HIERARCHICAL MODEL PREDICTIVE CONTROL FOR COMPLEX BUILDING ENERGY SYSTEMS

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ABSTRACT

In this paper, a hierarchical Modelica-based Model Predictive Control (MPC) is presented in order to control complex building energy systems with different dynamics. The hierarchical MPC concept tackles the problem of controlling buildings with slow dynamics such as thermally activated building systems (TABS) and fast actuators such as air handling units (AHUs). It further addresses prediction errors of system disturbances (e.g. weather, occupancy) and ensures anticipation, reactivity and real-time capability. The benefits compared to single MPC, Rule-Based-Control (RBC) and Proportional-Integrative-Derivative (PID) strategies are demonstrated in simulations on nonlinear Modelica models including detailed models for solar shading and visual comfort.

INTRODUCTION

Energy consumption in building energy systems accounts for approximately 40 % of global energy consumption. Heating, ventilation and air-conditioning (HVAC) units are responsible for half of the energy consumed in buildings and hence, yield a great potential for energy savings and reduction of CO_2-emissions (Pérez-Lombard et al. 2008). Control of HVAC systems is challenging due to inherent nonlinear dynamics as well as time-varying system dynamics, set-points and disturbances (Afram & Janabi-Sharifi 2014). RBC in the form of on/ off or bang-bang control action and PID control dominate the control approaches currently implemented in building energy systems. They mainly represent inflexible corrective control concepts, which are unable to control inert systems with large time delays, to minimize energy to stay between bounds and perform badly outside the tuning conditions (Afram & Janabi-Sharifi 2014). MPC has gained a lot of attention in the building control domain and suggests great benefits compared with conventional controllers tackling the aforementioned challenges. It is capable of considering conflicting optimization goals such as energy consumption and occupant comfort, makes use of a system model for an anticipatory control concept, and handles future disturbances and time-varying building dynamics with time delays as well as thermal and technical constraints.

The practical implementation of MPC on an office building in Prague demonstrated energy consumption savings of 15 to 28 % compared to the existing control based on a heating curve (Cigler et al. 2013). Ma et al. (2012) applied the MPC concept on the operation of a large-cooling system in a university building in Merced resulting in an increase of 19 % in terms of a coefficient of performance against a reference control. The figures coincide with further energy savings of more than 20 % in a research laboratory in Illinois (Bengea et al. 2014), more than 20 % primary energy reduction in an office building in Brussels (De Coninck & Helsen 2016) and primary energy savings of 17 % for a large-scale simulation in a Swiss Office Building (Sturzenegger et al. 2016).

Apart from the aforementioned challenges, the implementation of MPC in buildings faces the complexity of different dynamics and time scales of the integrated systems, such as the rather slow and inert TABS compared to rather fast AHUs. An approach to tackle this complexity is hierarchical MPC that divides the optimization problem into levels of slow and fast dynamics with adapted prediction horizons and sampling times (Touretzky & Baldea 2016).

According to the experiences of experts regarding MPC in building control and its practical implementation, the modeling part is the most essential part of the MPC implementation, taking up most of the time and costs (Cigler et al. 2013). Findings of the large-scale building control project OptiControl-II, which studied seven months of MPC in a Swiss office building, conclude that a "framework allowing the fast generation of MPC suitable models is a key factor to the widespread adoption of MPC in building control" (Sturzenegger et al. 2016). The language Modelica (Mattsson et al. 1997) could be a potential candidate for building the basis of such a modeling framework for several reasons. Modelica is an open-source, equation-based, acausal and object-oriented modeling language with a graphical interface to connect components, which underlines its flexibility and user-friendliness (Schweiger et al. 2018). Modeling of building energy systems in Modelica is advanced by international projects such as the IEA EBC Annex 60 project, from which an open-source library emerged, the Modelica IBPSA library (Wetter & van

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Treeck 2017). Several research groups have used this library as the basis for extending and adapting the library, for instance, the AixLib (Müller et al. 2016). Modelica supports the Functional Mockup Interface (FMI) standard that enables model exchange or co-simulation with different simulation programs and is suitable for both simulation and optimization due to the language extension Optimica. The ongoing IBPSA Project 1 focuses, among other things, on the development of a Modelica framework and library for both design and operation of building energy systems as well as the development of translators from Building Information Models (BIM) to Modelica (Wetter et al. 2019). Both subprojects aim to increase the suitability of Modelica for a wider range of practical implementations in building control.

The studies in this work are conducted in an extended version of JModelica (Åkesson et al. 2010) which enables the derivative-based optimization of Modelica models and is capable of solving large-scale nonlinear problems. A recent work on building MPC based on JModelica implements an MPC approach for building systems with linear, time-invariant building envelope and steady-state nonlinear HVAC models (Jorissen et al. 2018). It is demonstrated in a full-year simulation on a terraced house showing approximately 12,8 % energy savings compared to a state-of-the-art RBC (Jorissen & Helsen 2019).

In this work, a multi-time scale hierarchical Modelica-based MPC concept is presented to control complex building energy systems with different dynamics. The hierarchical aspect tackles the increasing complexity of building systems and the increasing importance of storages for the energy turnaround. Storages can be both active in the form of batteries or thermal storages and passive such as TABS. The applied hierarchical concept takes into account all time scales and ensures anticipation and reactivity. Additionally, this work considers active solar shading and visual comfort in the form of a norm-based model for Venetian blinds (Fig. 1). Blinds constitute an essential part of building control as they influence visual and thermal comfort and can be controlled to regulate solar gains in winter to reduce heating energy or to avoid overheating in summer. The use of daylight compared to artificial lighting can increase comfort, satisfaction and productivity as well as reduce electrical consumption in office buildings. To the best of the author´s knowledge, the detailed modeling of the blinds, which is based on tracking of the sunray paths, is novel in building MPC. Generally, the modeling of blinds is simplified and the solar heat flow into the room is mostly integrated in the form of linear dependence on the blind position or as a direct control input (Sturzenegger et al. 2016).

This work is structured as follows. First, the model generation procedure for the MPC is described. Subsequently, the hierarchical MPC approach is outlined by describing the different layers, dynamics and the information exchange. The benefits of the approach are demonstrated and discussed in several AixLib-Modelica-simulation studies. The paper concludes with an outlook on further improvements and planned extensions of the framework.

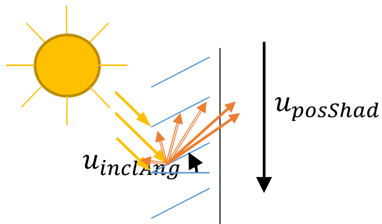

Figure 1: Draft of external Venetian blinds for solar shading incl. control inputs inclination angle $u_{inclAng}$ and vertical position $u_{posShad}$

MODEL GENERATION APPROACH

As mentioned in the introduction, the model generation is crucial for the implementation of building MPC. In this work, the existing open-source Modelica simulation library AixLib is used as a basis. The AixLib contains models of HVAC systems as well as high and reduced-order building models. An optimization library is generated by adapting the AixLib models for compatibility with the optimization framework JModelica and inherent solver IPOPT (Wächter & Biegler 2005). IPOPT is an open-source nonlinear solver capable of solving large-scale nonlinear problems. For use in IPOPT, models are required to have constraints and cost functions that are twice continuously differentiable with respect to the optimization variables. Accordingly, integer decision variables or non-finite entries in the Jacobian are not supported. Additionally, the Modelica-specific table look-up data reader CombiTimeTable is not supported in JModelica as it relies on external C code. In our framework, a data reader for external data (weather, occupancy, energy prices, etc.) based on the MPCPy framework (Blum & Wetter 2017) is integrated.

As an extension to the AixLib models, a Modelica model for active solar shading was developed that can be integrated into the AixLib window model. It models classical Venetian blinds with slats that can be controlled by adjusting the vertical position and the inclination angle of the slats. Based on the two control inputs and weather data the model calculates the total energy and light transmittance for direct and diffuse radiation. The model generation is based on norms (VDI 6007-2 (2015), DIN CEN ISO/TR 52022-2 (2018)) and considers tracking of sunray paths and varying view factors between the slat and opening surfaces as well as interactions between the glazing and shading layers. Using this model allows for consideration of visual comfort addressing e.g. recommended illuminance levels of 500 Lux in office buildings and necessary additional artificial lighting (DIN EN 12464-1 (2011)).

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MPC CONCEPT

MPC makes use of a system model to predict the future system states and calculates system control inputs minimizing a cost function over the prediction horizon while considering disturbances and constraints. The calculated inputs for the first time step are applied to the real system and the MPC procedure repeats at the next sampling time step (rolling horizon). MPC tries to solve the following general optimal control problem (OCP):

$$\boldsymbol{J^* = min_u\, J} \quad (1)$$

subject to

$$F(t, \dot{x}, x, w, y, u) = 0 \quad (2)$$

$$g(t, \dot{x}\,, x, y, u) = 0 \quad (3)$$

$$h(t, \dot{x}, x, y, u) \geq 0 \quad (4)$$

$$x(0) = x_0 \quad (5)$$

In this formulation, u are the control inputs, t the time, x the states, w the disturbances and y the algebraic variables. J is the cost function to minimize with respect to the control inputs, *F()* describes the model dynamics in a DAE form, *g()* the equality and *h()* the inequality constraints. Equation 5 describes the initial state condition.

To handle system dynamics and disturbances of different time scales, a hierarchical optimization strategy is used. The hierarchical MPC consists of two layers: one focusing on the slower dynamics and disturbances and one on the faster ones (Fig. 2). Slower dynamics characterize storages, both active and passive, faster dynamics arise in AHUs, convectors or radiators of lower inertia. Disturbances regarded as rather fast are e.g. occupancy or solar radiation, whereas outdoor temperature represents a rather slow disturbance. To be able to take all time scales of the overall system into account, longer prediction horizons and sampling periods are chosen for the slower MPC layer, whereas for the fast layer the horizon and sampling period are smaller. The slow layer ensures the anticipation of the control necessary for inert systems with time delay, the fast layer guarantees reactivity. A necessity for a reactive MPC can arise from forecast errors (e.g. weather or occupancy), unpredictable user influences (e.g. window/ door opening) as well as model errors and mismatches (controller model compared to the real building).

The layers communicate through interpolated state references that are calculated by the slow layer and are tracked as good as possible by the fast layer. For the slow layer, the cost function includes different forms of energy consumption, for the fast layer, it includes energy consumption and deviation from the reference state trajectories. The combination of the two layers increases the probability to preserve the real-time capability compared to a single MPC with a long prediction horizon and small sampling periods. Real-time capability describes the ability to solve the optimization problem and to calculate a new optimal input for the next control time step within the dynamic-specific sampling period. To improve the feasibility of the problem, slack variables are introduced that penalize leaving the comfort ranges in the cost function (“constraint softening”).

The MPC layers each solve a nonlinear programming (NLP) problem due to the characteristic nonlinearities inherent in the dynamics of HVAC systems. For use in building MPC, on the one hand, a model has to be simple enough to be solved in appropriate time, on the other hand, it has to be detailed and complex enough to reproduce the dynamics of the real building. Detailed nonlinear models enable a higher exploitation of potential savings closer to the theoretical performance-bound and provide more flexibility in formulating the model equations, constraints and cost function (Drgoňa & Helsen 2018). The higher model accuracy is at the expense of higher computational demand; however, optimization algorithms and solvers are improved continuously and due to the progress and developments of processors and cloud computing the available computational power is increasing exponentially (Serale et al. 2018). Works on nonlinear MPC (Bengea et al. 2014, Touretzky & Baldea 2016) are less common compared to linear MPC, however, they can have a high potential for future high-performant control systems (Drgoňa & Helsen 2018).

The used models in this work are first-principles physical white-box models preserving the accuracy of the nonlinear models over a wider range of operating conditions compared to grey-box or black-box models. The latter highly depend on the available existing training data and perform badly outside the training conditions. Studies by Picard et al. (2017) show that MPC performance proves sensitive to the prediction accuracy of the controller. In white-box models, the parameters and state variables have a physical meaning and a geometric equivalent in contrast to general grey-box and black approaches (Drgoňa et al. 2020), ensuring their explicit location, improved comprehension of the system behavior and fault detection. The white-box approach is planned to be extended by a calibration/ parametrization module where model parameters are calculated or updated in a “parameter estimation” optimization problem based on measurement data.

After solving the optimization problem, the fast MPC layer sends the control inputs for the first control time step to a simulation model, which simulates over one sampling period. The “measured” data is sent back to both the slow and fast layer, based on which the optimization states are updated and the optimization problem is solved again for the next sampling period.

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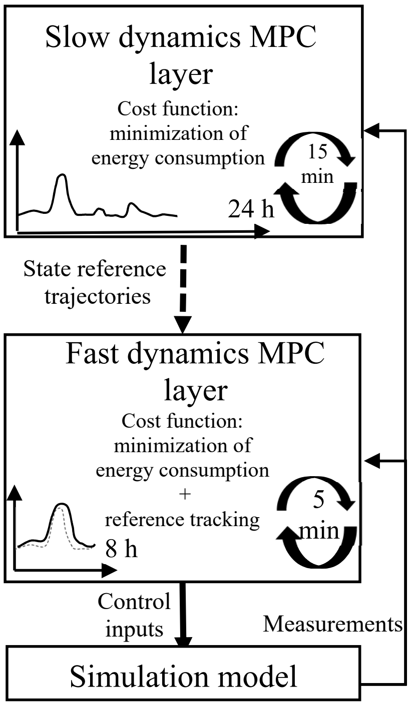

Figure 2: Overview of hierarchical MPC concept

SIMULATION

The hierarchical MPC concept is applied to a nonlinear white-box Modelica room model including TABS (realized as Concrete Core Activation (CCA) in the floor), a convector, pumps and a window with external Venetian blinds. A high-order model is chosen for the building, the wall including the window is regarded as external and the remaining walls are considered as adiabatic. The pumps supply the TABS and the convector with a water mass flow at fixed temperatures. Occupancy is considered through a model that calculates human heat emission according to typical office schedules with two occupants from 8 am - 12 pm and 1-6 pm. The MPC starts at 8 am with the beginning of the occupancy period. Weather data is included through an AixLib resource weather file for San Francisco in January 1999 (heating period). For the MPC approach, a perfect forecast is assumed.

Control inputs to the model are the heating water mass flows u_{Conv} and u_{TABS} for convector and TABS, the vertical position $u_{posShad}$ and inclination angle $u_{inclAng}$ for the blinds, accounting for thermal (air temperature comfort range 293 - 295 K) and visual comfort (minimum illuminance level of 500 lux). Artificial lighting u_{al} (luminous flux) is not modeled explicitly. The electricity demand to reach the comfort illuminance level is considered in the cost function and assumed to vary linearly with the provided artificial illuminance. The models in both MPC layers are identical and coincide with the emulator model.

The cost function for the upper, slow layer minimizes energy consumption for the convector, TABS and electrical artificial lighting and includes a quadratic penalization term for temperatures outside the comfort range (through introduced slack variables) (Equation 6). The lower, fast layer complements these terms by reference tracking, in the form of quadratic penalization of deviation from the reference temperature states (Equation 7).

Cost function for slow layer:

$$J_{slow} = \sum_{k=0}^{N-1} \alpha_{Conv} * u_{Conv}(k) * \left(T_{supply,Conv} - T_{return,Conv}\right) + \alpha_{TABS} * u_{TABS}(k) * \left(T_{supply,TABS} - T_{return,TABS}\right) + \alpha_{Light} * u_{al}(k) + \delta * \left(\overline{\varepsilon}(k)^2 + \underline{\varepsilon}(k)^2\right) \quad (6)$$

Cost function for fast layer:

$$J_{fast} = \sum_{k=1}^{N} \gamma * \left(y_{Temp}(k) - y_{Ref,Temp}(k)\right)^2 + \sum_{k=0}^{N-1} \alpha_{Conv} * u_{Conv}(k) * \left(T_{supply,Conv} - T_{return,Conv}\right) + \alpha_{TABS} * u_{TABS}(k) * \left(T_{supply,TABS} - T_{return,TABS}\right) + \alpha_{Light} * u_{al}(k) + \delta * \left(\overline{\varepsilon}(k)^2 + \underline{\varepsilon}(k)^2\right) \quad (7)$$

subject to

$$\underline{T}_{room,air} - \underline{\varepsilon} \leq T_{room,air} \leq \overline{T}_{room,air} + \overline{\varepsilon} \quad (8)$$

$$\underline{\varepsilon}, \overline{\varepsilon} \geq 0 \quad (9)$$

$$illum_{dl} + illum_{al} = illum_{set} \quad (10)$$

In these formulations, α_{Conv} and α_{TABS} are weighting factors for the control inputs of convector and TABS including the heat capacity of water, α_{Light} a weighting factor for the energy consumption of artificial lighting, γ a penalization factor for deviations from the reference trajectory and δ a factor penalizing room temperatures outside the comfort range. ε are slack variables, quantifying temperatures outside the comfort ranges. $illum_{dl}$ is the daylight, $illum_{al}$ the artificial light and $illum_{set}$ the set-point illuminance. The slow layer has a prediction horizon of 24 h and a sampling period of 15 min, the fast layer a horizon of 8 h and a sampling period of 5 min.

To evaluate the performance of the hierarchical MPC it is compared with two other control strategies. The first strategy is a simplified combination of an RBC for solar shading and two PI-controllers manipulating the heating water mass flows of convector and TABS. The blinds are shut and closed to an inclination angle of 90° if the direct solar radiation hitting the respective façade exceeds a value of 200 W/m². The parameters of the two PI controllers are tuned to show a smooth behavior with higher reactivity for the convector compared to TABS and to track the lower bound of the comfort

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range. The second control strategy is a single MPC that is configured in two variations with sampling periods of 15 min and 5 min. The prediction horizon is 24 h for both variations, consequently, the latter is more reactive, but has a greater computational demand.

The MPC strategies are solved in JModelica 2.14, with IPOPT 3.13.1 and the linear HSL solver ma97 (HSL 2013). For solving the MPC problems, an OpenStack instance with a Linux machine, Ubuntu 18.04, 4 VCPUs and 24 GB RAM is used.

RESULTS

The different control strategies are compared in terms of the performance measures energy consumption, discomfort and computation time (Table 1). The performance measure for energy consumption evaluates the weighted sum of energy consumption for TABS, convector and artificial lighting. The performance measure for discomfort calculates the amount of Kelvin hours (Kh) that the indoor temperatures are outside the comfort range. Further performance measures quantify the total time spent in the optimization as well as the computational time ratio, which expresses the relation of the computation time to the sampling time. If the ratio is smaller than one, the system is real-time capable.

In Figure 3, the results for the combination of the RBC and PI-approach are depicted. During the period of higher solar radiation between hours 5 - 9 the indoor temperature exceeds the upper comfort bound. The RBC reacts at a direct solar radiation of 200 W/m² on the façade and closes the shading to minimize solar heat gains, however, due to thermal delay the room overheats at hours 5-6 and 8. The PI controllers increase the mass flows for CCA and convector during hour 10 - 24 in a reactive manner when demand arises but reach the maximum operating limits of 0,2 kg/s resulting in a slight undershooting of the temperature.

In Figure 4, the control performance of the single MPC with a sampling period of 15 min is shown. By adjusting the shading position before the peak of the direct solar radiation on the façade, it partially reduces the overheating peaks by increasing the shading position but reopens the shading too early. The inclination angle remains nearly constant for the entire period. The CCA is preheated during the first hours in such a way that the heating systems do not reach their maximum bounds, whereas the mass flow to the convector mass flow just slightly differs. At hour 20 indoor temperature slightly leaves the lower comfort bound. Compared to the RBC + PI control energy consumption is reduced by 6,9 %, but the discomfort increases by 37,0 %.

In Figure 5, the results for the hierarchical MPC are depicted. The trajectory of the indoor temperature shows very small overheating by dynamically increasing the shading position with increasing direct radiation on the façade. The inclination angle remains nearly constant with an abnormality at hour 6. The convector mass flow starts with small values during the beginning of the period and increases slightly to a value where it remains nearly constant. Similar to the single MPC, the CCA is preheated during the beginning of the period but first, it decreases to avoid overheating. During the overheating period, the reactive fast layer follows a slightly different trajectory to avoid overheating compared with the reference trajectory. Similar to the single MPC with a sampling period of 15 min, indoor temperature undershoots the minimum comfort bound around hour 20. Compared to the RBC + PI control energy consumption can be decreased by 1,8 % and discomfort by 12,7 %.

The results for the single MPC with a sampling period of 5 min are not shown here in a figure. Using this approach, the discomfort could be reduced by 25,4 % compared to the RBC + PI approach at the expense of an increase of 12,1 % energy consumption and increased computation time of 23,4 % compared to the hierarchical approach.

The gained results apply to the studied use case but are not necessarily representative of other cases. All approaches preserve real-time capability with computational time ratios of 0,05 (single MPC with sampling of 15 min), 0,19 (single MPC with a sampling of 5 min) and 0,15 (hierarchical MPC). Accordingly, the hierarchical approach is 6 to 7 times faster than real-time.

The MPC approach was tested for different configurations of the heating systems, different MPC start times and the superimposition of sinusoidal curves to the outdoor temperature to examine the robustness of the control concept. The obtained results were similar to the ones gained in the studied case while preserving real-time capability in all cases. Different time scales for the upper and lower layer do not result in better MPC performance for the studied configuration of the heating systems and the considered simulation horizon of 24 h. Further analysis of varying time scales of the slow and fast layer for different configurations of the heating systems, consideration of forecast errors and longer simulation horizons is part of future work.

Table 1:
Comparison of performance measures for the different controls strategies (in %: compared to RBC + PI)

	Energy consumption (kWh)	**Discomfort (Kh)**	**Computation time (s)/ ratio (-)**
RBC + PI	4,802	1,73	79/ ~0
Single MPC (15 min)	4,472 (-6,9 %)	2,37 (+37,0 %)	2 407/ 0,03
Single MPC (5 min)	5,382 (+12,1 %)	1,29 (-25,4 %)	16 039/ 0,19
Hierarchical MPC	4,715 (-1,8 %)	1,51 (-12,7 %)	13 002/ 0,15

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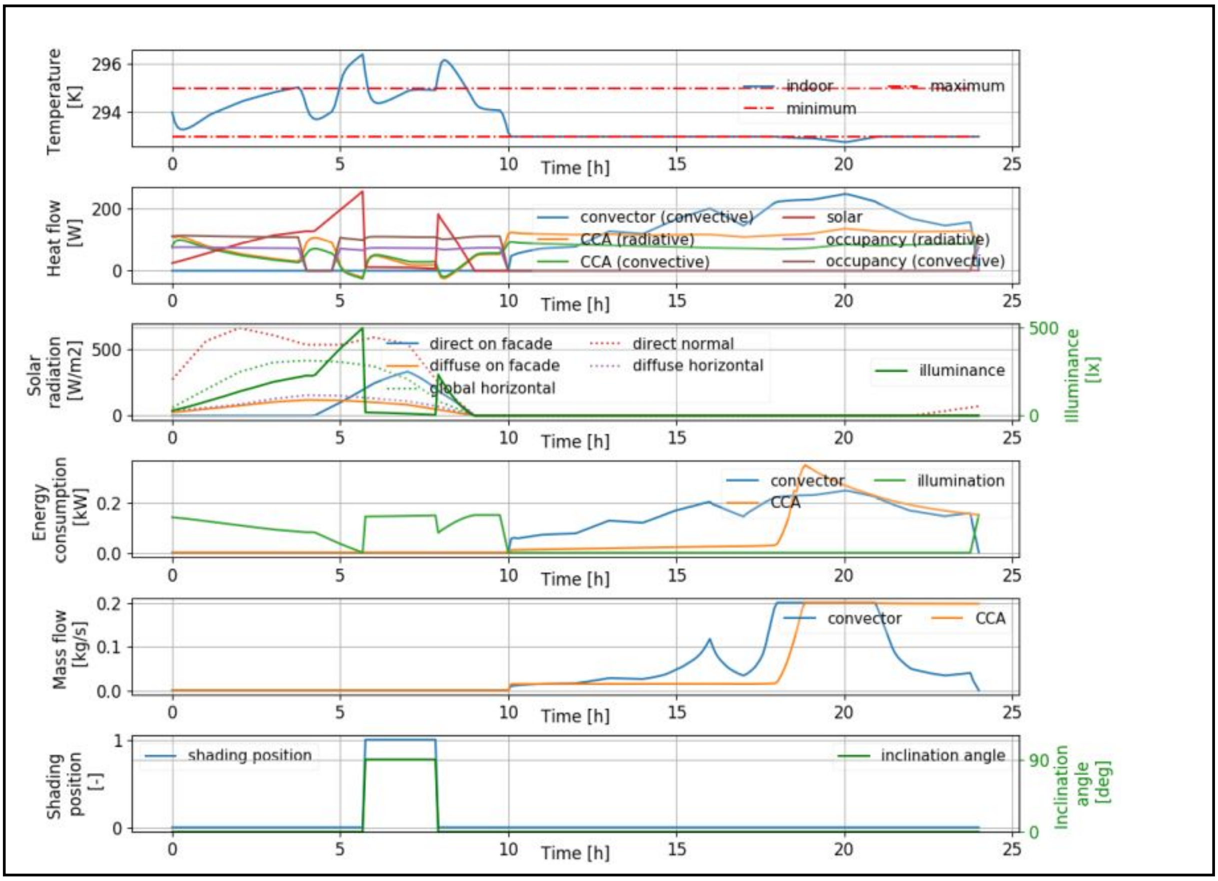

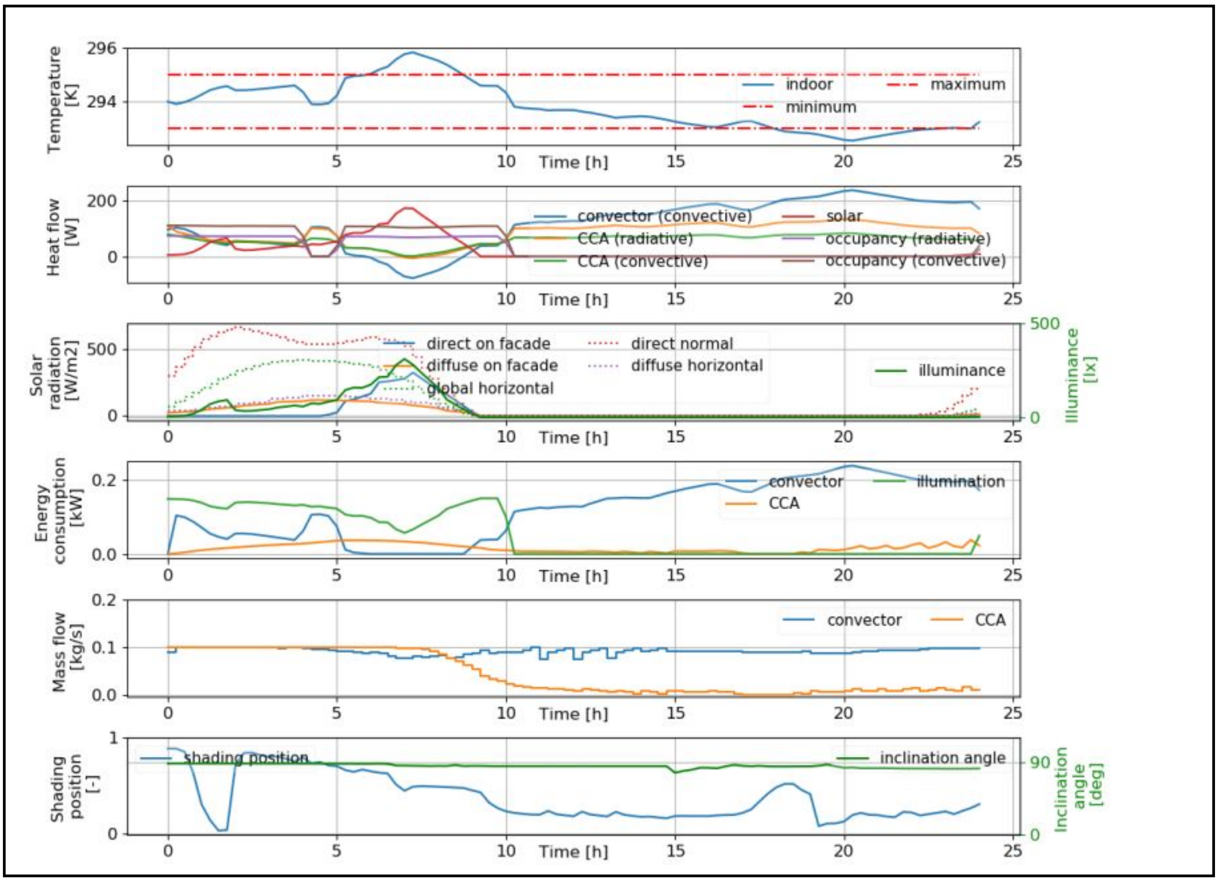

Figure 3: RBC + PI control
Figure 4: Single MPC (sampling period of 15 min)

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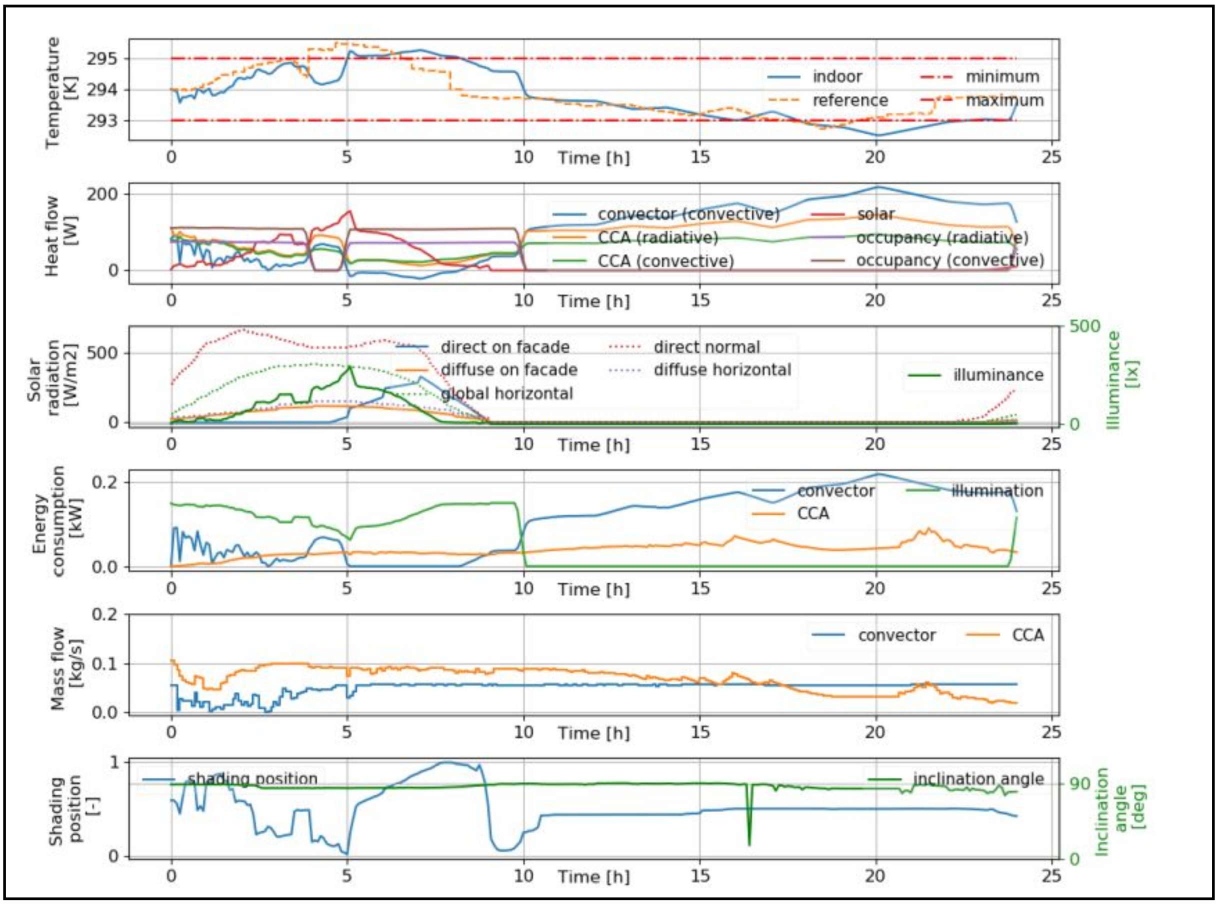

Figure 5: Hierarchical MPC

CONCLUSION

In this contribution, we present a Modelica-based hierarchical MPC approach for building energy systems with components of different dynamics. It accounts for different time scales within complex building energy systems and ensures both reactivity to forecast errors or unpredicted disturbances and anticipation for systems with time delays and high inertia. The presented approach further includes visual comfort by integrating a detailed model for active solar shading through Venetian blinds. The concept is verified on a detailed nonlinear Modelica room model including a convector, TABS and a window with integrated blinds. It is compared to a conventional RBC + PI concept and single MPCs with short and long sampling periods in terms of energy consumption, discomfort and computation time. The results demonstrate the good overall results for the proposed approach with preserved real-time capability for nonlinear Modelica models and underline the benefits of predictive control for shading blinds.

In future versions of the framework, it is planned to integrate models of different complexity for the different layers, to include more detailed comfort models (e.g. for air quality), to improve the shading control concerning user acceptance and glare, to enable integer optimization, to consider energy prices and to implement the approach in a real building.

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