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Ten questions concerning model predictive control for energy efficient buildings

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ABSTRACT

Buildings are dynamical systems with several control challenges: large storage capacities, switching aggregates, technical and thermal constraints, and internal and external disturbances (occupancy, ambient temperature, solar radiation). Conflicting optimization goals naturally arise in buildings, where the maximization of user comfort versus the minimization of energy consumption poses the main trade-off to be balanced. Model predictive control (MPC) is the ideal control strategy to deal with such problems. Especially the knowledge and use of future disturbances in the optimization makes MPC such a powerful and valuable control tool in the area of building automation. MPC compromises a class of control algorithms that utilizes an online process model to optimize the future response of a plant. The main benefits of MPC are the explicit consideration of building dynamics, available predictions of future disturbances, constraints, and conflicting optimization goals to provide the optimal control input. MPC technology has been applied to process control for several decades and it is an upcoming field in building automation. This is a consequence of the large potential for saving energy in buildings and also allows to maximize the use of renewable energy sources. Furthermore, the added flexibility enables to integrate such buildings in future smart grids. In this work ten questions concerning model predictive control for energy efficient buildings are posed and answered in detail.

1. Introduction

The building sector accounts for 20%–40% of the energy consumption in developed countries, including both residential and non-residential buildings [1], thus, efficient usage of energy in buildings is an important task. Two main but conflicting optimization goals occur in building automation: 1) maximization of user comfort, and 2) minimization of energy consumption. Model predictive control (MPC) optimally utilizes predictions of future disturbances (ambient temperature, solar radiation, occupancy), and it is the ideal control strategy to deal with conflicting optimization goals. Furthermore, MPC is perfectly suited for including thermal and technical constraints in the optimization statement, considering large time constants (due to thermal mass and good insulation), and decoupling of multi-variate control problems, thus rendering MPC a powerful control scheme [2].

Originally developed for the refining industry in the late 1970's MPC has been established as the core method in advanced process control with many commercial software tools [3]. Fundamental components of a building MPC are 1) a real-time-capable dynamic building model, 2) predictions of the main disturbances, 3) a performance criterion combining conflicting goals, and 4) a real-time optimizing algorithm. At each time-step the predictions of the disturbances together with the candidate MPC inputs (e.g. heat supplies) are used as simulation inputs to the building model. This simulation is carried out over the prediction horizon, which typically lies between 8 and 72 h in building applications. The optimizer evaluates the performance criterion for each simulation run and adapts the candidate MPC inputs until an optimal solution is obtained. Only the very first MPC input is actually supplied to the building, then the optimization is restarted at the next sampling instant. Therefore, this control scheme is also termed “receding horizon control”.

An exemplary comparison is given in Fig. 1, where MPC is compared to conventional proportional-integral-derivative (PID) control and PID control with external temperature compensation (PIDc). At time t_0 the ambient temperature drops sharply (Fig. 1 top), thus requiring a higher heat supply. However, PID control

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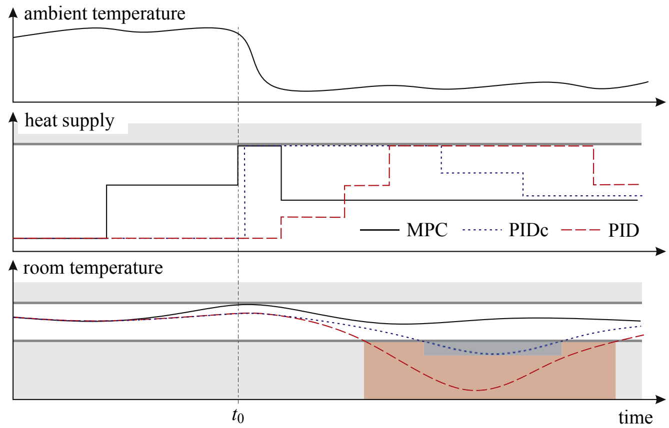

Fig. 1. Comparison of MPC, PID, and PID with external temperature compensation (PIDc). Top: ambient temperature, at t_0 a steep drop occurs. Middle: heat supply to the building with maximum constraint; heat supply is coarsely quantized. Bottom: Mean room temperature and comfort band. Blue and red ranges indicate comfort violations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

only acts as soon as a control error between set-point and actual room temperature has occurred (Fig. 1 middle). Due to the large time-constants of the building dynamics the magnitude of the error increases further on. Eventually the heat supply is constrained by some maximum value, and a severe comfort violation (red range in Fig. 1 bottom) results. PIDc performs better since the compensation kicks in at the very instant the ambient temperature drops. However, the large time-delay still leads to a comfort violation (blue range in Fig. 1 bottom). By exploiting the ambient temperature prediction *and* the building model, MPC starts preheating the building before the temperature drop occurs. The comfort band is not exceeded and the maximum available heat supply is incorporated in the optimal input selection.

Currently, MPC for building control is on the cusp of commercial availability. The theoretical foundation is sound, specific adaptations for building automation have been presented, and many experimental implementations have proven the high economic and environmental potential of MPC. Furthermore, MPC is ideally suited for optimal usage of renewable energy sources and the future integration in smart grids. This high potential comes at the price of several risks: Setting up a suitable building model for MPC is the crucial part, and the modeling effort is difficult to assess in advance. Typically each model is tailored for one specific building, thus, expert knowledge on building modeling and MPC design is called for.

The questions and answers contained in this paper address the current status of MPC in building control, highlight the most important issues of a prospective MPC implementation, and discuss fundamental aspects of future developments in building automation. If some practitioners are considering MPC for building control, to the authors' opinion, these are the questions they should be asking.

2. Ten questions (and answers) concerning model predictive control for energy efficient buildings

2.1. Are there significant benefits of MPC over conventional building control?

Answer: The great benefits of MPC are the exploitation of available predictions of disturbances (ambient temperature, solar radiation, occupancy), the knowledge of building dynamics (important for control performance), and guaranteed compliance with technological and thermal constraints. Additionally, the on-line optimization secures an optimal user-adjustable trade-off between user comfort and energy consumption [2].

The main advantage of MPC in building automation is the optimal consideration of available predictions of future disturbances in the optimization algorithm [4]. By including the predictions of ambient temperature, solar radiation, and occupancy in the optimization algorithm a significant reduction in energy supply can be obtained [5]. Occupancy information in building control creates an additional significant energy savings potential, however, this information is not available for all buildings. Nevertheless, in Ref. [6] different occupancy patterns for different buildings are presented and discussed. Besides occupancy profiles MPC in combination with readily available future solar radiation data and weather predictions can increase the energy efficiency in buildings while respecting user comfort [4]. The combination of disturbance predictions, a dynamic building model, and explicit consideration of constraints allows for optimal compensation within safe operating regions. Note that constraint handling in conventional control poses big challenges since the delayed consequences are difficult to incorporate in the design. The predictive nature of MPC guarantees optimal handling of input, output, or internal state constraints, respectively (see also Fig. 1).

Since a dynamic building model is utilized to represent the large time constants of the building, energy storage strategies can be easily integrated into MPC design. Thermal storage presents opportunities for peak load shifting and reducing operating costs. Buildings with large thermal capacity can be utilized as storage by pre-heating or pre-cooling the building during the off-peak periods, which is easy to handle for MPC. The additional use of thermal storage tanks leads to even further improvements [7]. With conventional non-predictive controllers the optimal management of the stored energy is not possible as the future demand cannot be incorporated.

For building MPC also a number of specialized formulations have been developed. The authors of [8] present a distributed MPC for building temperature regulation. Another distributed MPC is given in Refs. [9], where a cooperative nonlinear MPC for energy efficient building temperature control is discussed. A stochastic MPC approach for buildings is given in Refs. [10] and [11], where the benefits of MPC over conventional building control is emphasized one more time. These structures allow for modular implementation and extend the application of building MPC.

A further benefit of using MPC in building automation systems is the possibility of easy integration in smart grids. Predictive controller strategies as MPC include all features that are advantageous for smart grid integration: The predictive character is ideal to benefit from flexible pricing, constraint handling allows to support load curtailment strategies, and the on-line optimization optimally resolves conflicting goals. MPC can be used to control both energy production and consummation. Therefore, the usage of renewable energy can be easily handled by MPC, thus maximizing the on-site usage of renewables without increasing the grid load.

Last but not least an important benefit is the typical control structure of MPC building control presented in Fig. 2. MPC can be integrated in an existing control structure as supervisory control retaining the existing local control loops.

Thus, MPC is not in contradiction to conventional building control but it can be seen as an additional layer in a supervisory function. This enables retrofitting with minimal intervention in existing building management systems.

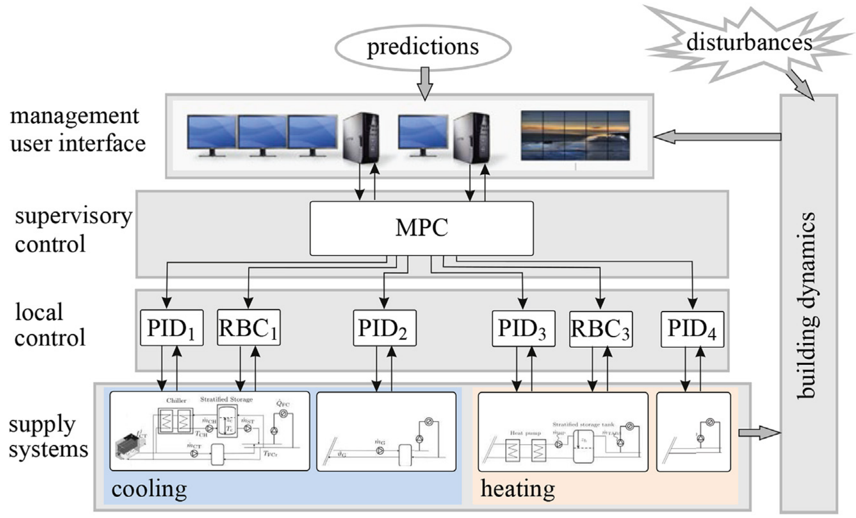

Fig. 2. Typical control structure of MPC building control. MPC is implemented as supervisory controller delivering set-points to the underlying local PID and rule-based controllers (RBC).

2.2. What is the price of these advantages?

Answer: While designing and implementing MPC can be done efficiently, obtaining the building model is typically the most time-consuming part ([12], see Question 3), easily surpassing the effort of designing a conventional controller. It is to be noted that the performance of MPC strongly depends on its underlying model. Furthermore, a "plug-and-play software" for generating a building model for control design is currently not available. For each individual building a specific model (structure, zoning, parametrization) has to be established. This is probably the main reason why the use of MPC has not yet became broadly adopted. Although there exist numerous publications on building climate control using MPC (see e.g. Refs. [4,5,9,13,14]), the number of applications of MPC in real buildings is still limited, e.g. Refs. [15–20]. The most crucial drawback is the fact that MPC needs a mathematical model of the controlled system which should be able to predict the behavior of the building.

As already mentioned, developing a model of the building suitable for MPC is the most challenging task. The authors of [21] introduced the Building Resistance-Capacitance Modeling (BRCM) Matlab Toolbox that facilitates the physical modeling of buildings for MPC. The toolbox provides a means to quickly generate (bi-) linear resistance-capacitance type models from basic geometry, construction and building systems data. However, in general the implementation and design of MPC for commercial products is not possible without expert knowledge during the phase of design and implementation. Each MPC in the building automation field is a unique and individual predictive controller, especially designed for the specific building. Unfortunately, each implementation of a building model has some drawbacks, such as extensive computational requirements or necessity of a mathematical model of the building.

In conclusion, the modeling and control design require expert knowledge, currently no user-friendly software tools for these tasks exist, and due to the prototype character of the implementation a higher economical risk results.

2.3. Is there a silver bullet for obtaining a suitable building model for MPC design?

Answer: For calculating a suitable model for MPC design no silver bullet exists. Preparing a proper model for control in building automation is the most time-consuming part [12]. Furthermore, the "best" model-type for MPC in case of building-automation does not exist in general. In literature three main model-structures are common: 1) white-box models, 2) black-box models, and 3) gray-box models. For control purposes in buildings, reference [22] gives an overview of all three model structures. In addition, a suitable model for MPC design can be both linear as well as nonlinear. Each modeling approach has its own advantages and disadvantages:

White-box modeling:

White-box models, also known as physics-based, analytical models, are developed by understanding the process physics and underlying principles. This model type has a good prediction accuracy over a wide range of operating conditions but this critically depends on expert knowledge how to select structure and parameters. Furthermore, the number of parameters is huge and in case of MPC purposes a reduced-order model is necessary to decrease model complexity. A multiplicity of simulation tools exist, such as TRNSYS [23], EnergyPlus [24], or DYMOLA [25]. For the application of such simulation tools the availability of the correct data is necessary and the key aspect of such simulation. In most buildings, however, the plan data differ from the actually used materials. This major issue leads to wrong parametrization, furthermore, the whole procedure needs to be repeated for every single building, and the complexity of such models is not useful for MPC design. In Ref. [26] the concept of a linear time-dependent predictive controller is verified on a set of numerical experiments using a high fidelity model created in such building simulation

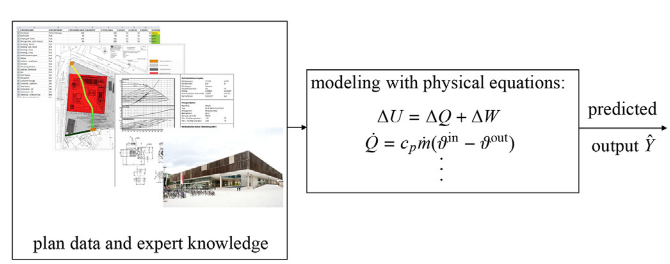

Fig. 3. Concept of white-box modeling. The model includes only physical equations and the parametrization results from planning data and/or expert knowledge.

environment. The basic idea of derive a white-box model is given in Fig. 3.

Black-box modeling: Black-box models, also known as data-driven models, are developed by measuring the necessary inputs and outputs of the system and fitting a linear or nonlinear mathematical function to approximate the operation of the building. One advantage of black-box models is the limited number of parameters, and also the complexity of the model structure is low and perfectly suited for MPC design. Disadvantages stem the fact that most parameters do not have physical meaning. Therefore, they are not interpretable for building operators. One data-driven model approach is given by local linear model networks (LLMN), [27]. For a LLMN the so-called partition space needs to be chosen correctly to map the most significant nonlinearity of the system. An effective method to obtain such Fuzzy black-box model for multi-zone office buildings is presented in Ref. [28]. Therein, the overall heating dynamics are identified by the proposed approach. The authors of [29], in contrast, use a Fuzzy black-box model to estimate only the indoor illuminance in buildings. Another approach for black-box modeling for MPC is a neural-network-based one. The approach presented in Ref. [30] deals with predictive control of heating, ventilation and air conditioning (HVAC) systems based on neural networks for thermal comfort and energy savings in non-residential buildings. The predictive models in Ref. [30] are implemented by radial basis function neural networks identified by means of a multi-objective genetic algorithm. A neuro-fuzzy MPC approach for residential buildings is discussed in Refs. [31], the proposed MPC is designed for typical Australian residential buildings and provides the prediction of the indoor temperature. An energy management supervision strategy based on Fuzzy logic rules are presented in Ref. [32]. Therein, the research focuses on commercial buildings integrating photovoltaic and electrical storage system. However, typical black-box models often require long training and validation periods and are limited to building operation conditions covered during the training period. Furthermore, because of the dependence on measurements in buildings often only closed-loop data are available, which renders system identification difficult (underlying controller loops may be active). The general structure of black-box modeling is illustrated in Fig. 4.

Gray-box modeling: A combination of white-box and black-box models gives the gray-box modeling approach. Although the inner structure of the system dynamics is not entirely known, the main system dynamics and the overall model structure is given by expert knowledge. This model (see Fig. 5) does, however, still have a number of unknown free parameters which can be estimated using system identification. In [33] a gray-box model for an HVAC system of residential buildings in Canada is presented. The model of [33] is given by energy balance equations and the free parameters are estimated by using nonlinear least-squares optimization. An additional gray-box model approach is given in [34]. The overall model

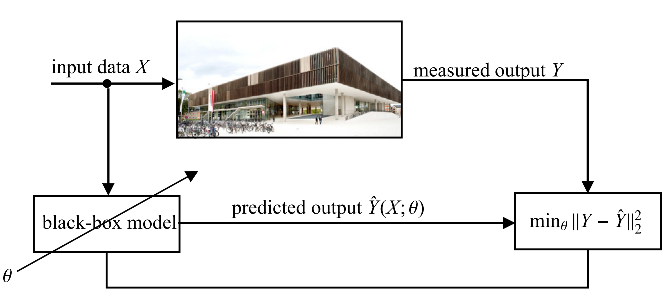

Fig. 4. Basic idea of black-box modeling concept, where the model is generated by minimizing the model error between the predicted and the measured output. The optimization parameters are denoted by $\theta \in \infty \mathbb{R}^{n_\theta \times 1}$.

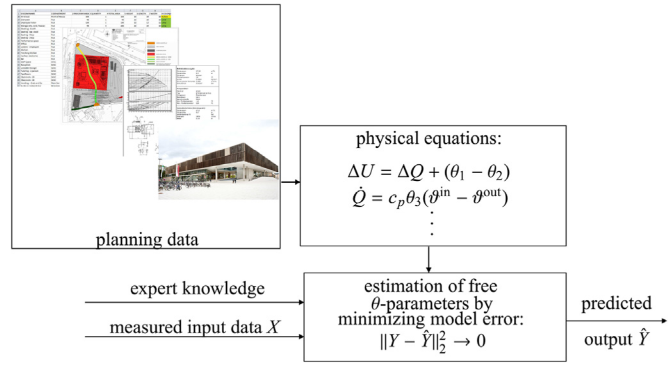

Fig. 5. Gray-box models combine ideas of both black-box and white-box modeling, where plan data, expert knowledge and measurements are included to find a suitable model.

structure is derived from resistance-capacitance (RC) networks analogue to electric circuits to describe the dynamics of the building. The parameters are estimated using the continuous-time stochastic modeling (CTSM) toolbox implemented in *R*, which uses maximum likelihood estimation (MLE). Further building models based on RC models are given by the authors of [35] and [36]. A different gray-box modeling approach is given in Ref. [9]. The authors of [9] use a data-driven LLMN for which the partition space, the model order and the number of local linear models is given by expert knowledge, thus, a gray-box model results. Creating a gray-box model often requires 1) long calculation times due to the parameter optimization process, and 2) expert knowledge during the model development process (general structure of the model, order, most important measurements, etc.). However, for MPC design it represents a good trade-off between physics, expert knowledge, and data-driven modeling approaches.

Furthermore, the selection of the model type depends on the specific building type. The knowledge of measurements and the use of the specific optimization goal of the MPC are key decision factors. One coarse classification is that into residential and non-residential buildings. In addition, radiation is one of the most relevant disturbances in building control, thus a partitioning in different zones is essential in most buildings, see [28,37]. For both cases **residential** [38], and **non-residential** buildings [28,35], a careful division into building zones is one of the most important tasks to attain the best possible results with an MPC strategy in building automation.

In general parametrization of building models remains a difficult part and has to be carried out with care for each individual building. Plug-and-play models are not going to be available in this application field. Furthermore, white- and gray-box models seem to be advantageous for building applications, because a certain degree of expert knowledge is beneficial for each MPC implementation.

2.4. How can conflicting control goals be resolved?

Answer: The primary challenge in building control is that the energy consumption and the comfort level in a building environment are typically conflicting objectives. In most optimizations this conflict is lying on a so-called Pareto front (best possible compromise).

In Ref. [39] the energy consumption and the overall comfort level are considered as two control objectives in system design. Multi-objective optimization is utilized to generate the Pareto-front which is compromised up of Pareto-optimal solutions, where the user can select a particular solution a-posteriori, depending on his/

her preferences. These trade-off solutions allow informed decision-making for energy and comfort management in complex building environments. The authors of [40], however, found out that when the energy efficiency improvement problem is faced in its real-world dimensions, it possesses inherent difficulties that complicate both the modeling and the multi-objective optimization solution approach, because the corresponding decision models and calculations of their solutions are expected to be far more complicated.

A further multi-objective genetic algorithm is employed in Ref. [41] to find the optimal solutions including life-cycle costs and design alternatives for both economical and environmental criteria. In the case of residential buildings [42], uses a multi-objective optimization algorithm to design low-emission and energy efficient residential buildings. A combination of an artificial neural network and a multi-objective evolutionary algorithm is discussed in Ref. [43]. The authors of [44] achieved an energy efficiency of 31.6% with an 8.1% improvement of comfort index using a hybrid multi-objective genetic algorithm for optimization.

Another possibility is the use of cooperative distributed MPC, which is introduced for the linear case in Ref. [45] and for nonlinear systems in Ref. [46]. An extension to a special form of nonlinear cooperative MPC is established in Ref. [47]. The theoretical developed approach of [47] is also used in the field of building automation, see Ref. [9]. An alternative approach to deal with conflicting optimization goals is presented in Refs. [48], where a hierarchical MPC structure splits the overall optimization problem in two less complex optimization problems (maximization of user comfort a minimization of energy demand). The review paper [49] presents a comprehensive and significant overview of research conducted on state-of-the-art intelligent control systems for energy and comfort management in smart energy buildings. This challenging problem of conflicting optimization goals arises in residential buildings as well as in non-residential buildings.

MPC is in fact ideally suited for optimally resolving conflicting control goals, however, this can only be achieved at the cost of more involved mathematical formulations and the necessity of a real-time optimization algorithm.

2.5. What are the main challenges of an MPC implementation?

Answer: The current situation for MPC-implementations in building control systems seems to be similar to that in the early 90's in the process industry: Prototype implementations of MPC clearly demonstrate the high potential of a theoretically well-developed method, but only very few experts in the field know how to set up and commission such a control system successfully. Nevertheless, a combination of economic pressure by the market and competitors, increasing availability of software tools for modeling and control design, and incorporation of MPC courses in control education [50] led to the acceptance of MPC as core method in advanced process control [3]. As such, its application is still limited to important process steps within the production facilities or it is used as supervisory control.

A recent publication [15] discusses the costs and benefits of an MPC implementation in a building relative to classical rule based control. As reported by others [17,18] cost reductions in energy usage vary between 34 and 80%. Nevertheless, the authors in Ref. [15] point out that "… the necessary engineering effort for constructing a model still remains the largest unknown factor on the cost side …". Furthermore, significant costs related to training of personnel would arise if MPC were to be included in the portfolio of a building automation company. Other costs like hardware installation, software configuration, acquisition of predictions, and maintenance should be comparable to existing industrial control systems. An additional advantage of MPC in retrofitting is that it can be implemented as a supervisory control on top of existing local control loops [17] (see also Fig. 2).

Another problematic aspect is the acting personnel's willingness to adopt new control strategies in the building automation industry. Existing building automation systems are fairly conservative, especially in residential buildings [19]. Companies have their tried and tested tools, and personnel does not necessarily need an academic background in control engineering. The step to incorporate MPC in the product portfolio is thus afflicted with many unknown and initially additional costs. In Ref. [20] it is reported that a software tool may increase the usage of sustainable building material in the industry. Such software tools for MPC implementations in buildings are currently missing, but they could significantly contribute to minimizing risks and boost acceptance in industry. Another important feature to minimize risks is to implement fall-back security to the old system with bumpless transfer when retrofitting existing buildings.

Summing up, the main challenges and possible solutions for MPC implementations are:

- **Engineering effort for building modeling and control design**: As emphasized in the answer to Question 3 the careful choice of an appropriate and efficient modeling approach is paramount to establish an economically successful MPC implementation. Also, the design of the MPC scheme needs to be adapted to each specific building. Effective MPC control schemes for buildings are currently being refined, and past experience from process industry [3] has shown that user-friendly tools are feasible and will soon be emerging. However, systematic approaches to modeling and parametrization of buildings are still needed to lower entry barriers.
- **Qualification of control engineers**: The qualifications needed for building modeling and MPC design call for an academic education. Although teaching material on MPC for practitioners is available (e.g. Refs. [2,16]) it also needs additional efforts from educational institutions to foster MPC knowledge. In China such initiatives are actively pursued, as can be seen in Refs. [51,52]. A quick solution for building automation companies may be to hire experienced experts from process automation areas.
- **Risk mitigation of MPC implementations**: For retrofitting of existing plants a comparatively low effort will suffice to implement fall-back security to the old system with bumpless transfer. This will especially facilitate commissioning of the MPC system, as unwanted operational states can be ended with minimum risk. Possible interim solutions like the Smith predictor [53] may be used, but they offer only limited functionality (e.g. no constraint handling).
- **Industry's reluctance to adopt innovations**: This is coupled to the above listed challenges; from an investment point of view, there is a considerable risk for building automation companies to expand their portfolio with MPC strategies. Nevertheless, aside from a deeper understanding of the building's dynamics, which is beneficial for any automation approach, the first companies to provide such service and expertise can expect to acquire a larger market share. Considering the potential of MPC in building control and possible future legislative obligations, an increasing demand for implementations is quite realistic. This pull from the market will be decisive for the spreading of MPC in commercial implementations.

2.6. Are the necessary measurement signals already available in modern buildings?

Answer: The importance of a suitable and reliable building model has already been stressed in Question 3. Although analytic building models and black- or gray-box models are generated by a variety of widely differing methods, the measurements necessary for obtaining a valid model are basically the same. Although surprising at first glance, this fact becomes clear from the fundamental phases of modeling, validation, and control. As shown in Fig. 6 all phases require the same consistent input-output measurements (Fig. 6a) in order to come up with a functional and performing closed-loop control.

Regardless of the modeling process (either analytical or black-/gray-box as in Fig. 6b) the validation of the building model (Fig. 6c) requires the same measurements as system identification (Fig. 6c) and closed-loop operation (Fig. 6d). This is a direct consequence of the MPC concept, since the building model is simulated in real-time at each sampling instant of the controller.

The *available* measurements, however, differ vastly between non-residential (mainly office) and residential buildings:

Non-residential buildings: In most countries legislation defines compulsory standards for working conditions. This may include important comfort factors such as air temperature, humidity, and air exchange rates. These output measurements are therefore often available for each room, together with additional information such as occupancy, status of lighting, temperature set-point corrections, etc. The overall number easily amounts to several hundreds of signals. The number of manipulated variables is much smaller because typically for each zone of the building only few manipulated variables exist [54,28]. The number of building zones can vary between 1 and around 20 depending on the grouping of rooms (cardinal directions, storeys, etc.). Typical manipulated variables for each zone are:

- supply air temperature
- supply air humidity
- air exchange rate
- heating and cooling power (positive/negative heat flows)
- position of window blind

Note that in modern office buildings heating and cooling power may be provided by two or more independent systems, e.g. fan coils for each room and thermally activated building systems for the whole zone. Typical measured disturbances are outside temperature and humidity, radiation, and occupancy. Where occupancy cannot be measured, statistical methods may be a remedy [6]. Although these signals are almost always measured and stored, a prediction necessary for MPC is rarely available in existing systems. However, such predictions can be obtained for most geographical locations from service providers at moderate cost.

Note that the large number of measured output signals requires suitable reduction procedures. These can be either selection of representative channels [54], averaging over zone measurements [28], or specific data fusion [55]. To accomplish these tasks efficiently, standardized communication systems in the building are necessary [56]. All modern office buildings do possess some implementation of such a system and are therefore suitable for MPC retrofitting [57].

Residential buildings: In residential buildings the paradox situation arises that large apartment buildings with numerous flats rarely collect output data on the comfort parameters of individual rooms or flats. Central HVAC systems are also quite uncommon in residential buildings [58]. This may be partly due to privacy considerations and costs, but also to the widely differing comfort set-points of the individual residents. In most residential buildings two very simple local control loops for each flat are in use: A central room thermostat located in the living room, or boiler control for supply temperature (possibly with to outdoor temperature compensation) [19]. In this case the necessary measurements for MPC are not available, and retrofitting of the whole building would be quite costly.

However, in individual flats and detached houses the increased utilization of home automation systems provides the opportunity to implement MPC schemes. Although required measurements for MPC are usually not existent, necessary sensors and communication can be provided by wireless sensor networks [59] which allows for cost effective retrofitting. Depending on the integration of home appliances (which requires both additional signals and compatible appliances) either only heating control [13] or combined optimization [14] becomes possible. Due to the large potential for demand-side-management, residential buildings are specifically focused on regarding integration in smart grids [60,61].

In conclusion it can be said that in most modern non-residential buildings the necessary measurements are directly available and the main problem is the proper selection or aggregation of channels. In residential buildings, however, signals necessary for MPC do not exist, but in the special case of individual flats or detached houses wireless sensors and communications provide a flexible means for obtaining the required signals.

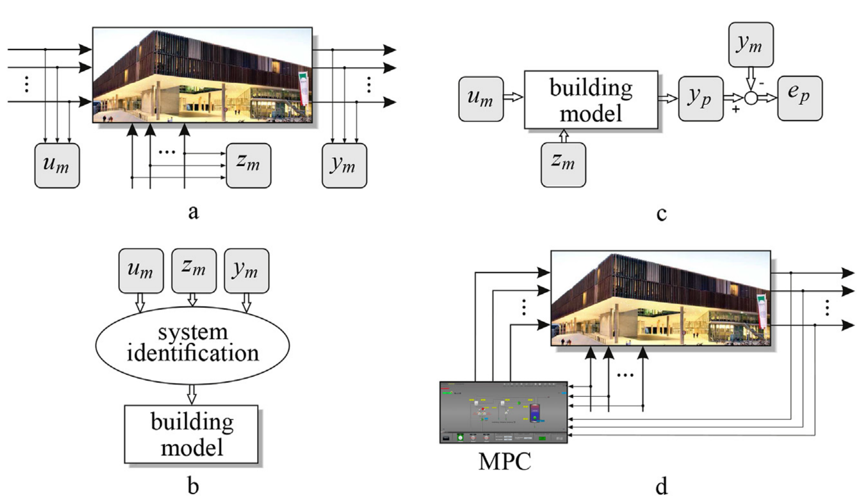

Fig. 6. Measurements for building modeling and control: u_m manipulated variables, z_m measured disturbances, y_m measured outputs, y_p predicted outputs, e_p prediction error. (a) measurements on the real building. (b) black- or gray-box identification. (c) model validation using the model's prediction error. (d) closed-loop operation.

2.7. Why is MPC well-suited for incorporation of alternative energy sources?

Answer: Alternative energy sources for buildings are mainly represented by solar radiation, heat pumps and chillers (either geothermal or air-based), free-cooling, biomass and biofuels, wind, and hydropower. Biomass and biofuels are quite similar to conventional fuels regarding the building automation system; hydropower is rarely available for individual buildings. On the other hand, solar energy and free-cooling can be utilized either as electrical or thermal energy at almost any geographical location, and wind energy may also be available by utilizing the high rooftops of urban buildings. Heat pumps and chillers perform best when coupled to geothermal sources, however, for small residential buildings air-based aggregates have much smaller investment costs. A common characteristic especially of solar radiation, wind, and ambient air temperature is their strongly time-varying intensity (see Fig. 7) in a detailed pattern.

Although chillers and heat pumps connected to geothermal sources have an almost constant supply temperature level, their operation is typically intermittent. So, on time scales from 15 min to 24 h, the availability of these important alternative energy sources varies considerably. For sun and ambient temperature most of the variation is periodic and only on a small time-scale stochastic variations occur (e.g., due to clouds). Although the availability of these alternative sources is externally driven they can be predicted by appropriate forecast methods [10,4].

Supply and demand within an office building may be shifted 12 h and more: free-cooling may only be feasible during night hours while cooling power is mostly needed during working hours. A straightforward way to deal with this problem is the usage of thermal storage tanks. In Ref. [7] a stratified storage tank is operated with a chiller and cooling towers. Model predictive control is shown to effectively balance the load on chillers and cooling towers. In Ref. [62] it was also shown that mixed-integer model predictive control can facilitate smaller storage tanks and therefore less investment costs. A combination of stratified storage tank and photovoltaics with MPC is investigated in Ref. [63].

What is even more attractive for MPC is using the large building mass itself as thermal storage. This is most effective if thermally activated building systems (TABS) such as concrete core activation are available. These have slow dynamics (12 h [64] up to several days [28]) thus constituting a thermal storage with large capacity. They are ideally suited for utilizing alternative energy sources by MPC [9]. A building with such a control system is at the same time fit for active integration in modern smart grid architectures [65].

Because of the large thermal storage capacities of buildings (even without dedicated storage tanks), the strongly varying characteristics of alternative energy sources, and the readily available predictions, MPC is the ideal control scheme to incorporate alternative energy sources.

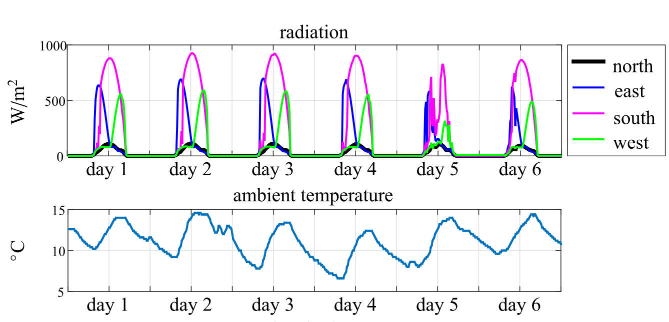

Fig. 7. Ambient measurements of air temperature and solar radiation for a building in Salzburg, Austria, over 6 days.

2.8. Is it possible to utilize MPC for a building energy management system?

Answer: A building energy management system (BEMS) is a system to monitor, measure, and control the generation, transmission, and storage of energy. The physical domain of application can be e.g. a hybrid vehicle transmission system, an electric utility grid, or the energy supplies and storages of a building. Either the whole building including supply and comfort zones is considered [14,66,67] or the supply and storage systems are treated separately from the building [48,62,68,69]. Both cases can be controlled by MPC, however, the split into a hierarchical structure is favorable from an implementation point of view. As shown in Fig. 8 the hierarchical approach allows for a separate design of comfort-level control and energy-management control.

The basic idea in this case is that the energy consumer's demand is the input (set-point/trajectory) to the energy supplier's control system [48,62,68]. The building dynamics therefore are no longer part of the BEMS, thus the control design is more flexible.

Energy management systems in a modern building typically comprise several redundant components especially when renewable energies are utilized: For heating, solar heat as well as heat pumps may be operated together with district heating or boilers using fossil fuels. For cooling, chillers may be operated together with free-cooling or forced ventilation. Furthermore, photovoltaics may be operated additionally to the utility grid, and stratified storage tanks of varying size can buffer demand and supply. While some energy supplies are modeled and controlled in a continuous way [37,69], most building energy management systems use a hybrid model [14,62,66,68]. Hybrid in this context means that some components change their operating state in a discontinuous fashion. This is quite common in building supply systems: Tanks are either charged or discharged, pumps and chillers are switched on or off, etc. Sometimes also latency or hold times have to be considered, e.g. after switching on the chiller it must operate for a minimum up-time until it can be shut off a gain and vice versa. Such hybrid systems consist of switched elements as well as continuous variables. The respective optimization is termed mixed-integer (MI) optimization, as both integer and real variables are to be optimized. In principle any general non-linear optimizer can be utilized such as

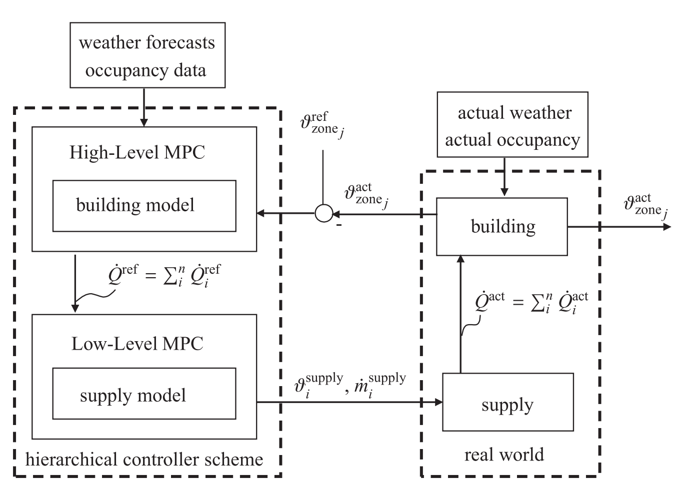

Fig. 8. Example of hierarchically decoupled MPCs for building and BEMS, respectively (from Ref. [48]). The index i describes the different supply sources, j the specific building zone (see Question 3), $\dot{Q}$ heat flows, and ϑ denotes temperature.

genetic algorithms [70], but the incorporation of predictions [71] calls for MI-MPC.

While such an MI-MPC is numerically more involved than a conventional MPC, it is capable of optimizing also switching instances (this is also called scheduling). Applications include heat supply using a heat pump and district heating with stratified storage tanks [62], scheduling of thermal and non-thermal appliances in a residential building [14], control of a simplified solar absorption cooling system with chiller [68], and a residential HVAC system with photovoltaic thermal energy generation and phase change material thermal storage [66].

The core task of such a BEMS is the accurate delivery of a prescribed power trajectory with minimum cost. The considered costs can also reflect life cycle costs such as wear due to switching, investment costs, variable electricity prices, etc. As these goals are conflicting, MI-MPC is an effective means to obtain an optimal solution. It is therefore quite likely that future building management systems will be based on hybrid system models and some realization of MI-MPC as the potential for cost saving and integration of renewables is high.

2.9. Which building control strategy is best suited for integration in smart grids?

Answer: Smart homes and buildings are important components of smart grids [72]. The reasons for this importance are numerous: On the one hand, just residential thermostatically controlled loads such as air conditioners, heat pumps, water heaters, and chillers amount to 20% of the total electricity consumption in the United States, in commercial buildings this number can be up to 35% [73]. On the other hand, large storage capacities for electrical energy are currently not disposable (environmental aspects) while the thermal storage capacities of buildings already exist. They can however only be utilized if a suitable control strategy taps the full potential of these capacities.

Requirements for implementing a building control strategy in a smart grid are:

- knowledge about current thermal energy storage capacity in the building
- ability to optimally handle predictions of electricity prices
- implementation of load shifting (shift peak demands to earlier or later time periods)
- demand response management (adjust own consumation/production of energy to external constraints)

Furthermore, MPC in smart grids enables load curtailment strategies and is able to balance conflicting goals (user comfort vs. energy consumption vs. monetary costs). MPC includes all features that are advantageous for smart grid integration: The predictive character is ideal to benefit from flexible pricing, the building model facilitates an accurate estimation of the thermal energy stored in the building (thus enabling load shifting and demand response management), constraint handling allows to support load curtailment strategies, and the on-line optimization optimally resolves conflicting goals. In a recent survey MPC is by far the most frequently used control strategy of smart sustainable buildings [49].

Load management of a modern office building including load shifting and demand response can be readily integrated in building MPC [65,74,75]. Especially for the case of real-time electricity pricing MPC has been shown to be an effective tool [76]. This is even more important if photovoltaics on the building also enable local production of electricity [63]. This is an especially important feature: Whenever renewable energy sources are available locally at the building, MPC allows for maximization of the on-site usage of the renewables thus minimizing the load on the smart grid. This advantage has also been shown for a heat pump combined with a stratified storage tank [62].

Although most development have focused on non-residential buildings so far, increasing interest has been placed on residential buildings in smart grids [60,61]. The requirements formulated there can also be covered by MPC functionality. Furthermore, MPC was shown to enable grid frequency regulation using ancillary power supplies in commercial buildings [73]. Another increasingly important application of MPC in smart grids is load curtailment, which enables safe operation of the grid during periods of high loads. The method reported in Ref. [77] relies on the existence of MPC controlled buildings in the grid. Overall, there is no other single control strategy for buildings in smart grids which features the same suitability and versatility as MPC.

2.10. What is the current and future market penetration?

Answer: Only ten years ago MPC has not been considered in a survey on building automation systems [78]. In contrast, a recent survey reports that the majority of publications on intelligent control schemes for optimized building control is based on MPC [49]. While this clearly indicates that the technology readiness level has risen to the point where industrial solutions become feasible, currently mostly prototypes of MPC implementations for large non-residential buildings exist [15,54]. Nevertheless, in Ref. [57] a wide variety of building archetypes suitable for MPC implementation is listed. The authors identify office buildings and secondary schools as primary targets for MPC as they both satisfy several criteria for effective MPC implementation. It seems most probable that this will be the first area of commercially available building MPC, where we will see the first implementations in the next few years. Such a development, however, would require the automation suppliers to hire or train experts in the field of building modeling and MPC design. As already discussed in the answer to Question 5, the availability of competent and trained experts in this field may be the real bottleneck for market penetration.

Another emerging market is the smart home automation area. Originally focused on a user-friendly interaction of comfort and entertainment features of the private home, a strong trend towards incorporating energy management features using MPC has developed. In this context either only building heating is considered [13] or also home appliances are integrated in the energy optimization [14]. Smart home automation products currently show a strong increase in sales numbers, and possible future variable electricity pricing will be an additional strong incentive to buy such solutions. An additional attractive feature could be the adaptive nature of such solutions [13], which renders dedicated modeling and MPC design phases unnecessary. It is therefore quite likely that the number of MPC implementations in building automation in a few years will be highest in small residential buildings.

3. Conclusion

Nowadays the implementation of MPC structures in real buildings is proven, but it is far from widespread commercial use. Anyone taking an MPC for building automation purposes into account has to ask some relevant questions. Ten questions considering most important by the authors are answered in this work.

The benefits of MPC in the field of building control are the optimal use of predictions (ambient temperature, radiation, occupancy) easy handling with large time-constants (large buildings in general have slow dynamics), and the possibility to simply include thermal and technical constraints into the underlying optimization.

The disadvantages are clearly the high modeling and parametrization effort, where currently no commercial tools exist to derive easily a suitable model for MPC design. Furthermore, engineers typically active in the automation of buildings are no experts in modeling and/or predictive (smart) controller schemes. Thus, MPC design for each building is at present an individual design-procedure for a specific building.

The high potential of MPC usage in building control, however, is proven in several references and many actual implementations in real buildings promise great benefits over conventional controllers.

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