprets the incoming modes as follows: In cases 'LOAD' and 'UNLOAD' the BAC system is forced to use energy recovery as much or as little as possible, depending on the outside air temperature. 'FIXUSAGE' adopts the suggested value of the HLC. For further details see [3].

For energy recovery operation, three cases could be distinguished: (i) $Tfresh > Troom$, (ii) $Tin_{min} < Tfresh \leq Troom$ and (iii) $Tfresh \leq Tin_{min}$. Because for all three cases the same rules resulted, only case (i) is discussed in detail. The following figure sketches the ventilation system behavior in the case (i). (Sketches of the cases (ii) and (iii) can be found in B.

Recall, that power is added up at each node of the system 2.3. The amount of power transferred to the room node by the ventilation system, $Pin = hPowMev - cPowMe$v, is proportional to the air change rate $nMev$ times the difference of room and inlet temperature $Troom$ and Tin, respectively. Tin is lower and upper bounded by Tin_min and Tin_max due to comfort requirements. $nMev$ is lower bounded. In case $nMev$ is also upper bounded, Pin is limited. If only the mechanical ventilation system is used to heat or cool the room, the achievable inlet temperature range is limited by Troom and Tfresh and additionally due to the ERC efficiency ε_{ERC} which is smaller than 100%. This range is marked by the red dotted

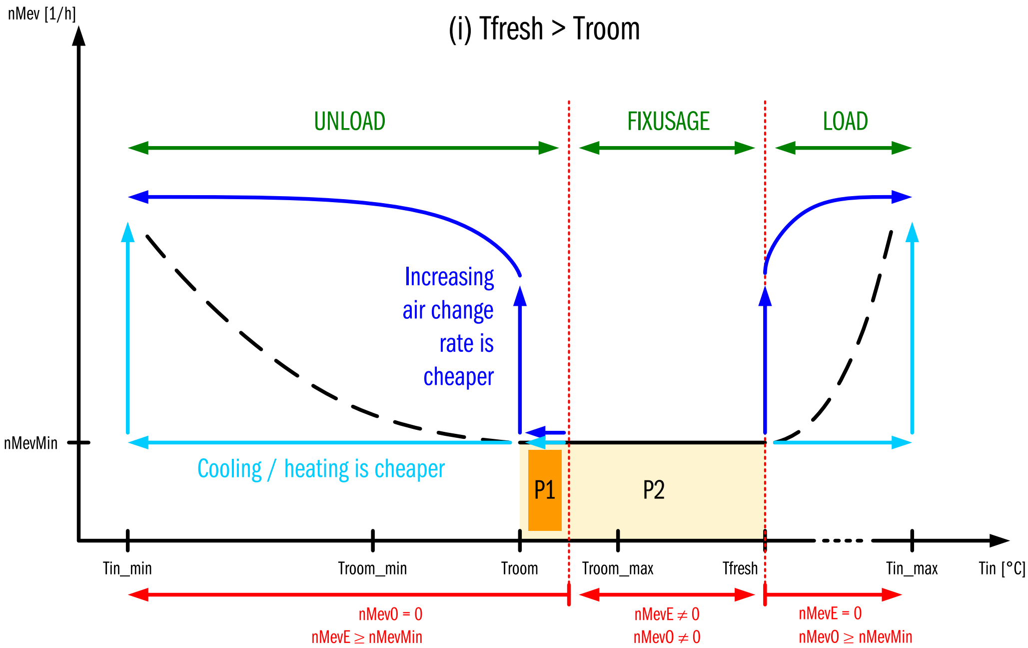

Figure 5: Demonstration of the energy recovery operation. $P1 \sim (1-\varepsilon_{ERC}) \cdot (Tfresh - Troom) \cdot nMevMin$, $P2 \sim (Tfresh - Troom) \cdot nMevMin$, whereas ε_{ERC} is the efficiency of the ERC.

line.

If$P1 < Pin < P2$, $nMev0$ and $nMev$E add up to $nMevMin$ and Tin is adjusted by the ratio of $nMev0$ and $nMevE$, which can easily be justified by cost arguments. If Pin was in this range, the mode 'FIXUSAGE' was chosen.

If $Pin < P1$ shall enter the room a cooling device has to be activated. The appropriate mode is 'UNLOAD'. If $Pin > P2$, either the air change rate has to be increased or the heating device has to be activated. The appropriate mode is 'LOAD'. Rules 1) to 3) were designed to distinguish these cases. 4) distinguishes the cases (i), (ii) and (iii).

3.1.3 Development of Rules for Mechanical Night Time Ventilation

The rules for mechanical night time ventilation had to be such, that they do not disturb regular operation during day time, i. e.., they had to be applicable generally for mechanical ventilation. Note, that the low-level controller interprets the modes as follows: 'LOAD' is the standard operation mode; ventilation is operated normally. When 'UNLOAD' is chosen, the LLC forces the use of mechanical ventilation, i. e., the air change rate is increased to its maximum unless a constraint is violated.

To ensure, that 'UNLOAD' is only chosen, if the ventilation is really used for cooling at night, the following conditions are necessary: (i) The energy recovery unit is never in use when the building is cooled with fresh air, (ii) The temperature of the outside air has to be smaller than the room temperature and (iii) the lower air change rate bound $nMevMin = 0$.

3.1.4 Development of Rules for Blind Movement

If restrictions on blind movement exist, as in the existing RBC strategies, the suggested numerical control value is sent directly to the LLC and the OM is set to 'FIXPOS'. Only if blind movement is without restrictions rules have to be developed.

3.2 Design of MMSTOC, a Modification of MSTOC

Only one OM-based controller was implemented during phase I. and II.: The MSTOC (see [3]). It was compatible with RBC strategies only.

Because rule-based HLCs do not include a model of the system dynamics, meaningless demands can result (e. g., the HLC requests free cooling although the outside temperature is not low enough). In MSTOC, these demands were filtered out by thresholds rules. The thresholds were calculated from universally used parameters, which "were determined by experience, rules of the thumb, and systematic simulation studies."[3]. The parameters included all necessary information about thermodynamics, economics etc. of a building and its BAC system.

Model-predictive HLCs include a model of the system dynamics and optimize a cost function. As a consequence, their suggested output includes an evaluation of the information contained in the model and the cost function. Further rules, which are an approximation of the model, constrain the behavior of the HLC unnecessarily or are redundant and are therefore dispensable.

Therefore a new mode-based LLC, the MMSTOC was designed, which operates without using additional parameters and rules. The code of the MSTOC was copied and the following threshold rules were removed:

- The LLC part for free cooling operation no longer a check, if the outside wet bulb temperature is smaller than the room temperature minus a threshold;
- The LLC part for mechanical night time ventilation no longer checks, if the outside temperature is smaller than the room temperature minus a threshold;
- The maximal and minimal air change rate for natural night time ventilation is no longer limited beyond the limits set by the HLC.

Besides, the LLC part for energy recovery operation has a new mode: 'FIXUSAGE'. As the name indicates, it allows receiving a set point directly from the HLC.

3.3 Towards Predictive Rule-Based Control

The RBC strategies developed within OptiControl do not include predictions. However, weather forecasts, internal gains predictions or occupancy predictions could easily be included to existing sets of rules.

The determination of a good blind position was found to be crucial in earlier studies within OptiControl [7]. Therefore, the focus was laid on the improvement of the blind positioning in the strategies RBC-1 . . . 4. The following section describes briefly the crucial points of blind positioning strategies. On them of course the focus should be laid when the strategies are further developed. In 5.3 some ideas are sketched. Unfortunately, there was not enough time to implement the ideas and prove their performance by simulations.

3.3.1 Main Development Areas of Blind Positioning Strategies

In the existing RBC strategies the procedure of determining the final blind position contains two crucial steps: The OM selection ('LOAD', 'UNLOAD' or 'FIXPOS') and the calculation of the shading position, in case it is required. Hence, the performance of RBC strategies can basically be improved in two ways:

- The OM selection procedure can be redesigned such that predictions are included.
- The calculation of the shading position can be improved.

4 Simulations

This chapter is structured as follows: (i) all used weather data sets are introduced, (ii) the used experiment sets are introduced and explanations concerning the chosen parameters are given, and (iii) the simulation setups are introduced. All abbreviations used in the following are listed in A.1

4.1 Weather Data Sets

A weather data set contains information about (i) TA: ambient temperature, TW: wet bulb temperature, (iii) RG: global radiation, (iv) RGN: global radiation north orientation, (v) RGE: global radiation east orientation, (vi) RGS: global radiation south orientation and (vii) RGW: global radiation west orientation. The names of the files contained in the corresponding set can be found in the appendix. All files are available on the OCWDB.

4.1.1 W1 - Perfect Weather Predictions

This set contains measurements of the year 2007 for the sites Zurich (SMA) and Marseille-Marignane (MSM).

4.1.2 W2 - Kalman-Filtered Weather Forecasts

This set contains weather predictions of the year 2007 for the sites SMA and MSM. The predictions were computed with help of the numerical weather prediction model COSMO-7 (C7). Then the data was Kalman-filtered by MeteoSwiss. No local filter was applied.

4.2 Experiments Sets

In this section, first the 5 BA systems introduced in [2] are reproduced. These systems are typical combinations of devices in present-day buildings. Second, the experiments sets are introduced.

4.2.1 Building Systems

Table 3 shows the building systems considered within the OptiControl project.

4.2.2 Experiment Set E1

E1 has the following properties:

Unlimited Power for "High-Cost" Actions Note, that the power for "low-cost" actions is always limited.

	Building System				
Automated Subsystems	*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 3: Reproduced from [2]. Building systems considered within the OptiControl project.

1. Limiting the power for "high-cost" actions can lead to comfort violations which lead to infeasibility when computing with hard constraints. Formulating the problem using soft constraints is possible in BACLab, however, the cplex solver has to be available. This was not the case for the development of $bac\_CreateModes$.

2. If comfort violations occur, the evaluation of the results becomes more complicated because comfort violations and costs have to be considered when two control strategies are compared. For the development of the translation rules it was more efficient to work with hard constraints.

3. A drawback of using this configuration is, that the system inputs have to be checked a posteriori if they are reasonable. Excessively high input powers have to be detected and eliminated to ensure reasonability of the results. In the first simulations using E1, the air change rate of the mechanical ventilation, $nMev0$, was found to be unrealistically high for some cases (peaks up to $20/h$). All simulation runs were repeated and $nMev0$ was limited to $4/h$.

Blind Movement No restrictions on blind movement were considered.

Site	MSM	MSM	SMA
Thermal Level	sa	sa	pa
System Variant	$02, 03, 04$	$02, 03, 04$	$02, 03, 04$
Orientation	S	S	S
Construction Type	h	h	h
winAreaFraction	wl	wl	wh
intGainsLevel	ih	ih	ih
TRoomBounds	trbTairW	trbTairW	trbTairW
NTotBounds	ntbW1U, ntbOccupU	ntbW1U, ntbOccupU	ntbW1U, ntbOccupU
UCostsMethId	pUCTE	pUCTE	pUCTE
Number of Cases	6	6	6

Table 4: Experiment Set E1

Selection of Site, Building Type and Building Automation Parameters The 18 combinations listed in Table 4 are common real-world configurations. (For example: a Swiss average building usually has a low window fraction and is not equipped with building system S5.)

Room Temperature Bounds A wide comfort band gives more freedom to the controllers such that one can distinguish more clearly the different controller behaviors. Note that the absolute level of the comfort band is not important, because only the relative performance of the controllers is important.

Total Air Change Rate Bounds The lower bound was varied between 'ntbOccupU' and 'ntbW1U'. A CO_2 controlled ventilation ('ntbOccupU') gives more freedom to the controllers such that one can distinguish more clearly the different controller behaviors. 'ntbW1U' was also considered, because most ventilation systems in reality have a constant air change rate.

4.2.3 Experiment Set E2

This experiment set fulfills the following three requirements: (i) the set contains very few cases, (ii) the selected cases are very common and (iii) it includes at least one case with building system S1.

(i) was important, because the same set was used for simulations with a hybrid MPC (HMPC) in [13], which were very time consuming; (ii) because the simulations should still be representative and (iii) because modeling building system S1 for HMPC is the easiest case.

E2 has the following properties:

Power Limits Power for "high-cost" actions was limited in this setup. Therefore comfort violations and costs were considered for the evaluation of the performance.

Restricted Blind Movement The blind movement was restricted to the beginning of each hour.

Case	*Parameters*									
1	SMA	02	pa	S	h	wh	ih	trbTairW	ntbOccupL	pUCTE
2	MSM	02	sa	S	h	wl	ih	trbTairW	ntbOccupL	pUCTE
3	SMA	03	sa	S	h	wl	ih	trbTairW	ntbOccupL	pUCTE
4	SMA	04	pa	S	h	wh	ih	trbTairW	ntbOccupL	pUCTE
5	SMA	01	pa	S	h	wh	ih	trbTairW	ntbOccupL	pUCTE
6	SMA	01	sa	S	h	wl	ih	trbTairW	ntbOccupL	pUCTE

Table 5: Experiment Set E2

Selection of Site, Building Type and Building Automation Parameters Table 5 shows all Cases considered in E2. Cases E2-1 to E2-4 are a subset of E1, except that the air change rate was upper bounded (ntbOccupL). Details on each parameter can be found in Paragraph 4.2.2. Cases E2-5 and E2-6 are identical to Cases E2-1 and E2-3, except that for the BA S1 was chosen.

4.3 Simulation Setups

Each simulation was done for the length of one year. The simulated plant model was the bilinear model described in [5] discretized with a time step of $T_S = 1h$.

For all simulations $Tfresh = Tair$ (ambient air temperature) was chosen.

4.3.1 SS1 - Simulation Setup for Translation Rule Design

The following controllers were used for this simulation:

- MMPC, with a horizon of $T_H = 48h$. For LLC the MMSTOC was used.
- PB48-L2STOC
- RBC-3-MSTOC

All controllers were aware of the true building parameters and perfect weather predictions were available, i. e., the weather set W1 was used.

For this simulation experiments set E1 was used.

4.3.2 SS2 - Performance Assessment

In reality a lot of building parameters and disturbances on the system are uncertain or even unknown. This affects all model predictive strategies and typically leads to a lower overall performance.

The purpose of this simulation series was to assess the performance of the MMPC compared to other control strategies in presence of uncertainties. The series was split into two parts: In the first part, SS2a, all parameters and disturbances were assumed to be exactly known for the length of the horizon T_H, except for the weather data. For that, weather forecasts were used. In the second part, SS2b, all parameters and disturbances were assumed to be exactly known for T_H, except for some building parameters, e. g., the building mass.

For the series experiments set E1 was used.

SS2a - Simulations Using Weather Forecasts The following control strategies were simulated in this part of the series:

- MMPC, with a horizon of $T_H = 48h$. For LLC the MMSTOC was used.

- CE-MPC48-L2STOC
- RBC-3-MSTOC

For this simulation the weather set W2 was used.

SS2b - Simulations Using Perturbed Building Parameters The following control strategies were compared in this part of the series:

- MMPC, with a horizon of $T_H = 48h$. For LLC the MMSTOC was used.
- CE-MPC48-L2STOC
- RBC-3-MSTOC

Two sets of building parameters were defined: TBvar01 and TBvar02. Within a set the building parameters were changed such that their effects on the behavior of the system accumulate:

- TBvar01 changes the building parameters such, that the HLC model is more susceptible towards environmental influences than the real building.
- TBvar02 changes the building parameters such, that the HLC model is more resistive towards environmental influences than the real building.

Table 6 shows the effects of the changes on the HLC model. For this part of the series

Perturbation of the HLC model compared to the real building	*TBvar01*	*TBvar02*
Change u-values windows by . . . %	10	-10
Heat transmission coefficients change by . . . %	-15	15
Energy Recovery Efficiency Ventilation change by . . . %	-15	15
Building mass change by . . . %	-10	10
g-value and visual transmission of windows change by . . . %	10	-10

Table 6: Parameter Perturbations

perfect weather predictions were used (weather data set W1).

4.3.3 SS3 - Performance Assessment with Limited Power and RBM

In these simulations (i) power for "high-cost" action was limited, (ii) $T_H = 24$ and (iii) weather forecasts were used. All simulation runs were done once with RBM and once without.

In Table 7 the controllers used for this simulation are listed. All controllers were aware of perfect building parameters. For weather forecasts the weather set W2 was used. The simulations were done for all Cases in E2.

With RBM	*Without RBM*
MMPC_RBM - MMSTOC	MMPC - MMSTOC
CE-MPC24-RL2STOC	CE-MPC24-L2STOC
RBC-4-MSTOC	RBC-3-MSTOC

Table 7: Simulation Setup SS3

5 Results

5.1 Set of Translation Rules

Figures 6 to 10 graphically present the final set of translation rules. The entire code of the translation rules can be found on the appended CD.

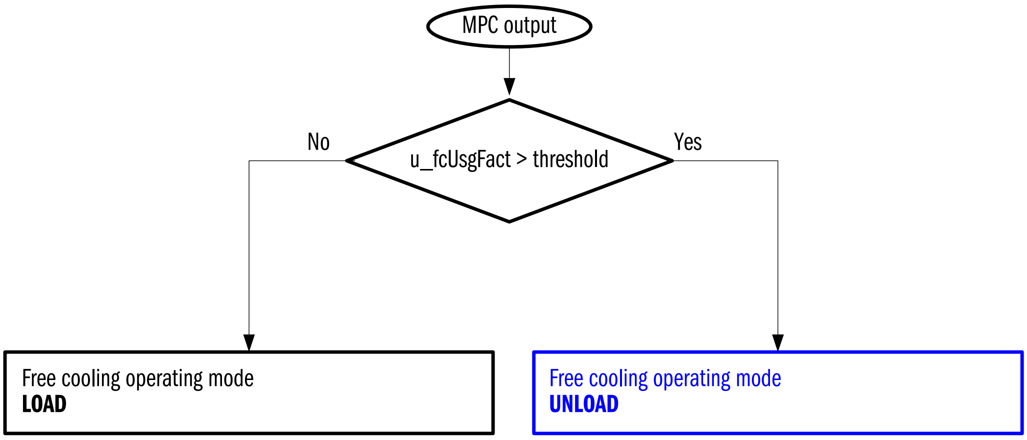

Figure 6: **Free Cooling Operation**: Translation of $u\_fcUsgFact$ into OMs. $u\_fcUsgFact$: Free cooling usage factor. The two OMs 'LOAD' and 'UNLOAD' were distinguished with a threshold to translate $u\_fcUsgFact$. The threshold was set to $0.5 \cdot umax\_fcUsgFact$.

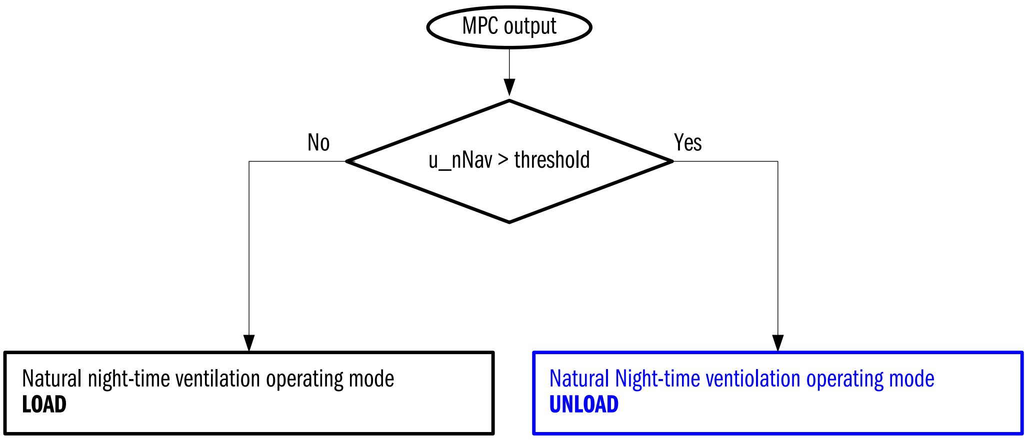

Figure 7: **Natural Night-Time Ventilation**: Translation of u_nNav into OMs. u_nNav: Natural night-time ventilation. The two OMs 'LOAD' and 'UNLOAD' were distinguished with a threshold to translate u_nNav. The threshold was set to $0.5 \cdot umax\_nNav$.

5.2 Performance Assessment

5.2.1 Performance of the Final Set of Rules

In this section the result of SS1 is shown when the final set of rules is used. Figures 11 and 12 depict the absolute and relative yearly costs of the simulated strategies for all 18 Cases

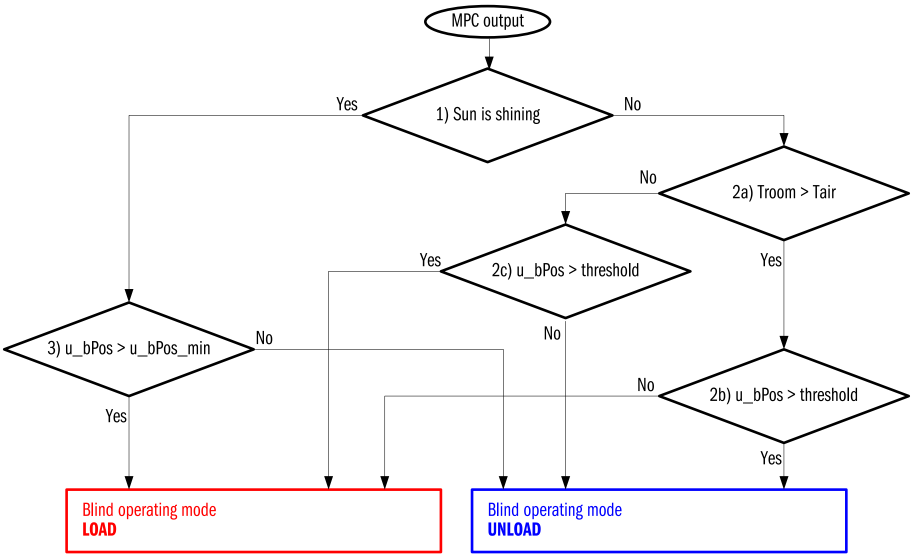

Figure 8: **Blind Position without Blind Movement Restrictions**: Translation of u_bPos into OMs. u_bPos: Blind position. The two OMs 'LOAD' and 'UNLOAD' were distinguished with a set of rules. The threshold values were set to $0.5 \cdot umax\_bPos$.

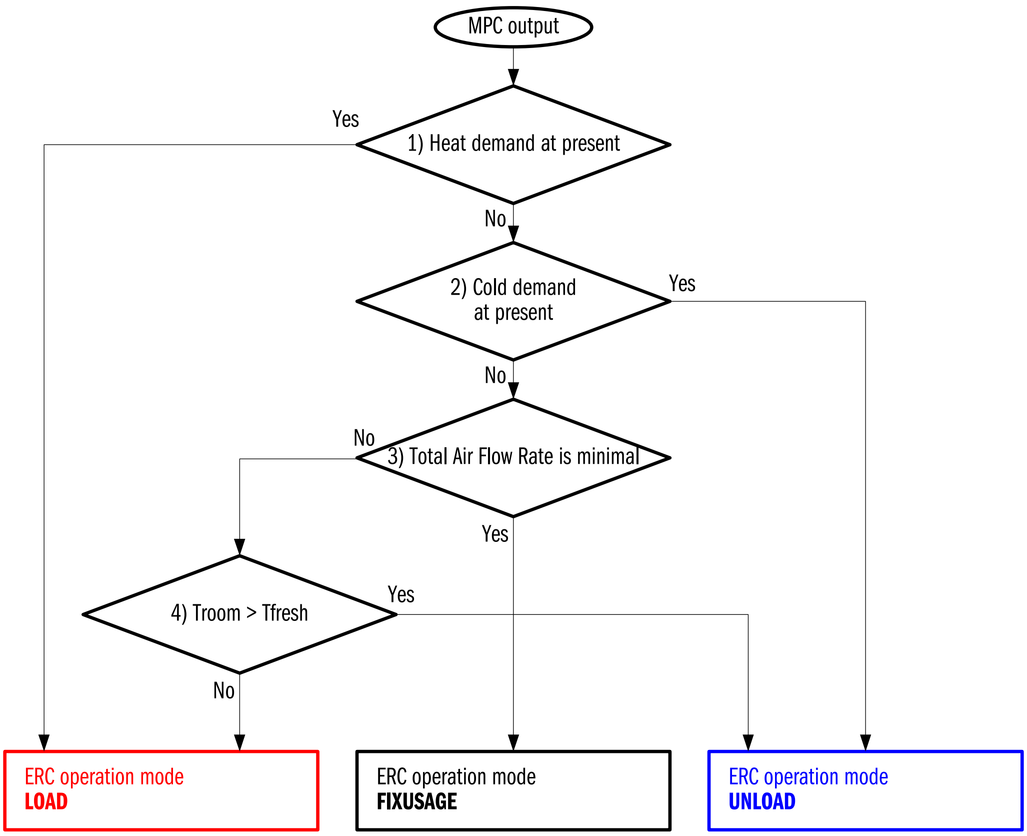

Figure 9: **Energy Recovery Operation**: Translation of u_nMevE into OMs. u_nMevE: Air change rate of the mechanical ventilation with ERC. The translation of u_nMevE needs three modes: Besides 'LOAD' and 'UNLOAD' also 'FIXUSAGE' was used for translation.

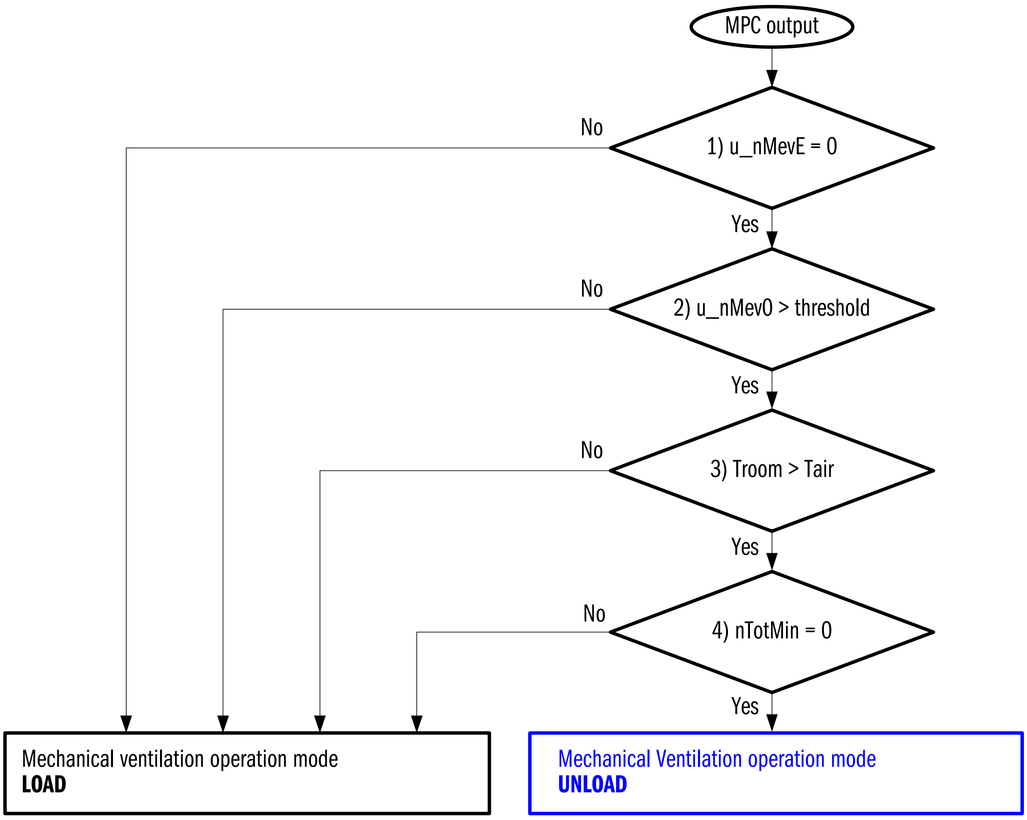

Figure 10: **Mechanical (Night-Time) Ventilation**: Translation of u_nMev0 into OMs. u_nMev0: Air change rate of the mechanical ventilation without ERC. The two OMs 'LOAD' and 'UNLOAD' were distinguished to translate u_nMev0. The threshold was set to $0.5 \cdot nMev0Max$.

of E1. Recall, that cost is defined here as usage of non-renewable primary energy (NRPE) per square meter.

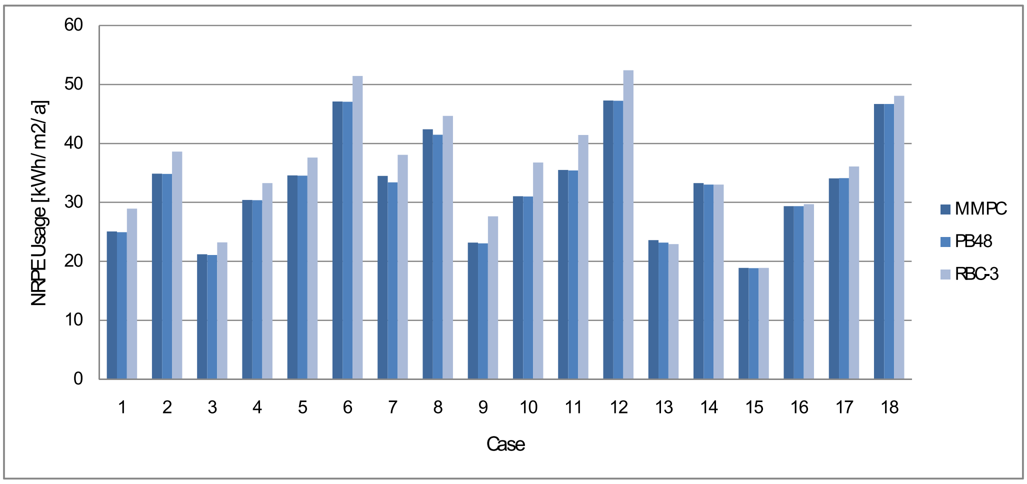

Figure 11: Comparison of the yearly costs of MMPC, PB48 and RBC-3. The cost of the MMPC lies between the cost of PB48 and RBC-3 for all Cases except Case 13 an Case 14.

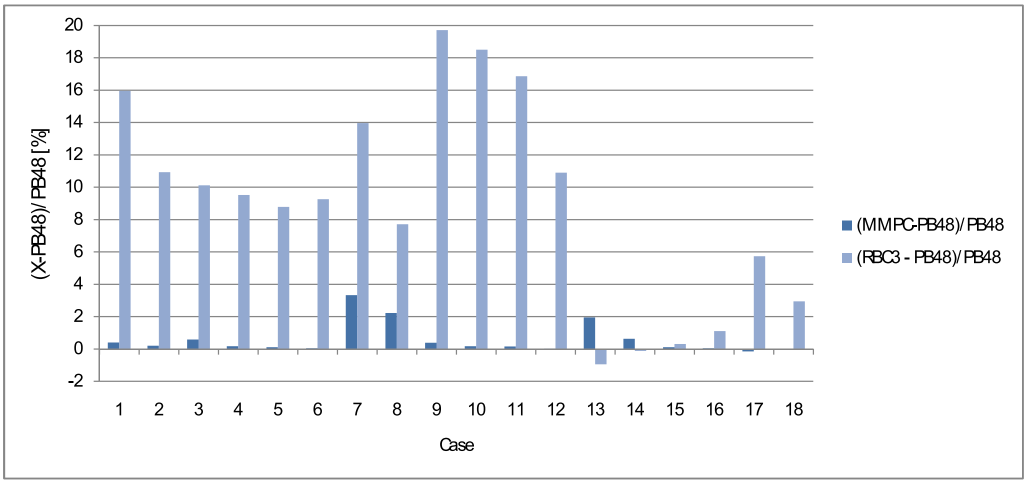

Figure 12: Comparison of the additional yearly costs of MMPC and RBC-3 relative to the costs of PB48. In Cases 7, 8 and 13 the additional relative cost of MMPC is the largest. The cost difference arises mainly from a differing ventilation system behavior (which can be seen in BACPP.c.C7.perf_Perf.perf.txt on the appended CD). In most Cases MMPC loses almost no potential compared to PB48, while RBC-3 loses $7-20\%$ for building systems S2 and S3 (Cases $1-12$) and up to 6% for S4 (Cases $13-18$).

5.2.2 Performance in Presence of Weather Predictions

Figures 13 to 15 present th results of SS2a. As a reference also the results of SS1 are shown. In the values are given as the mean over all Cases with the respective identifiers.

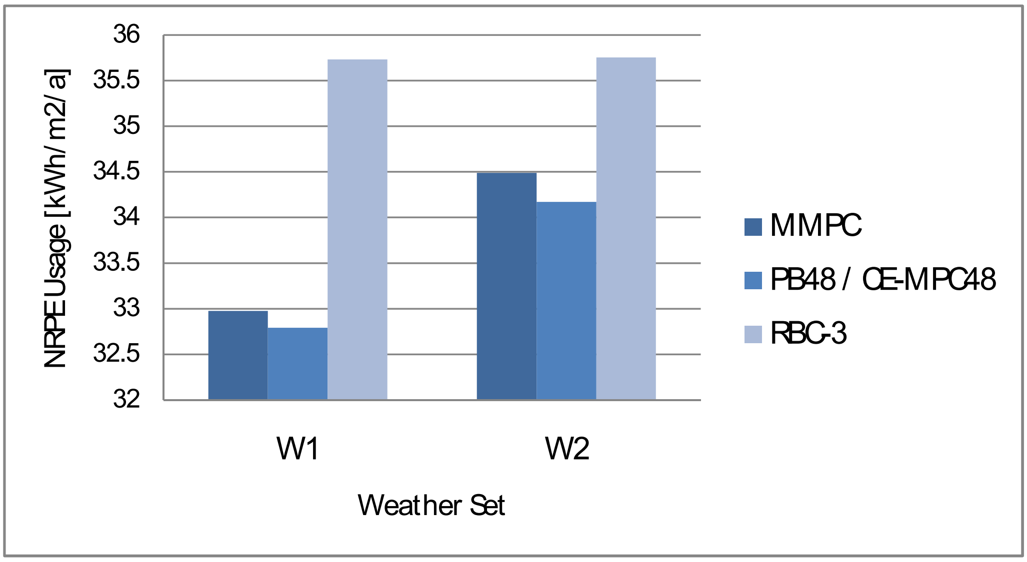

Figure 13: Comparison of the yearly cost of MMPC, CE-MPC48 and RBC-3 using weather forcasts (simulation set SS2a). As a reference the yearly cost of MMPC, PB48 and RBC-3 using perfect weather predictions are shown (SS1).

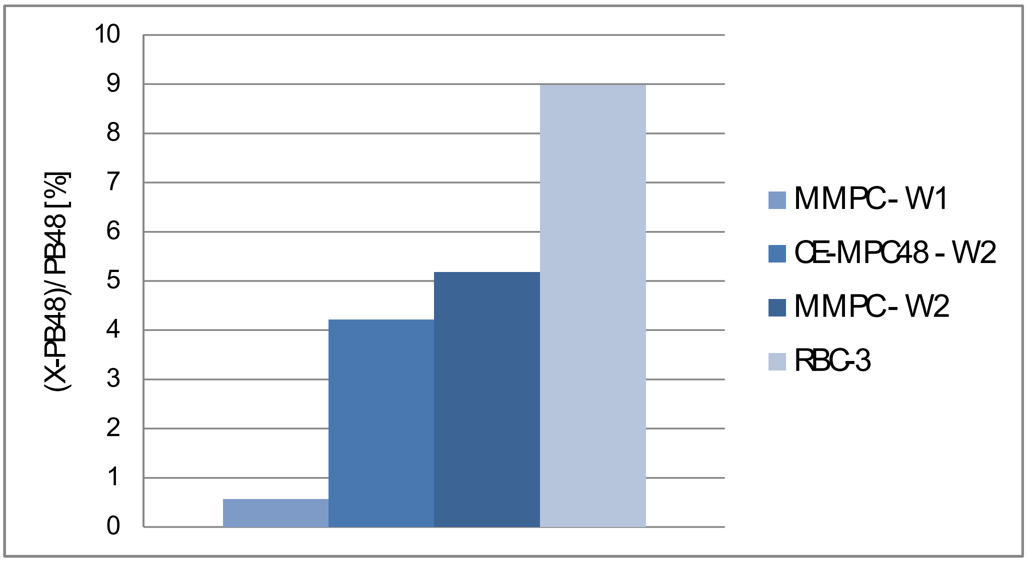

Figure 14: Comparison of the relative cost increase of MMPC with weather set W1 and W2, CE-MPC48 with W2 and RBC-3 with W1 compared to PB48. MMPC-W1 loses about 0.5%, whereas MMPC-W2 and CE-MPC48-W2 lose 4% and 5%, respectively.

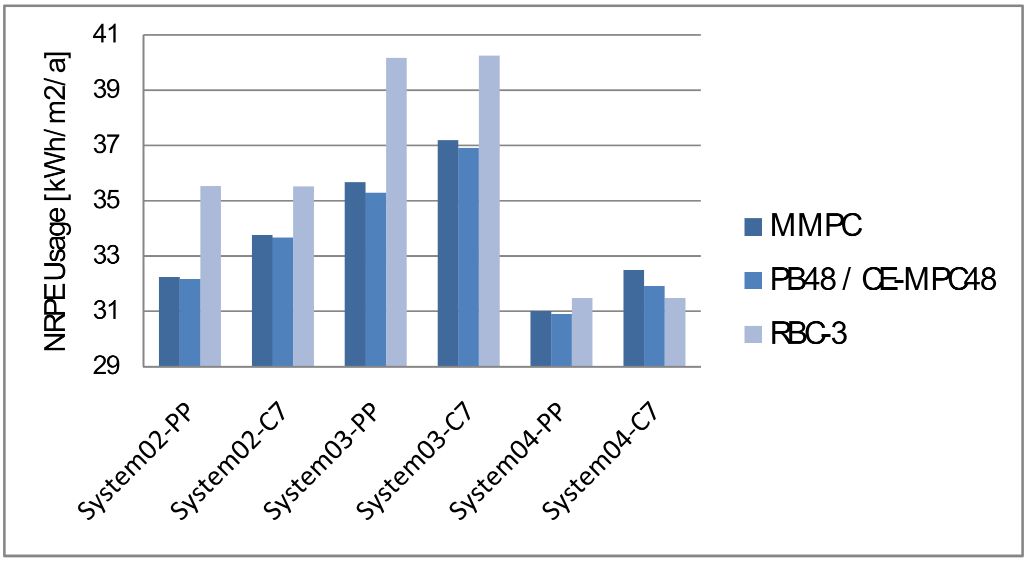

Figure 15: Comparison of the yearly cost of MMPC, CE-MPC48 and RBC-3 using weather forecasts and perfect predictions (PP), assorted by building system.

5.2.3 Performance in Presence of a Perturbed Building Model

Figures 16 to 18 present the results of SS2b. As a reference also the results of SS1 are shown. All values are given as the mean over all Cases with the respective identifiers.

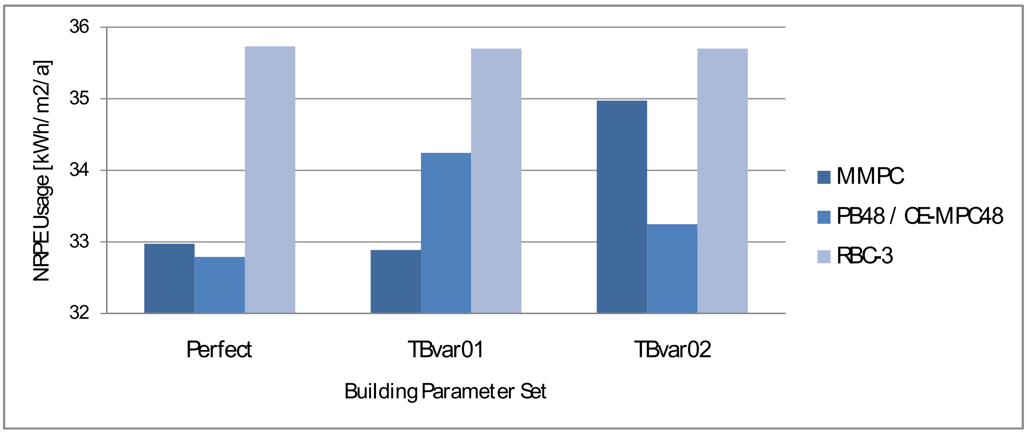

Figure 16: Comparison of the yearly cost of MMPC, CE-MPC48 and RBC-3 with perturbed building parameters (simulation set SS2b). As a reference the yearly cost of MMPC, PB48 and RBC-3 using perfect building parameters are shown (SS1).

5.2.4 Performance of MMPC with RBM and Limited Power for "High-Cost" Actions

In this section the results of SS3 are presented. Figure 19 depicts the costs and the violations for each controller and for each Case in E2. Figure 20 shows the costs for all controllers. In general, the costs and violations are distributed in the same fashion for all Cases except Case 4 (Case 4 is the only Case containing building system S4): RBC-3 and MMPC have

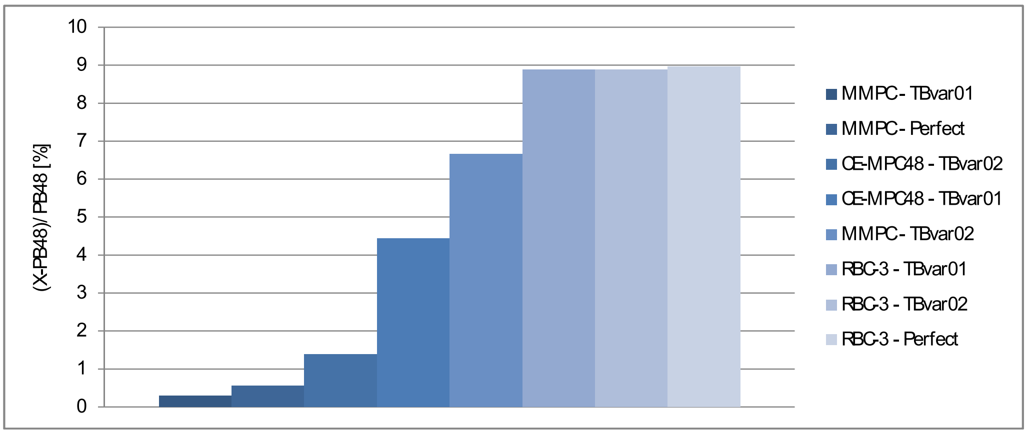

Figure 17: Comparison of the performance of the MMPC, PB48 / CE-MPC48 and RBC-3 with perfect and perturbed building parameters, assorted by increasing cost.

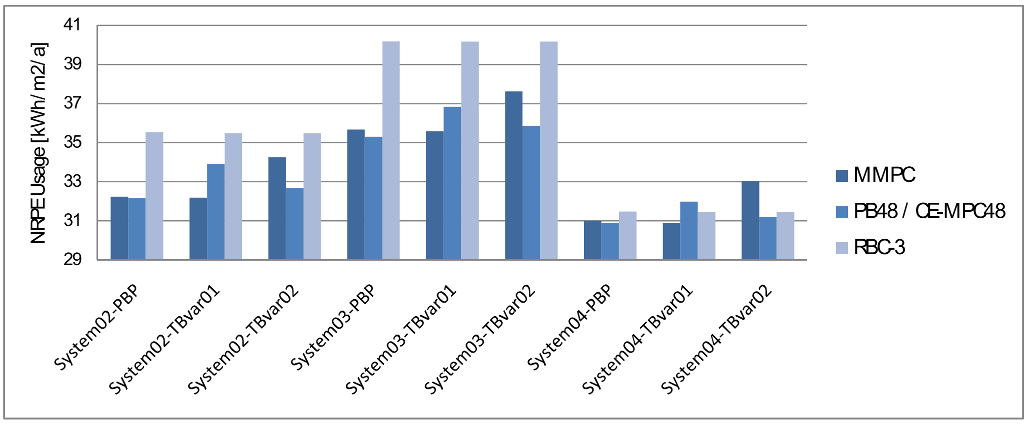

Figure 18: Comparison of the yearly cost of MMPC, CE-MPC48 and RBC-3 with perturbed building parameters, assorted by building system. PBP: Perfect building system.

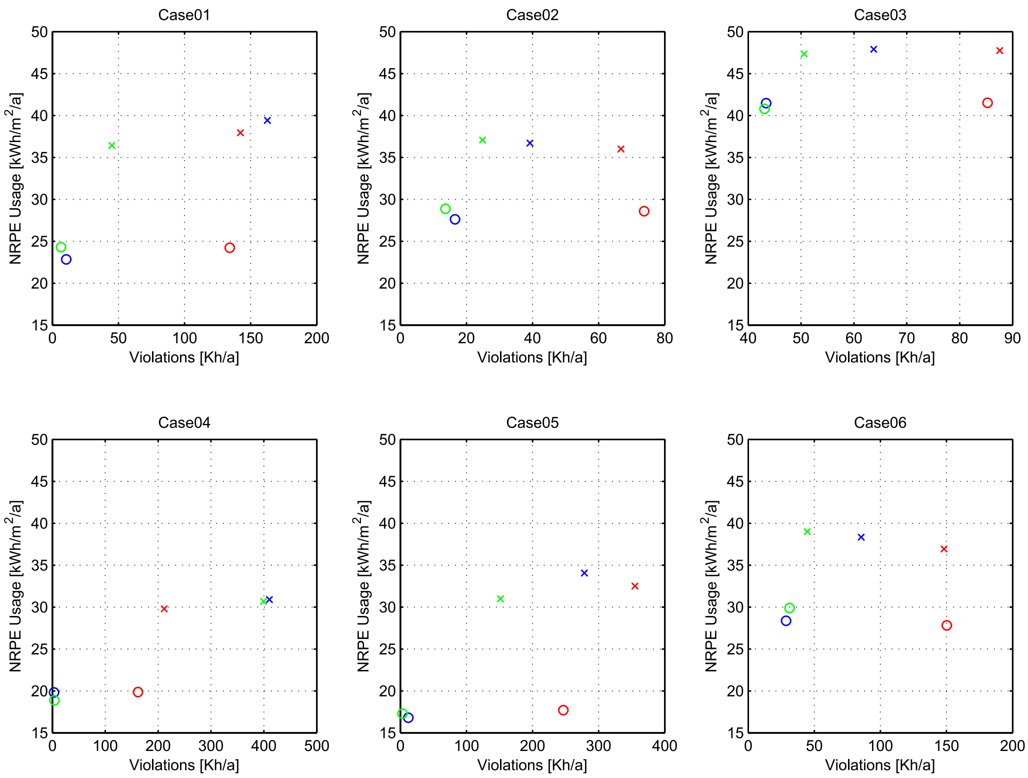

Figure 19: This figure shows all results of SS3. Legend: x: CE-MPC24 with RBM, o:CE-MPC24 without RBM, x: MMPC, with RBM, o MMPC without RBM, x: RBC-4, o RBC-3. Violations are defined as the sum of the violations of the upper and lower bounds of the thermal range in Kh.

similarly low costs and few violations. RBC-4 has considerably higher costs; CE-MPC24 has a considerably higher amount of violations. The strategies with the most violations, but not necessarily the highest costs are CE-MPC24 and MMPC_RBM in all cases except Case 4.

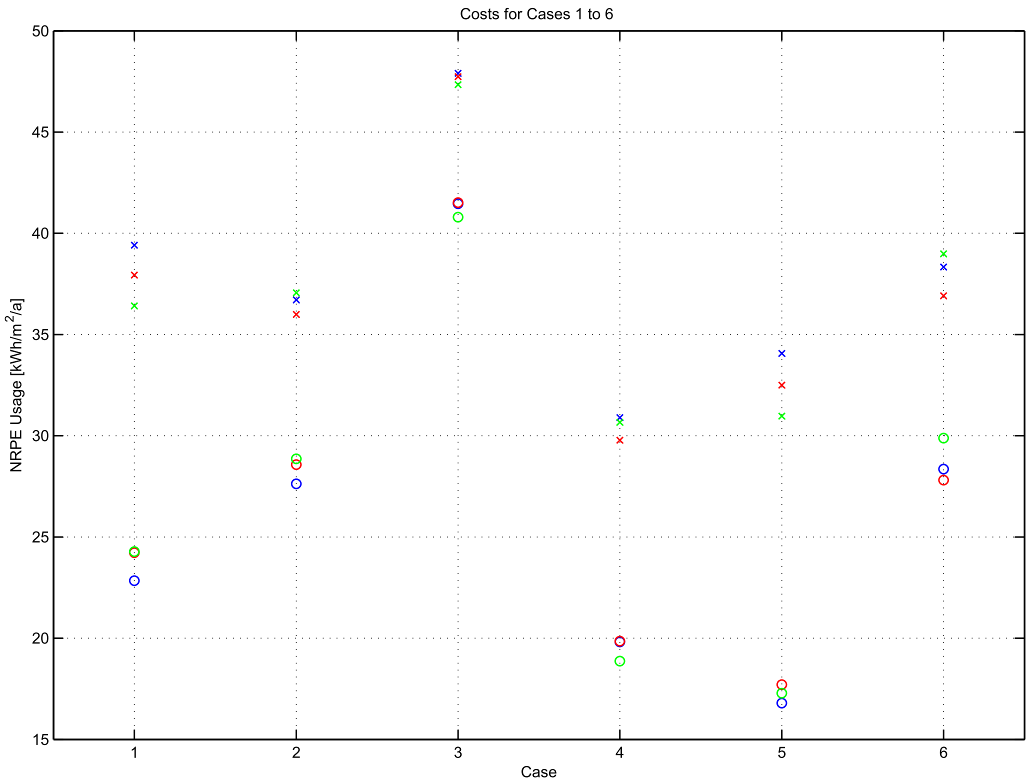

Figure 20: This figure shows the costs of simulations in SS3. The legend can be seen in Figure 19.

5.3 Approaches for Predictive Rule-Based Control

In this section (i) an approach for adding predictions to RBC-1 and RBC-2 is introduced, (ii) possible restrictions on blind positioning are stated and (iii) some ideas are presented, how such restrictions could be coped with.

5.3.1 Improvement of the OM Selection Procedure in RBC-1 and RBC-2

In RBC-1 and RBC-2 the measured total solar gains are compared to a threshold (see [3]). Instead, one could compare the predicted total solar gains of the next time step with a (other) threshold.

5.3.2 Including Weather Predictions in RBC-4

In RBC-4 the blind are set according to the luminance set point, which is calculated with help of the global radiation RG of the last timestep. Instead of using RG of the last time step, a prediction of RG for the next time step could be used for the calculation.

5.3.3 Possible Restrictions on Blind Movement

To ensure user acceptance of the end user, which is a very important criteria for the commercial success (see [1]), restrictions on blind movement should be considered.
In RBC-4 the blind movement was restricted to once at the beginning of the hour. Other restrictions might be more realistic, some suggestions are listed below:

- Blinds are allowed to be moved in fixed time steps different from one hour, e. g., every 6 hours;
- Blinds are allowed to be moved once within an interval;
- Blind movement is only allowed during non-occupied time and once at noon;
- After movement, blinds are not allowed to be repositioned for a certain period.
- etc.

All approaches immediately call for weather, internal gains and occupancy predictions.

5.3.4 Optimal Blind Positioning with Restrictions

In this section the path is laid for the calculation of the optimal blind position in the case blind movement is restricted for T_b. In a first step perfect knowledge about future weather is assumed. Like this, the potential of this approach can be estimated. In a second step weather forecasts can be used instead.
Figure 21 shows a situation which is very typical during day time in summer.

The (constant) optimal blind position for a period of duration T_b is referred to as u_bPos_opt. The momentary ideal blind position is referred to as u_bPos_ideal. In this case, u_bPos_ideal is constant over one hour, because weather data is only available on an hourly basis. Now, two cases can be distinguished which both have some undesired consequences:

1. $u\_bPos\_opt < u\_bPos\_ideal$: There is not enough light in the room and additional electric lighting is used. This needs energy, costs money and produces heat. In return a part of the solar irradiation was prevented from entering the room. This reduces the demand for cooling in future.
2. $u\_bPos\_opt > u\_bPos\_ideal$: There is additional solar irradiation into the room, which causes additional cooling energy demand.

In a further step all demands can be weighted by costs and the overall cost can be minimized.

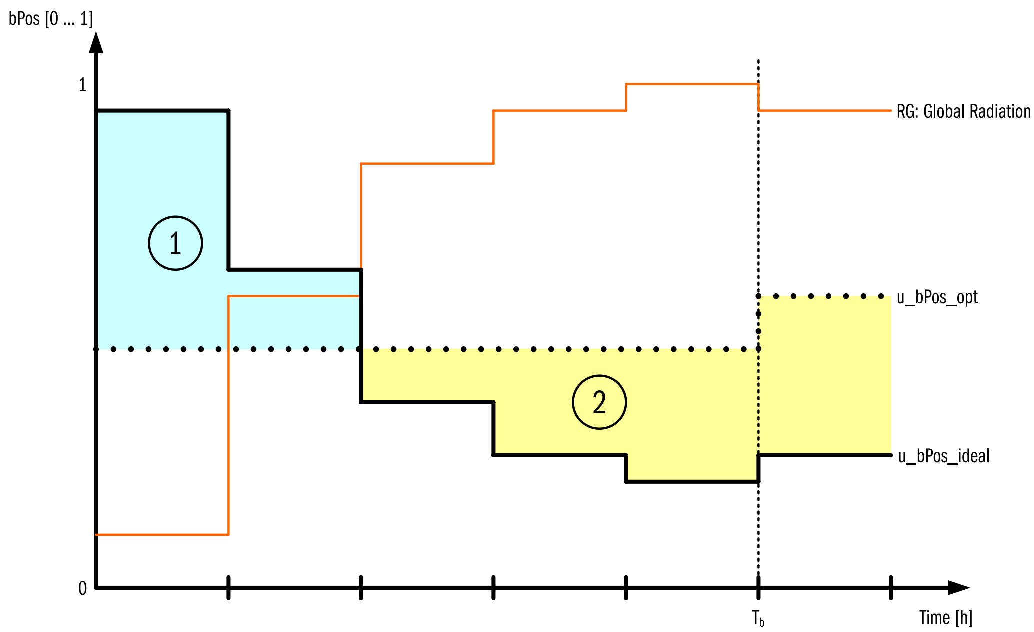

Figure 21: A typical situation during a summer day. The global radiation increases until noon and the ideal blind position follows the slope of the shading position, which decreases during the day. Here the assumption was made, that the optimal blind position has to be fixed at time 0 for the time T_b.

6 Discussion

Translation rules for devices which can only be used for either heating or cooling turned out to be rather simple: For the translation of free cooling and natural night-time ventilation a threshold was sufficient for acceptable performance (Figures 6 and 7). This threshold can be used for fine tuning: Higher values lead to a more conservative behavior, whereas lower values lead to increased free cooling or ventilation during night, which bring advantages, especially in regions with high cooling demands (such as MSM).

The translation rules for the other devices are more involved, because each device is used for more than one task, e. g., heating and cooling. However, suitable translation rules were found, which allow for an overall performance similar to PB48 in almost all Cases in E1 (Figure 11).

In the case of the ERC the entire information provided by the HLC is incorporated in the OM, no information is lost, because the translation is very precise. Because the LLC provides additional information to the control task, overall more information is available and the control task can be solved such that the performance is better or at least equal to the original control task. Unfortunately, this cannot be seen in the presented results, because always more than one translation rule was used at the time.

The translation rule for mechanical night-time ventilation is rather restrictive: More situations would generate need for night-time ventilation, but not all are recognized by the rule. That is the reason for the high deviation of the MMPC compared to the PB48 in the Cases E1-7 and E1-8 (Figure 12): In these Cases, MSM is chosen as site, which has a much higher cooling demand than SMA.

Cases E1-1 and E1-2, which are also located at MSM, do not induce higher costs (Figure 12) for the MMPC. This leads to the assumption that the simple rule chosen for free cooling is sufficient and that the threshold is already well tuned or no tuning is necessary at all.

If weather forecasts are used instead of perfect predictions, about half of the performance surplus compared to RBC-3 is lost by the CE-MPC (Figure 14). MMPC loses slightly more. The performance is still comparable to CE-MPC48 (Figure 13). In Figure 15 can be seen, that the performance of the MPCs depends strongly on system. With building system S3 MPC strategies are able to save a lot of energy compared to RBC-3, whereas with building system S4 that is not the case. There is almost no potential for a MPC, because RBC-3 has already rather low cost. Accordingly, both MPC strategies show a worse energy balance than RBC-3 when weather forecasts are used.

As Figure 16 shows, the performance of CE-MPC and MMPC is better than RBC-3 even if the model is perturbed. In the case TBvar01 was used, the MMPC performed even better than with perfect building parameters (Figure 17). In the case TBvar02 was used, CE-MPC48 performed best. Figure 18 confirms this trend and shows again the large dependency on the used building system: RBC-3 performs almost as well as PB48 on building system S4 which leaves no room for errors in model parameters.

Generally, with RBM and limited power for "high-cost" actions, the violations of all controllers are high (Figure 19). In most Cases of E2, violations exceed $70Kh/a$, which is a reasonable measure for the yearly violations (see [11]). CE-MPC24 tends to have more violations than all other strategies, no matter if blind movement is restricted or not. MMPC without RBM and RBC-3 always have a similar amount of violations (Figure 19). In the Cases E2-3 and E2-4, RBC-3 has lower cost than MMPC, whereas in the other Cases MMPC has lower cost than RBC-3(Figure 20). MMPC has lower cost than CE-MPC24 in all Cases except in case E2-6.

Note that Case E2-3 corresponds to Case E1-11 and Case E2-4 corresponds to Case E1-15, except that power is limited for "high-cost" actions in E2. In E1-15, for the case weather forecasts are used the cost of MMPC is higher than the cost of RBC-3, which aligns with the result of E2-4. However, in E1-11 using weather forecasts MMPC performs better than RBC-3, which is contrary to the result of E2-3. Note, however, that RBC-3 as well as MMPC has more than $40Kh/a$ violations in E2-3.

7 Conclusions

The presented set of translation rules and the simulations show, that it is possible to find rules which translate the output of a MPC to OMs with little cost increase compared to PB48. The potential loss MMPC-PB48 is negligible. This allows the controller to fit into a conventional BAC setup.

The presented rules for ERC translation show, that rules sometimes allow for cost savings, because room is left for interpretation to the LLC. The presented translations rules for mechanical and natural night-time ventilation require further improvement: Either tuning or a complete redesign is necessary.

The results of the simulations with weather forecasts show, that MMPC and CE-MPC48 lose about half of the potential reserve compared to RBC-3. Furthermore, the use of weather forecasts neither favors nor rejects the usage of OMs. The translation rules are robust against perturbed weather data, however, they do not allow for cost reduction compared to CE-MPC48, which could have been a possible result.

This set of translation rules is not able to compensate reliably for building parameter errors. However, the MMPC performance with TBvar01 shows that translation to OMs has the potential to almost reach the performance bound, even if the HLC model is perturbed. Some investigation into tuning of the rules could lead to similar performance for an arbitrary set of building parameters.

With RBM and limited power for "high-cost" actions the MMPC generally performs better than CE-MPC24 in terms of violations, because the translation to OMs avoids a part of the violations caused by the MPC algorithm However, the avoided violations lead to an increase of costs. RBC-4 performs best in terms of violations and in terms of cost. Without RBM but with limited power for "high-cost" actions, MMPC performs comparable to RBC-3 in terms of violations and slightly better in terms of costs. CE-MPC24 performs the worst.

The usage of improved weather forecasts would probably increase the performance of model-predictive and predictive rule-based strategies compared to conventional rule-based strategies. This could be done, e. g., by a local Kalman filter as proposed in [8]. However, this was not assessed in this thesis.
First conclusions made about cases with limited power for "low-cost" actions have to be verified. Further investigations are necessary and a comparison to cases without power limitations has to be done. That is, because E2 consists of only 6 cases.

The approaches for P-RBC strategies are found to be easy to implement in the existing simulations environment BACLab. Future assessments of these simple strategies should be able to give important hints about the performance of a more complex P-RBC.

8 Outlook

For the following issues need further investigation:

- The designed translation rules can be further tuned and assessed, such that they deliver robust results in presence of various disturbances.
- The performance of other model-predictive-based controllers using translation rules can be assessed.
- Predictive rule-based strategies can be developed. Thereby it is important to constrain the used information such, that the strategy is still easily applicable in practice.
- Further investigations in blind control under restrictions can be done.
- An algorithm can be developed which recognizes bad or missing weather forecasts. A fall-back solution can be developed. Weather forecasts can be corrected, e. g., with a local Kalman filter.

A Nomenclature and Symbols

A.1 Abbreviations

Abbreviation	*Description*
ALC	Artificial Light Correction
BA	Building Automation
BAC	Building Automation and Control
C7	COSMO-7
CE	Certainty Equivalence
ERC	Energy Recovery
HLC	High-Level Control / Controller
HVAC	Heating Ventilation and Air Conditioning
IRA	Integrated Room Automation
LLC	Low-Level Control / Controller
Mev	Mechanical Ventilation
MMPC	Model Predictive Controller which outputs Operation Modes
MPC	Model Predictive Control / Controller
MSM	Weather Station in Marseille-Marignane
NRPE	Non-Renewable Primary Energy
OM	Operating Modes
RBC	Rule-Based Control / Controller
PB	Performance Bound
T_H	Optimization Horizon
T_{OL}	Open Loop Control Time
T_S	Sampling Time
P-RBC	Predictive Rule-Based Control
RBC-X	Rule-Based Control Strategy
Siemens BT	Siemens Building Technologies
SMA	Weather Station in Zurich

A.2 Variables in BACLab

Identifier	*Description*	*Unit*
bPos	blind position [0: closed ... 1: open]	[-]
hPowSlab	heating power (slab), positive values = heating	[W/m2]
cPowSlab	cooling power (slab), positive values = cooling	[W/m2]
fcUsgFact	free cooling usage factor [0: off ... 1: on]	[-]
nMevE	air change rate mech. vent. with ERC	[1/h]
nMev0	air change rate mech. vent. without ERC	[1/h]
hPowMev	heating power (mev), positive values = heating	[W/m2]
cPowMev	cooling power (mev), positive values = cooling	[W/m2]
nNav	air change rate natural ventilation	[1/h]
hPowRad	heating power (radiator)	[W/m2]
Tair	outside air temperature	[degC]
Tfresh	fresh air temperature mech. ventilation	[degC]
TfreeCool	free cooling temperature	[degC]
Illum	daylight illuminance with fully closed blinds	[lux]
dIllum	additional daylight illuminance with open blinds	[lux]
Troom	room temperature	[degC]
nMev	sum of air change rate mech. vent (nMevE+nMev0)	[1/h]
Tin	inlet temperature mech. vent.	[degC]

A.3 BACLab Functions

Function Name	*Description*
bac_DoMPC	Calls the MPC algorithm
bac_CreateModes	Numerical control values for "low-cost" actions are translated into OMs. This function is contained in *bac_CalcU_MMPC*
bac_CalcU_X	Routine in which the control strategy X is defined

B Figures

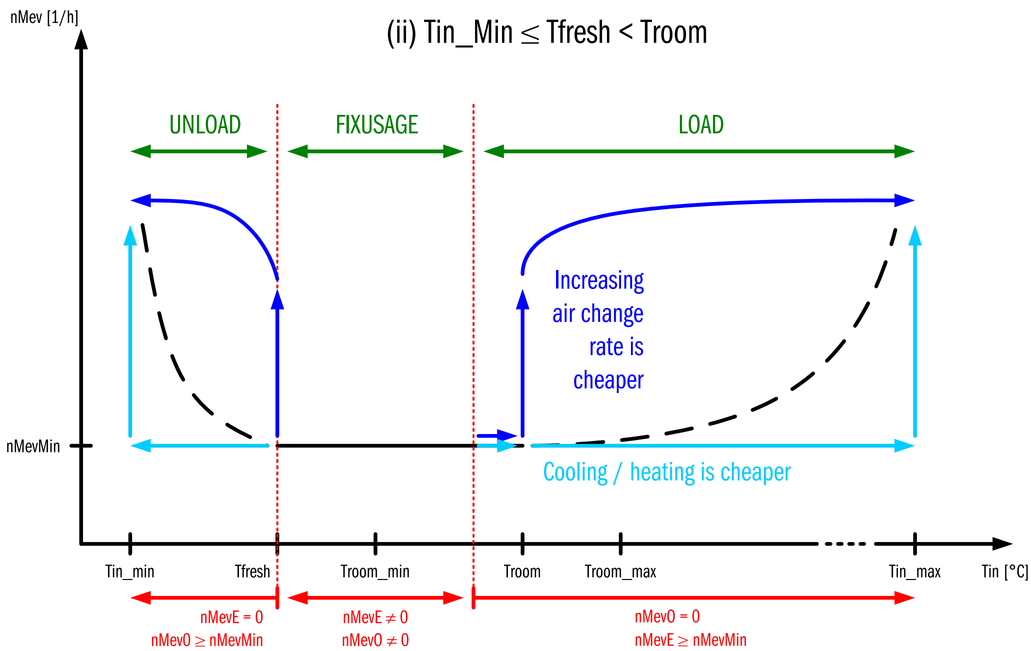

Figure 22: Demonstration of the energy recovery operation for Case (ii) $Tin_{min} < Tfresh \leq Troom$).

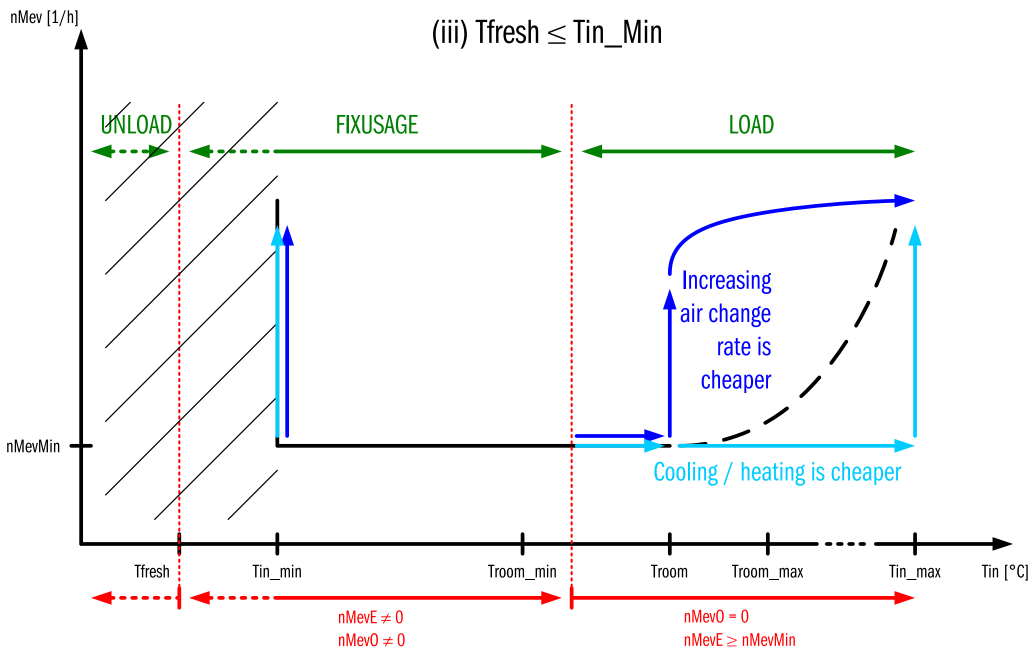

Figure 23: Demonstration of the energy recovery operation for Case (iii) $Tfresh \leq Tin_{min}$.

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