Beyond theory: the challenge of implementing Model Predictive Control in buildings

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Abstract
Model Predictive Control (MPC) of buildings has gained lot of attention in the recent years. Several research projects have demonstrated that MPC can provide substantial energy savings and improve indoor comfort as compared to traditional control approaches. However, the application of MPC requires extensive knowledge in the areas of mathematical and computer modeling, hard- and software systems, data processing, and optimal control. Therefore its application implies considerable additional cost. The key issue is if corresponding energy savings and comfort improvements can balance this cost. The present paper discusses challenges encountered during the implementation of MPC in two different pilot case studies. The first study focuses on a 50 years old building with Thermally Activated Building Systems (TABS), while the second one deals with a newly built office building. Our experience suggests that a simple (not to be confounded with simplistic) model is sufficient to economically operate MPC on a building. However, firm guidelines allowing investors to assess whether it is worth to embark in MPC for a particular building are still lacking. In our opinion the situation could be much improved if building control would be considered already at the very early stages of the building and technical systems design. In this case we believe that MPC presents an attractive option for optimal supervisory control, in particular for buildings with large thermal storage capacity.
Keywords - Predictive control; energy savings; controller deployment

1. Introduction

In developed countries, energy consumption in buildings reaches almost 40% of total final energy and more than half of this amount is consumed in Heating, Ventilation and Air Conditioning (HVAC) systems [1]. Reducing and optimizing the buildings' energy consumption however presents a challenging task.

Meanwhile, several research groups have shown that advanced control algorithms can contribute to substantial energy cuts in buildings. The Model Predictive Control (MPC) technique has received particular attention. Among other results, [2] showed for MPC a 19 % energy savings potential when applied to the control of a university campus building in Berkeley; [3] found in a simulation study based on the TRNSYS building energy simulation software that MPC provided 5% savings as compared to a conventional control strategy; [4] analyzed savings potentials of MPC by means of simulation and found savings in the range of 16-26%; and finally, the OptiControl project [5] using several thousand simulations showed that MPC bears in many cases substantial savings potentials (up to 40%) compared to state-of-the-art rule-based controllers.

These promising results should however not hide the fact that the implementation of MPC on real buildings presents considerable challenges. Here we first present these challenges in more detail. Then we report on how we applied MPC to two basically different buildings. In the last section we discuss our experiences, and draw some conclusions for future MPC applications.

2. Challenges

Mathematical modeling: MPC inherently requires an appropriate model of the controlled plant, which is then used for the computation of the optimal control inputs. This model must be sufficiently precise, in order to yield valid predictions of the relevant variables (e.g. room temperatures), but at the same time, the model must be as simple as possible for the optimization task to be computationally tractable and numerically stable.

In the HVAC engineering community, Building Energy Performance Simulation (BEPS) tools (e.g., EnergyPlus, TRNSYS, etc.) are typically used for modeling of the building physics. These tools contain numerous complex calculations, non-linearities, switches and iterative procedures that make their usage in online optimization prohibitive. An attempt to use a BEPS model within an optimization routine was reported in [6], but generally researchers seek models with lower complexity and computational demands.

Much more suitable for use within an MPC framework are so-called Linear Time Invariant (LTI) models. These result into a convex optimization problem that in general can be well solved by state-of-the-art optimization software. Obtaining an appropriate LTI model of the controlled building is, however, a delicate and laborious task even for experienced and knowledgeable engineers. The following three approaches are in principle available:

a) Black-box identification. The model structure and parameters are identified in a statistical-empirical manner from on-site measurements or from signals generated from BEPS. The following identification methods are available for buildings (see also [7]):

- Subspace State Space System Identification (4SID) methods: belong to the black-box identification algorithms and provide an LTI model in a state space form. The main advantage of 4SID methods is their ability to handle large amount of data without any knowledge about the system's structure. The latter is automatically detected by the algorithm – but precisely for this reason availability of a high quality identification data set is here particularly important [8].
- Prediction Error Methods (PEM): belong to the most commonly used black box identification techniques. The objective here is to minimize one-step ahead

prediction error. This technique has not received much attention in building modeling because PEM are mainly suited for the identification of single-input and single-output systems.

- MPC Relevant Identification (MRI): is an approach minimizing multi-step ahead prediction errors [9]. The horizon for error minimization is commensurate with the prediction horizon of the predictive controller. A multi-step ahead prediction error cost function for selection of a building model was examined in [10].

The black-box approach is conceptually simple but technically tricky, and it depends crucially on the availability of appropriate input data sets that encompass sufficient long sequences of all relevant excitation-response signal pairs. These are very hard to obtain from a real building during normal operation.

b) Grey-box modeling. This approach describes a building's thermal dynamics based on a thermal Resistance Capacitance (RC) network [2], [3], [5], [11], [12]. It presents an analogue to an electric circuitry, with temperature gradients and heat fluxes replacing electric potentials and currents. A plausible model structure (RC network topology) is first specified a priori, and then the model parameters are identified from measurements or BEPS simulations. The advantage of this approach is that basic knowledge about possible thermal interactions (e.g., neighbourship of building zones) can be easily introduced. However, the parameter identification is far from trivial.

c) *White-box modeling.* This approach also relies upon a thermal RC network. Here both, the RC network's topology as well as its R and C elements (the model parameters), are derived directly from detailed geometry and construction data (e.g. [12]). Compared to grey-box modeling this approach has an even stronger physical basis. However, similar to BEPS studies, it requires availability and processing of a large amount of building-specific information.

Controller design: An important aspect is the tractability of the resulting optimization task that is in the heart of MPC controller. In the case of large multi-zone buildings, even simple mathematical models describing the building's thermal dynamics can result into long computation times for the optimal control inputs, in particular when a *centralized* MPC approach is considered. An alternative consists in using a *distributed* approach [13], where several MPC controllers minimize a global cost function. By using this technique, the overall computation time can be significantly reduced and, at the same time, the robustness of the whole control system can be increased. However, this solution comes at the cost of increased communication effort and sub-optimal performance.

The hierarchy of the HVAC system controllers plays also an important role. MPC is generally only suitable as a top-level controller and the question always is how to best achieve a symbiosis between low-level control loops and the top-level MPC.

Hard- and software: Programmable Logic Controllers (PLC) typically operate large buildings. For MPC implementation PLC could rely on (i) pre-generated look up tables (so called explicit MPC), or (ii) the deployment of optimization libraries on the PLC hardware. However, both approaches are severely hampered by the size of the MPC optimization problem. Moreover, present-day PLC lack sufficient memory, processor speed and also software support for numerical optimization. Accordingly, a recent attempt to run an MPC controller directly on a PLC [14] did not prove very successful. A further alternative, yet to be explored in practice, consists in identifying PLC-compatible trees of simple "if-then" rules generated by application of machine learning to MPC control sequences as obtained from simulations [15]. At present, an external MPC computational core needs to be connected to the building's automation system. This requires specification of what signals to communicate, a communication protocol, and the implementation of mechanisms to handle communication and optimization problems (e.g. infeasibility or too long computation time).

Data availability and processing: MPC requires not only an appropriate model but also a wealth of input data during operation. Required at the begin of each optimization are predictions for the expected disturbances (e.g., internal gains due to occupancy and equipment, solar gains, outdoor air temperature) plus quantitative information on the current state of the building. The latter is typically processed by a Kalman Filter (KF) that is used to estimate the MPC model's current state as a starting point for the optimization. To obtain valid KF estimates the sensor network in the controlled building and the building model need to be carefully adjusted to each other. Moreover, the sensors should provide data of high quality since outliers can significantly impact the MPC optimal solution. Generally, the MPC system has to be made robust by including mechanisms to detect and filter out erroneous input data and to handle communication and other failures.

3. University building in Prague

Our first case study dealt with the building of the Czech Technical University (CTU) in Dejvice, Prague (Fig. 1). The building was constructed in 1963 and it has a gross floor area of 70,000 m^2. It is fully used by CTU faculties for normal university operation, and it has served during the last years as a platform for a pilot MPC application. Various MPC experiments involving different controllers and settings (e.g., cost function formulations, weights, constraints, etc.) have been in operation since 2009. First experiments with the building are reported in [16] and performance of the first MPC controller was evaluated in [11].

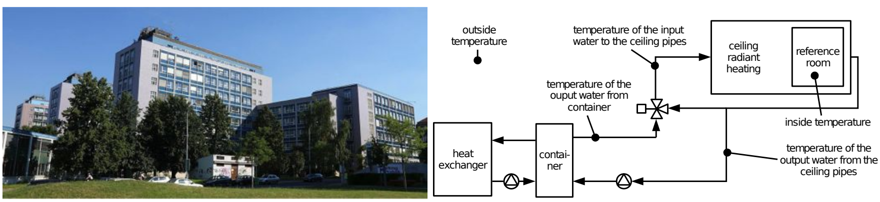


Fig. 1: Building of the Czech Technical University (Dejvice, Prague)

Building description: The building is composed of four five-floor blocks, three eight-floors blocks, and seven four-level intermediary parts located inbetween neigbouring blocks. All blocks have the same construction and are used in a similar manner. Each block is divided into a southern and a northern zone, where each zone has its own heating/cooling circuit. The building has a "Crittall" type ceiling radiant heating and cooling system that employs pipes embedded into the concrete ceiling, very similar to present-day Thermally Activated Building Systems (TABS).

A simplified scheme of the heating system of one zone is depicted in Fig. 1. Heat from a district heating system is transferred to an intermediate storage tank by a vapor-liquid heat exchanger. The tank supplies the zone's heating circuit and receives its return flow. The supply water temperature is accurately controlled by a three-port valve with a servo drive. There is one temperature measurement in a reference room per zone and circuit. MPC is used as supervisory control. The control variable for each zone is the valve's set point temperature. In total, the MPC controller determines 18 water temperature set points, based on knowledge from 18 reference room temperatures and 18 return water temperature measurements.

Mathematical model: Due to the building's low automation level only few measurements were available for use in black-box identification methods. Initially, 4SID methods were employed to obtain a simple model describing the building's average temperature dynamics. To improve identification results, an identification experiment was conducted. The experiment consisted in applying step changes to the supply water temperature set points and recording the associated indoor temperature responses. In this context the 4SID algorithm was adopted to allow for inclusion of knowledge of the system structure (north/south division of a building block) [17]. This initial model was however found to be appropriate only in the particular operating point given by the prevailing weather conditions during the identification experiments. Grey-box modeling, based on the same step experiment data and a separate RC model for each building block [11], resulted in a much more reliable model, especially when solar radiation was taken into account. We also estimated separate LTI models for each block using MRI techniques, and with this approach good results were even obtained when using measurements from normal operation [10].

Controller design: Thermal interactions between neighbouring building blocks were found to be negligible such that we were able to use several decentralized MPCs. The objective of each MPC is to minimize energy consumption (by minimizing the one norm of the temperature set point signal) while meeting thermal comfort requirements (enforced by penalizing indoor temperature range violations as measured by a quadratic norm). The optimal control problem formulation further considered various constraints on system variables (minimum/maximum values, rates of change, etc.).

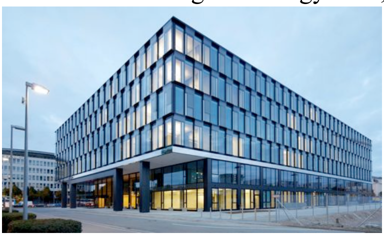
Hard- and software: Initially, we implemented the MPC controller in the non-commercial Scilab computing environment using the "qpsolve" standard library for numerical optimization. Due to problems with the solver's numerical stability and the need for flexible experimentation with the optimal control problem's formulation we later switched to the commercial Matlab software in combination with the YALMIP toolbox [18] that supports rapid prototyping of optimization problems. The interconnection between the computational core (implemented in Matlab/Scilab) and the PLCs controlling the process was realized using a proprietary protocol that was developed specifically for this application. Note that since MPC could not be run directly on the PLCs it had to be implemented on a server that asynchronously communicated with the PLCs.

Data availability and processing: Temperature sensors were already available in the building. All measurements were stored in process database. It was, however, necessary to implement an interface from the computational core in Matlab/Scilab that was realized by the aforementioned proprietary protocol.

MPC evaluation: During the last four heating seasons MPC showed significantly better performance than the previous control strategy that was based on a heating curve. It is important to note that the previous control strategy had already been well tuned by the building operator. Over several years he had been able to reduce annual total energy consumption down to a low level when MPC operation started. MPC gave additional savings of between 15% and 28%. However, some issues remain to be solved, in particular the occurrence of oscillations in the optimal input signal as discussed in [19].

4. Icade Premier House 1 in Munich

Our second case study dealt with the newly built Icade Premier House 1 (IPH1) office building, located in Munich (Fig. 2). The focus was on evaluating the energy savings potential of MPC in the office part of the building as compared to the originally implemented rule-based control. The approach taken centered on simulations with a detailed BEMS model using the EnergyPlus[1], BCVTB[2] and Matlab software.



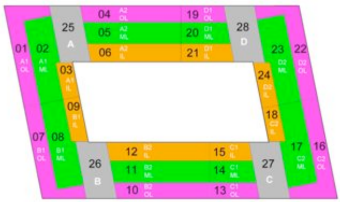


Fig. 2: View of the Icade Premier House 1 (Munich); used zoning of the third floor.

Building description: The building has six floors above ground and a total floor area of 20,000 m^2. The ground plan has four fully adjoining romboid parts that are grouped around an atrium. The window-to-wall ratios of the outer façades and the facades towards the atrium are ~70% and ~50%, respectively. Roughly 50% of the windows have interior blinds; the rest are double-skin façade like windows with in-between-glass blinds. Offices are located in the five upper floors. For this study we focused on the third floor, which has a floor area of 2,800 m^2. Based on usage, façade orientation, HVAC systems and physical considerations the floor's ground plan was subdivided into four romboid areas that contained a total of 24 zones. Each romboid area was assigned two groups of 3 zones, with each group consisting of an exterior, middle, and an interior (towards the atrium) zone (Fig. 2). Each zone lumped several spaces, most of them being open-space offices. The third floor has the following actuators: 16 convectors (one per exterior or interior zone); a large number of radiant ceiling panels for cooling and heating (each of them assigned to one of the 24

[1] EnergyPlus Energy Simulation Software, http://www.energyplus.gov
[2] Building Controls Virtual Test Bed, http://simulationresearch.lbl.gov/bcvtb

independently controlled groups); two Air Handling Units (AHU), covering the northern and southern half of the building, respectively with independently controlled supply air temperature; venetian blinds for all windows, controlled jointly in each of the 24 zones. Energy supply, i.e. hot and chilled water supply for the entire building, is provided by a central heating and cooling plant, which is located partly in the basement and partly on the roof. District heating is used for the building's heat supply. Mechanical chillers provide chilled water locally.

Mathematical model: We employed an LTI model describing the temperature dynamics in the third floor's 24 zones as a function of disturbance (outside air temperature, solar gains, internal loads etc.) and HVAC heat fluxes. Given the large number of inputs and outputs mentioned above considered was a huge multiple-input-multiple-output system. We chose not to embark into detailed RC modeling, but instead to use black-box identification. The only applicable method for the task at hand was the 4SID method. To produce the required input/output data set pairs the Matlab software (input signal generator) was coupled to a detailed EnergyPlus model of the third floor using the BCVTB middle ware. The definition of suitable excitation signals that covered all possible system states and transitions proved to be a very tedious task. Finally, the 4SID procedure was fed a huge data set that extended over 12 months at a sampling interval of 5 minutes. Although the 4SID method essentially boils down to the solution of a least-squares problem, processing of our data set required adaptation of the original algorithm to operate virtual memory in a more efficient way. The overall identification process is described in detail in [8].

Controller design: In the choice of controller (and model) we had to decide on the degree of non-linearity of the MPC optimization problem versus its size. An alternative to our actual choice would have been to use a relatively compact model containing switches and dead bands, as used for the current HVAC system operation. However, this would have resulted in a still too large, non-linear optimization problem that could not have been solved efficiently. The use of a much more basic (but instead much larger) LTI model implied that all HVAC system operation constraints and peculiarities had to be coded in the pre- and post-processing of the MPC optimization at each time step. A second problem was that the use of the comfortable and generic YALMIP environment proved to be far too slow for the huge LTI system at hand. Therefore we had to code the construction of the matrices that defined the Quadratic optimization Problem (QP) directly in the Matlab language. The gain in execution speed was balanced by (i) more difficult debugging, (ii) the need to adapt the QP matrix generation each time the optimization task was redefined, and this clearly presented a very delicate and error-prone programming task.

Hard- and software: This study used throughout a simulation model built with the EnergyPlus software. For controller development and operation we used the Matlab scientific computing environment. For run-time coupling of the two environments we used a co-simulation approach based on the BCVTB middleware.

Data availability and processing: An additional software layer had be developed to ensure the correct and flexible handling of the hundreds of signals involved in the coupling ot the EnergyPlus and Matlab environments [20]. Appropriate operation of the

EnergyPlus software also proved far from trivial. This was because EnergyPlus has been initially designed for energy performance assessment, not for controlller development. Although the simulations in principle provided all quantities of interest, considerable effort was needed to understand the internal functioning (modeling assumptions, run-time behavior, built-in controls) of the EnergyPlus software and to ensure correct driving of the HVAC system components by external signals.

MPC evaluation: Performance of MPC was compared in simulations to the performance of a well-tuned rule-based controller very similar to the one currently deployed in the real building. MPC yielded similar energy usage (to within 5%) as the reference controller at a comparable amount of thermal comfort violations. This result was mainly because of the building's relatively light construction (that provided little scope for predictive thermal storage management) and the high quality of the original control.

5. Discussion and Concluding Remarks

Our studies employed two alternative approaches. The first one (CTU building) was a long term comparison of conventional control and of MPC in a real building. The second one (IPH1 building) was entirely based on simulations with a detailed EnergyPlus model. In the second case the used interface between the controller and the EnergyPlus model represented the building's sensors, actuators and HVAC system constraints in a very realistic manner. Therefore we believe that this computer study still gives a good idea of the effort needed to implement MPC in the real building.

In both cases the MPC implementation took many months of research and development work. In the case of the CTU building the investments into the MPC implementation paid back approximately after the third heating season. In the case of the IPH1 building, the effort put into the MPC research will never pay back if this study is considered in isolation. The main reason for the difference in economic viability relates to the fact that the CTU building has slow dynamics that can be well exploited by predictive control. In contrast, the IPH1 building is much lighter, and it has a much more fine-grained actuation that allows for fast and precise indoor climate regulation already by means of a well-designed conventional control approach.

Table 1 shows the estimated portion of time dedicated to individual subtasks related to MPC implementation in the two buildings. Note that in case of the CTU building MPC implementation started in 2009 and it is an ongoing effort, while the IPH1 project extended, with major breaks, over roughly two years (2010–2012).

Table 1. Estimated fraction of time spent on particular tasks different buildings

Activity	CTU building	IPH1 building	Next building
Modeling	60%	55%	80%
Controller development	35%	25%	5%
Comm. & signal processing	5%	20%	15%

The largest portion of time (55-60%) was spent in both cases for the MPC model development (design of identification experiments, design of model structure, identification, model validation and refinement). This compares to the implementation of MPC on industrial processes, where modeling typically takes up to 80% of project time [21]. Development of the predictive controller (design, writing of optimization code, tuning of controller parameters, etc.) also required a considerable amount of time. Here IPH1 required a smaller fraction of time as compared to CTU because we could profit from previous experience with the CTU building. Quite differently, IPH1 required a much larger relative effort for communication and signal processing (even if having to deal with perfect simulated data only) because of the complexity of the HVAC system and the high actuation detail that had to be considered in the MPC task. Extrapolating from our current experience (last column in Table 1) we estimate that in a next project the modeling task would account for most of the work mainly because the controller core would be taken over from previous projects.

From our studies we could learn several things: (i) Application of MPC in a relatively simple (in terms of HVAC system) building such as the CTU building could be made must cheaper and faster if corresponding measurements, sensors and actuators were in place from the beginning (this is not a too costly investment nowadays). (ii) The deployment of MPC presents a long-term task that requires careful monitoring, tuning and adjustments, i.e. an ongoing commissioning similar to the one required for good conventional control (but with even better results). (iii) In case of the IPH1 building we suspected a low MPC potential from the beginning, but we were not really sure about this (and we were interested to conduct a research study anyway). Since MPC savings potentials show huge variation across building cases [5] planers should have simple methods at their disposal to quickly estimate the predictive control potential of a given building. The BACTool online calculator (www.bactool.ethz.ch) presents a possible way forward. (iv) The IPH1 case study clearly showed that depending on the characteristics and design of the underlying HVAC system an efficient implementation of MPC could be very difficult, if not even impossible. This is because MPC is best suited as a top-level controller that is used to optimize the set-points of lower level controllers, rather than to directly specify the low-level control actions (as this had to be done in the case of the IPH1 building). (v) Finally, the fact that MPC is not a proliferated technology implies the need for portable software components that can be easily adjusted to a given target building, and that allow for the flexible and safe experimentation with the underlying optimization task.

In summary, our experience suggests that for successful MPC implementation building control should be considered already at the very early stages of the building and technical systems design. In many cases MPC could then present a very attractive option for optimal supervisory control, in particular for buildings with large thermal storage capacity.

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