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Model Predictive Control for Smart Buildings to Provide the Demand Side Flexibility in the Multi-Carrier Energy Context: Current Status, Pros and Cons, Feasibility and Barriers

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Abstract

In this paper, a state of the art review of model predictive control (MPC) for smart buildings to provide demand side flexibility with the purpose of enhancing a high penetration of renewables into the integrated energy systems is carried, including MPC current development status, pros and cons, implementation feasibility and practice barriers. A two-layer hierarchical MPC-based controller is proposed in a case study for a newly-built multi-family building in Copenhagen. The simulation results show that buildings, as a flexible load to the multi-carrier energy system, whose thermal mass is a heat buffer with a large storage potential, can contribute to the grid ancillary services (load shifting or flexibility), based on the economic incentives that the energy/flexibility market offers to end-users.

Keywords: Demand side flexibility; energy management system; model predictive control; multi-carrier energy systems; smart buildings

1. Introduction

To fulfill the Danish 2050 100% fossil-free energy target, we need to choose a smart energy system solution and various short-term and longer-term storages across the different energy sectors. Traditionally, the different energy subsystems i.e. electricity, gas, district heating/cooling and hydrogen had relatively few interactions and were designed and operated independently of each other to handle a single energy carrier. However, today, there is

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significant interest in exploring the synergies between energy networks (e.g. power to gas energy storage and thermal storage providing demand response). Interactions take place through the conversion of energy between different energy carriers and its storage in order to provide services and ensure that each is operated in an optimal way [1]. This integration requires more flexibility in the entire energy system while ensuring security of supply, and it will challenge the existing energy (electricity, heating, transportation and gas) infrastructure and its control systems with more complicated dynamics and uncertain problems [2].

Energy consumption in buildings represents over 30% of society's energy demand and half of global electricity demand [3]. As part of the transition to a sustainable and integrated future energy system, on one hand, it is of extreme importance to improve buildings' energy efficiency; on the other hand, as shown in Fig.1, thermal capacity of the buildings can be used to become a flexible energy (both electricity and heating/cooling) consumer that can actively take part in the future smart energy systems by providing the demand side flexibility/ancillary services via the flexibility/electricity market (e.g. FLECH) for the transmission system operator (TSO), distribution system operator (DSO), district heating operator (DHO) and balancing responsible party (BRP), etc. [5].

Model predictive control (MPC) is seen as one of the key future enablers for an intelligent energy management in buildings to meet inhabitants' comfort needs in a more efficient way [7]. This control technique consists in an on-line predictive optimal control of the energy system according to the estimated future behavior of the system given a number of disturbances (e.g. weather, dynamic energy price, occupancy…) [8][9]. The energy management decision is supported by a variety of parameters: energy consumption, dynamic energy price, share of renewable energy sources (RES) in generating mix, CO_2 intensity of the power, and the deviation from an indoor temperature reference. Each of these parameter results in a different formulation of the control strategy. As highlighted in [10], trade-offs arise as part of the selection of the strategy, for example, to minimize energy consumption, to provide wind balancing service for BRP; or to reduce CO_2 emissions, etc.

The remainder of the paper is organized as follows: what is MPC-based building energy management systems (BEMS) for demand response, its pros and cons are introduced in section 2. A case study of MPC-based BEMS for a multi-family residential building in Copenhagen is conducted with a hierarchy controller design, followed by a discussion of its implementation feasibility and practical barriers in section 3. The conclusion is drawn in section 4, together with a description of future work.

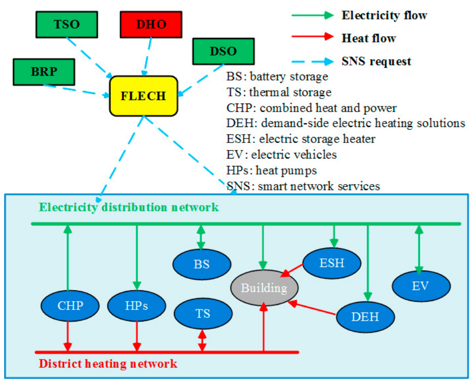

Fig.1. Enabling the use of demand side flexibility for smart network services in the future integrated energy system [6]

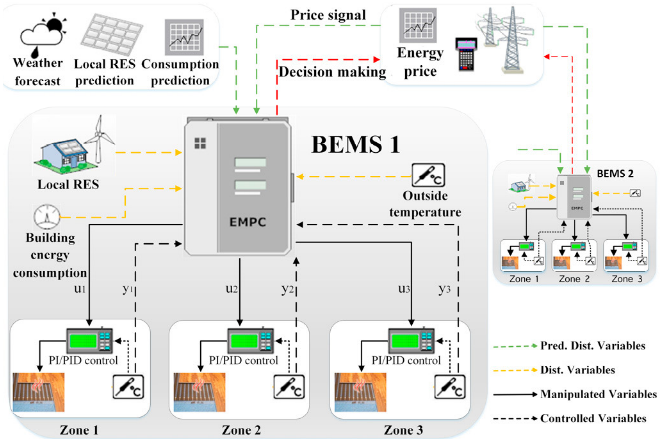

Fig.2. Two-level hierarchical MPC-based BEMS

2. Current status of MPC-based BEMS for demand response (DR)

2.1. What is MPC-based BEMS for DR?

Model Predictive Control (MPC) is a control algorithm that optimizes a sequence of manipulated variable adjustments over a prediction horizon by utilizing a process model to optimize forecasts of process behavior based on a linear or quadratic objective, which is subjected to equality or inequality constraints [10]. In MPC-based BEMS, during each sampling interval, a finite horizon (e.g. every 15 minutes) optimal control problem is formulated and solved over a finite future window (e.g. next 36 hours)[11]. The result is a trajectory of inputs and states into the future, respecting the dynamics and constraints of the building while optimizing some given criteria. In terms of building control, this means that at the current control step, a heating/cooling etc. control schedule is obtained for the next several hours or days, based on a weather forecast. Predictions of any other disturbances, time-dependencies of the control costs (e.g. dynamic electricity/heating prices), or of the constraints (e.g. thermal comfort range) can be included in the optimization. The first step of the control schedule is applied to the building, setting all the electricity, heating/cooling elements, etc., then the process moves one step forward and the procedure is repeated at the next time instant. This receding horizon approach introduces feedback into the system, since the new optimal control problem solved at the beginning of the next time interval; and it could be a function of the new state at that point in time, and of any disturbances that have acted on the building [12]. This can effectively incorporate the uncertainties incurred by model mismatch, time-varying behavior and disturbances [9].

Recently, MPC has drawn the attention of the energy system community, because it is based on future behavior of the system and predictions, which is appealing for systems significantly dependent on forecasting of energy demand and RES generation [13]; moreover, it provides a feedback mechanism, which makes the system more robust against uncertainty [8]. The MPC strategies, that employ an economic-related objective function for real-time control, have lately proved a numerically efficient approach to managing the portfolio of energy usage with provable stability properties. It is designated as an economic MPC (EMPC), which always copes with dynamically changing energy prices. Unlike the traditional MPC, EMPC optimizes the process operations in a time-varying manner, rather than maintain the process variables around a few desired steady states or tracking the reference. The process may thus totally operate in the transient state with EMPC [14] [15][16].

In addition, for multi-zone buildings, a centralized MPC topology is often difficult to implement, because computational demands required solving the centralized problem grows exponentially with the number of zones/subsystems. Another drawback of the centralized strategies is their poor flexibility and reliability, comparing to a decentralized or distributed control structure [12]. Reference [17] and [18] addressed heating and aggregator-oriented energy management with a decentralized and distributed MPC. The performance of the decentralized one strongly depends on the level of interactions between subsystems; while the distributed one, as each controller knows about control actions of its neighbors, keeps the same performance as the centralized one. Meanwhile, many studies have proven that the building sector can significantly benefit from replacing the current practice rule-based controllers (RBC) by more advanced control strategies [19]. However, the optimization-based control algorithms, such as MPC, impose increasing hardware and software requirements, together with more complicated error handling capabilities required from the commissioning staff. In recent years, several studies introduced promising remedy for these problems by using machine learning algorithms [20][21].

According to smart grids/ integrated energy systems concept, DR requests a block of smart buildings/community to actively participate in the grid operation by providing flexibility, assuming the form of price-volume signals specifying a maximum volume of energy to be consumed during a given time slot and a monetary reward assigned to the participants in case they fulfills the conditions. Except for smart start of the appliances in buildings with MPC strategies for DR program, the heating/cooling generation with electrification on the demand side in buildings provides the opportunity of power to heat solutions [22][23].

2.2. Pros and Cons of MPC

The evaluation results of the finished EU and national demonstration projects [24][25][26] show that MPC-based BEMS controller is an efficient feasible approach to manage the portfolio of energy usage, and its pros and cons are listed in Table 1. Implementation of MPC-based BEMS requires the interdisciplinary knowledge of computer science (e.g. big data analysis, cloud computing, etc.), building science, modeling and control theory. MPC relies on a model to determine optimal control actions, creating the need for control engineers to develop a building energy model. They are generally unable to use the model created during the design process because the model is too complicated to be used in a control environment (large building models may take up to several hours to run for optimization). Therefore building energy model reduction and parameter estimation are required [27]. As state in [28], the process of model identification (including data sampling and pre-processing) accounts for 70% of the effort for implementing an MPC controller. The most acceptable system identification for MPC application is the data-driven grey-box modeling approach [8][11][21].

Table 1 Pros and Cons of MPC

	Pros	Cons
MPC	• can take into account stochastic properties of random disturbance variables (e.g. weather forecast, occupancy profiles); thus it adjusts control actions appropriately;	• Challenges for non-technical users, and they require specific background knowledge of the methods.
	• can deal with variable energy price that can be easily included into the formulation of the optimization problem;	• Time consuming for data analysis and modelling
	• can realize the load shifting within certain time frame for dispatch and operation;	• MPC strategies require significantly higher investments which may not be compensated by additional savings in a short time.
	• can be formulated in a distributed manner and thus the computational load can be split among several solvers.	

3. Case study of MPC-based BEMS for a newly-built multi-family residential building in Copenhagen

In this section, a case of a newly built multi-family building in Copenhagen is investigated. All the installed sensors, control actuators and communication systems (KNX protocol-based) in this building are ABB's home automation products, which will be used to demonstrate the future smart energy solutions. The space heating in this building is a radiant floor heating system (RFHS). The hot water for the RFHS is provided by a potential low temperature district heating (DH) system connected with combined heat and power and waste incineration plants.

3.1. Control hierarchy design

A two-layer hierarchical MPC-based controller (see Fig. 2) is proposed for the BEMS with single loops of PID/PI controllers (thermostat in each zone) at the lowest level and a model based predictive controller at the top level. We designate an MPC-based BEMS such that both energy and associated costs are minimized. The objective function, system states, system operation and comfort constraints are formulated as shown in (1). The dynamical models of the subsystems were derived for simulation based studies and reduced order models were built for the purpose of controller design. The building thermal mass was modelled and verified by using real experimental and operational data.

$$
\begin{aligned}
&\min_{\tilde{U}_k=\{T_{set,k+j|k-1}\}_{j=0}^{N}} \quad \sum_{j=1}^{N} \hat{p}_{k+j|k}^{T} \hat{E}_{k+j|k-1}\left(\widehat{m}_{k+j|k-1}\right) \\
&\text{s.t.} \quad \hat{x}_{k+j+1|k-1} = A\hat{x}_{k+j|k-1} + B_u\hat{u}_{k+j|k-1} + B_d\hat{d}_{k+j|k-1} && j = 0,1,\cdots,N-1 \\
&\qquad \hat{z}_{k+j|k-1} = C\hat{x}_{k+j|k-1} + D_u\hat{u}_{k+j|k-1} + D_d\hat{d}_{k+j|k-1} && j = 1,2,\cdots,N \\
&\qquad \widehat{m}_{min,k+j|k-1} \le \widehat{m}_{k+j|k-1} \le \widehat{m}_{max,k+j|k-1} && j = 1,2,\cdots,N \\
&\qquad \hat{y}_{min,k+j|k-1} \le \hat{T}_{i,k+j|k-1} \le \hat{y}_{max,k+j|k-1} && j = 0,1,\cdots,N \\
&\qquad t_l \le \hat{T}_{sp,k+j|k-1} \le t_u && (1)
\end{aligned}
$$

3.2. Results and discussion

A two-week simulation results are shown in the Fig. 3, which are based on the operational data from January 2017 to April 2017, and the formulated optimization problem in aforementioned EMPC algorithm (1) with soft constraints is solved by the IBM CPLEX. It is observed that the flow rate reaches negative values sporadically and less frequently than in the case of hard constraints. This happens whenever the PID controller counteracts disturbances driving the controlled variable away from the set point. What is expected from these simulations is that the control signal (inside air temperature set points) will show correlation with the heat price. Whenever the price is relatively low the controller should take action by requesting a rise in the room temperature to drive it to the upper limit, so that in periods where the energy price is high, the controller does not have to buy energy, but relies on the accumulated energy in the apartment's thermal mass instead. Through an analysis of the operational data, it was found that the floor heating system in many rooms was deactivated because of a central ventilation system in the building. The central ventilation system in many cases overruled the RFHS to meet the needed thermal comfort level and even surpassed it, leading to temperature overshoot. It is suspected that the nature of the data from the apartment could only allow for deriving a heat load model of the apartment, and not a model for predicting indoor temperature variations, because the temperature varies around its set point. Due to the owner's thermal comfort preferences the set points are not allowed to vary considerably for an accurate predictive model in practice.

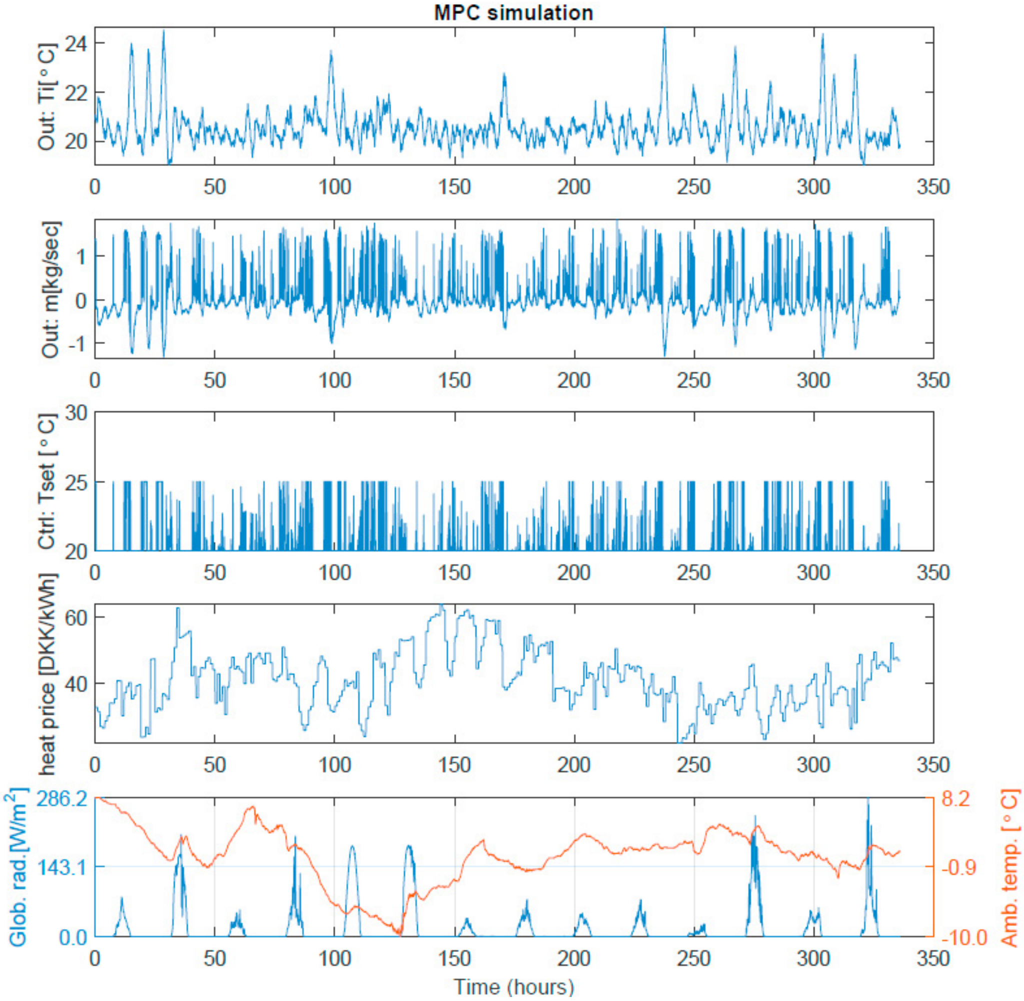

Fig.3. 14-day's MPC heating consumption simulation for a zone in a building with soft constraints

4. Conclusion

In summary, flexible consumption and smart energy systems must be developed with correlative dependence and interplay to meet the challenge of integrated fluctuating RESs. Buildings with large thermal storage capacity play a crucial role in this process. The experimental and simulation study demonstrated that EMPC implementation for BEMS is effective and attractive; but there are still some challenges and barriers, such as control-oriented models, hardware and communication and end user acceptance, which need to be effectively handled in practice. The experimental studies (e.g. step response, pseudo-random binary sequence, etc.) are extremely necessary to identify the system and well reflect the feasibility of the proposed idea and confirm the principle idea of the optimal operating the temperature set point in each apartment/zone. The proposed hierarchical controller setup compared to a central controller is more reliable due to the fact that local controller loops will handle disturbances locally. The fault propagation through the entire system is less probable compared to a centralized scheme. However it is still less robust compared to a distributed controller structure. Evaluations of the degree of optimality and robustness of the system to model mismatches or measurement errors are not investigated and are subjects of our future work.

Acknowledgements

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