DTU Library

# Challenges of using model predictive control for active demand side management

**Zong, Yi; You, Shi; Hu, Junjie; Han, Xue; Jiang, Chongxi ; Zhang, Yi ; Böning, Georg Martin**

*Published in:*
Proceedings. The 4th International Conference on Microgeneration and Related Technologies (Microgen4)

*Publication date:*
2015

*Document Version*
Peer reviewed version

# CHALLENGES OF USING MODEL PREDICTIVE CONTROL FOR ACTIVE DEMAND SIDE MANAGEMENT

Yi Zong[a]*, Shi You[a], Junjie Hu[a], Xue Han[a], Chongxi Jiang[b],Yi Zhang[c] and Georg Martin Böning[d]
[a] Centre for Electric Power and Energy, Department of Electrical Engineering, Technical University of Denmark, Risø campus, Frederiksborgvej 399, 4000, Roskilde, Denmark
[b] College of Electrical Engineering, Zhejiang University, Hangzhou, 310027, Zhejiang, P.R.China
[c] Electrical Power Research Institution, 350007, Fuzhou, P.R.China
[d] Technical University of Berlin, Straße des 17. Juni 135, 10623, Berlin, Germany
*corresponding author: yizo@elektro.dtu.dk

## ABSTRACT

When there is a high penetration of renewables in the power system, it requires coordinated management of large numbers of distributed and demand response resources, intermittent resources to maintain the grid reliability and improve operational economics. This paper presents a hierarchical architecture design for Model Predictive Controller (MPC), and discusses the challenges encountered during the implementation of MPC for active demand side management. The two different pilot case studies show that energy savings and load shifting can be achieved by applying MPC with weather forecast and dynamic power price signals.

*Keywords*: Active demand side management, modelling, model predictive control, MPC controller design, optimization

## INTRODUCTION

As a leading wind power country, Denmark has achieved a record of 39% penetration of wind power in 2014, and the nation is well on its way to hitting its 2020 energy goals-50% of traditional electricity supply must come from wind power. According to Danish government's energy policy, oil burners and coal must be phased out of power plants in Denmark no later than 2030. By 2050, the entire supply of energy and transportation sectors will be provided by renewable energy sources (RESs) [1].

As the largest energy consumer in the world, China should play a pivotal role in the global transition to a sustainable energy future in an increasingly 'carbon-constrained' world. The country is building the world's largest renewable energy system, with massive potential to harness a diverse range of RESs and technologies, both for power generation and for end-use sectors [2].

Both in Denmark and China, with increasing penetration of RESs, such as wind and solar power, it will challenge the existing energy (electricity, heat and gas) infrastructure and its control systems with more complicated dynamics and uncertain problems. On one hand, RESs need better control and management to get their value maximized; on the other hand, flexibility at the demand side provides opportunities at the end user level to smooth out the peak demand which can have major impact on system reliability and generation cost.

As a portfolio of measures to improve the energy system at the side of consumption, demand side management (DSM) ranges from improving energy efficiency by using better materials, smart energy tariffs with incentives for certain consumption patterns, and sophisticated real-time control of distributed energy resources (DERs) [3]. The combination of DSM with a novel automatic control of the DERs demand can be called "Active Demand Side Management" (ADSM) [4,5]. ADSM can modify the demand profile to reduce the losses in the grid, facilitate the RESs integration, decrease congestions, and save energy cost for the end users [6,7]. From a power grid perspective, ADSM for buildings could be technically enabled to provide ancillary services and participate in the electricity and flexibility markets.

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 behaviour based on a linear or quadratic objective, which is subjected to equality or inequality constraints [8]. In MPC, the optimization is performed repeatedly on-line. This is the meaning of receding horizon, and the intrinsic difference between MPC and the traditional optimal control. The receding horizon optimization can effectively incorporate the uncertainties incurred by model-plant mismatch, time-varying behaviour and disturbances [9].

MPC is now recognized as a powerful approach with well-established theoretical foundations and proven capability to handle a large number of industrial control problems [10]. Recently, MPC has drawn the attention of the power system community, because it is based on future behaviour of the system and predictions, which is appealing for systems significantly dependent on forecasting of energy demand and RES generation; moreover, it provides a feedback mechanism, which makes the system more robust against uncertainty [11]. MPC for building temperature control has been investigated in several papers before [12]-[17], mainly with the purpose of increasing the energy efficiency in the building. The potential of MPC in power management for EV, commercial refrigerators and heat pumps was investigated in [18]-[20]. [21] and [22] deployed a deterministic MPC to optimize operation of heating in a real office building with time-variable energy tariffs and weather forecast information.

Most of the results of the aforementioned literatures are based on the simulation study; however, the application of MPC requires extensive knowledge in the areas of mathematic modelling, hardware (sensors and actuators) data processing, state estimation, controller architecture design and optimization. The remaining of this paper is organized as follows: the detailed MPC strategy for ADSM, including controller design, is described in Section 2. Section 3 will focus on discussing the challenges encountered when we implement MPC in practice. Section 4 presents two different case studies on implementation of MPC in an office building and a residential building. Then, some results and analysis of running the MPC controller on a test platform are shown in Section 5. Finally, conclusion is drawn in Section 6, followed by the discussion on future research.

## MPC FOR ADSM

### MPC strategy

The basic concept of MPC is that at each step, a look-ahead finite-horizon optimal control problem is solved but only the first step of control sequences is implemented. Figure 1 presents the model predictive control scheme. The main principle of MPC is to transform the control problem into an optimization one and solve this optimization problem over a prediction horizon at each sample time, subjected to system dynamics, an objective function (linear or quadratic), and constraints on states, actions and inputs. At each control step the optimization obtains a sequence of actions optimizing expected system behaviour over the prediction horizon. Only the first step of the sequence of control actions is executed by the controller on the system until the next sample time, after which the procedure is repeated with new process measurements.

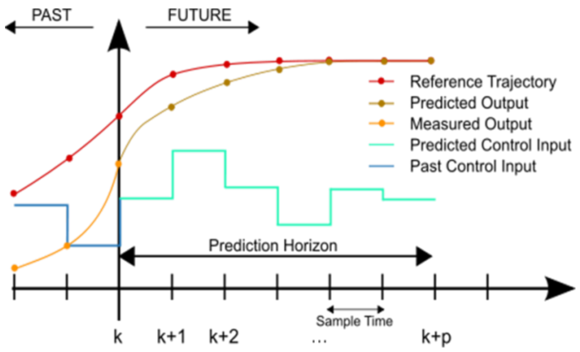


*Figure 1: Model predictive control scheme.*

### MPC controller architecture design

To fulfil the targets of MPC for ADSM, a hierarchical MPC, which takes both the low voltage distribution grid and the building domains into account, is proposed in this paper. As shown in Figure 2, for each building, a separated MPC-based Building Energy Management System (BEMS) controller is designed. The MPC-based BEMS aims at the local optimization for the whole building and determines the set points for the low-level (rooms or zones) controllers, which are connected to the building management systems (BMS) in order to optimize the operation of the building's significant energy components (electrical heating, ventilation and cooling systems, or heat pumps, etc.). At the top of the hierarchy in Figure 2, the MPC controller on grid level aims to optimize the complete system by providing variable set points and/or adapted weight coefficients in the MPC objective (cost) function and constraints for the MPC-based BEMS. The forecast information (weather, price or load) should be considered for all the MPC controllers at different levels as shown in Figure 2. This paper focuses on the investigation of MPC-based BEMS, which can communicate with the low level controller (BMS) through an application interface or can be directly integrated into BMS by adding MPC–based EMS functionalities.

The objective of MPC-based BEMS is to minimize energy consumption or operation cost (by optimizing the temperature set points) while meeting thermal comfort requirements. The optimal control problem formulation further considered various constraints on system variables (minimum/maximum values, rates of change, etc.).

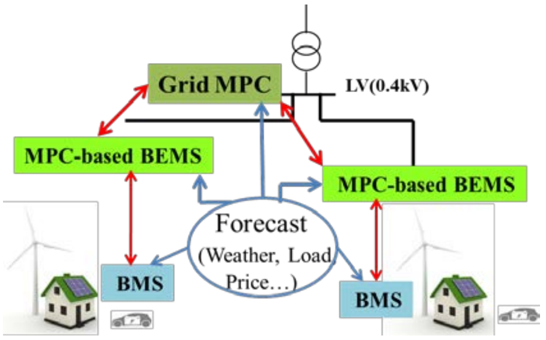


*Figure 2: Hierarchical MPC for ADSM.*

## CHALLENGES OF MPC IMPLEMENTATION FOR ADSM

According to the authors' experience on the implementation of MPC in different buildings ( see the Section of case studies) for ADSM, it presents considerable challenges in data analysis, modelling, hardware, optimization technique and state estimation ,etc.

### Data availability and analytics

MPC requires not only an appropriate model but also a wealth of input data during operation. Active buildings installed with smart meters and advanced, integrated building systems generate significant real-time or near-real-time data on energy usage and occupancy. The expansion of data including forecast data (weather, load, and price) presents great opportunities for improved building energy management practices, but the data collected is valuable only if it is analysed consistently and communicated effectively to both building decision-makers and distribution system operators (DSOs).

At level of building data management – simple, intermediate, or advanced – it is important to focus on the data worth collecting, the analysis worth sharing, and the problems that are worth solving with data and analytical tools for the coordination control on DERs. This is a time-consume and important preparations for the modelling and MPC controller design.

### Modelling

When large measurement data sets are available, a purely statistical approach for creation of a building model is preferred. MPC inherently requires an appropriate model of the controlled plant, which is then used for the computation of the optimal control inputs. Modelling of the building requires insight both into control engineering as well as into HVAC engineering. Moreover, it is also the most time demanding part of designing the MPC controller. The relevant dynamic behaviour of the active building for the ADSM control tasks can be divided into the thermal dynamics (room temperatures, thermal capacities, heat inputs and losses) as well as the relevant building services, such as heating, cooling, ventilation, photovoltaic (PV) systems or storage (battery and EV). The model for active buildings 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.

To ensure adaptive autonomous operation on the building MPC controller, the building thermal models should have the ability to be adjusted at least with the season's change. Based on the application needs, models with different fidelity and mathematical properties will be used, offering a combination of physics-based approaches, and data-driven approaches.

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 [23]:

a) Black- box modelling

A black box modelling considers the system as a box with inputs and outputs, its basis is the experimental data without having any prior knowledge of the system. More specifically, the physical description of the procedure is not available. The black-box approach is conceptually simple but technically tricky, and it depends crucially on the availability of appropriate input data sets.

b) White-box modelling

A white-box model allows defining a complete description of the system, which means that the prior knowledge of the physics is essential for the model. In building case, it requires availability and processing of a large amount of building-specific information. For example, a number of specified equations are needed to formulate the deterministic physical model based on a good understanding of the heat dynamics in the building.

In general, the white-box models require very detailed data and these models will be overly complex due to the complex nature of many systems and processes. Many physical systems can only be described by complex sets of equations, which make this approach not so efficient.

c) Grey-box modelling

Grey-box modelling is an approach between a black-box and white-box modelling. A grey-box model consists in differential stochastic equations building upon the prior knowledge of the physical dynamics of the system. The purpose of this approach is to provide a way of combining the advantages of both model types by allowing prior physical knowledge to be incorporated and statistical methods for parameter estimation to be applied. The information from the data can be used for the unknown parameter estimation by creating a discrete measurement equation. The data has to be "informative", which means that the measured signals must vary enough due to variation on the input signals. A commonly used input signal is a pseudo random binary (PRBS) signal [24]. In a word, grey-box models are not only physically interpretable but they also use real time data, which make it easier to implement for short and long- term predictions.

**Hardware**

At present, to implement MPC for ADSM, the common practice is to connect an external MPC computational core with the building's automation system (BAS). This requires specification on what signals to be communicated, a communication protocol, and the implementation of mechanisms to handle communication and optimization problems (e.g. infeasibility or too long computation time). The other potential solution is to "Bring MPC to Chip", for example, integration of MPC into the Programmable Logic Controller (PLC) [25][26] or Field- Programmable Gate Array (FPGA)[27 ][28], which have been widely used in BAS as field controller.

In addition, the sensors, actuators, smart meters, communication devices, in the MPC system should be able to detect and filter out erroneous input data and to handle communication and other failures. Moreover, to reduce the hardware investment on implementation of MPC for ADSM, it is necessary to optimize the installation allocation of the smart meters and sensors.

**Objective function & Multi-objective optimization**

Optimization is an indispensable part of MPC functionality, wherein it is applied towards the economic optimization and constraint handling objectives. The objective function of MPC for ADSM is always needed to consider trade-offs among multiple objectives, including economic operation based on time-of-use pricing and feed-in tariff, maximization of wind and PV production, maximization of user comfort, etc. In MPC, it is common to choose the structure of the objective function such that the optimal objective forms a Lyapunov function for the closed loop system, and hence will guarantee stability [22]. In practice, this requirement is generally relaxed for stable systems with slow dynamics, such as active buildings for ADSM.

In addition, the objective function is applicable only when the solution exists within limits. The original optimization objectives, however, needs to be redefined, if a solution does not exist within the predefined limits, and in such cases the optimizer should have the means to recover online from the infeasibility. The existing recovery techniques are based on the priorities of the constrained and controlled variables [29][30 ].

**State estimation**

In MPC for ADSM, all future (control) predictions begin from an initial state. The system model should be initialized to the measured/estimated current state of the building. Depending on what the state of the building is described, it might be impossible to measure everything directly. In this case, a Kalman filter can be used to estimate the current state of the building and the estimate is used as initial/ current state for control [21][22].

## CASE STUDIES

The MPC strategy for ADSM was applied to two buildings. One is used as an office building-PowerFlexhouse1 and the other is a residential building-PowerFlexhouse3 (see Figure 3 and Figure 4). The PowerFlexhouses facilities at the Technical University of Denmark (DTU), Risø campus have been equipped with sensors and controllable loads and heating equipment. They are interconnected in a configurable 400 V microgrid and communication platform [31]. The detailed description of the office building-PowerFlexhouse1 can be found in the reference [21]. The PowerFlexhouse3 facility is a 150 $m^2$ 3-floor house built in 1954 [32]. The outer walls of the house are brick constructed with a layer of insulation between them and the roof is tile. PowerFlexhouse3 is also well sized for parallel operation on the SYSLAB power grid as PowerFlexhouse1. All sensors (temperature, motion and contacts, etc.) in PowerFlexhouse3 support KNX standard communication. There are four types of heating radiators in the building [33]. In the basement there are three radiators of 2.7 kW total power; in the first floor there are 6 radiators of 6.1 kW total power and in the second floor there are 2 radiators of 2.1 kW total power. The total power consumption of the heating radiators is around 11 kW and they can be remotely controlled via electro-valves.

*Figure 3: An office building-PowerFlexhouse1.*

*(a) Back facade* *(b) Front facade*

*Figure 4: A residential building-PowerFlexhouse3.*

## Modelling

The heat flow in PowerFlexHouses is modelled by a grey-box approach, using physical knowledge about heat transfer together with statistical methods to estimate model parameters. To reduce the complexity, the model of heat dynamics of the PowerFlexHouse1 is formulated as one large room exchanging heat with an ambient environment. In PowerFlexhouse3, to keep the models as simple as possible, each floor is considered as a single room where all the radiators are grouped as one input for each floor. The house's entrance is in a mid-way position between the first floor and the basement. It was decided to group it in the first floor. Heat transfer due to conduction, convection and ventilation is assumed to be linear with the temperature difference on each side of the medium. When assuming these properties, the heat model can be formulated as an equivalent electric circuit with resistors and capacitors (an RC-circuit). In such a circuit, the resistors can be regarded as resistance to transfer heat and the capacitors as heat storage. The RC-network for the heat dynamic model for PowerFlexhouse3 is shown in Figure 5. The first-order stochastic differential equations, which can describe the heat flow in all floors, are expressed as (1) to (3). Table 1 explains the physical meaning for the symbols in Figure 5 and equations (1) to (3). The detailed description of modelling and the model validation for PowerFlexhouse3 and PowerFlexhouse1 can be found in the reference [34] and [21], respectively.

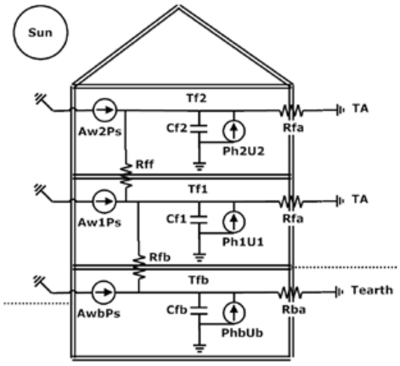


*Figure 5: RC-network for the heat flow in the PowerFlexhouse3.*

$$\frac{dT_{f2}}{dt} = \frac{1}{R_{ff}C_{f2}}(T_{f1} - T_{f2}) + \frac{1}{R_{fa}C_{f2}}(T_a - T_{f2}) + \frac{Ph_2u_2}{C_{f2}} + Aw_2P_s + \sigma_{f2}\frac{dw_2}{dt} \quad (1)$$

$$\frac{dT_{f1}}{dt} = \frac{1}{R_{ff}C_{f1}}(T_{f2} - T_{f1}) + \frac{1}{R_{fb}C_{f1}}(T_b - T_{f1}) + \frac{1}{R_{fa}C_{f1}}(T_a - T_{f1}) + \frac{Ph_1u_1}{C_{f1}} + Aw_1P_s + \sigma_{f1}\frac{dw_1}{dt} \quad (2)$$

$$\frac{dT_b}{dt} = \frac{1}{R_{fb}C_{f2}}(T_{f1} - T_b) + \frac{1}{R_{fba}C_{fb}}(T_{earth} - T_b) + \frac{Ph_bu_b}{C_{f2}} + Aw_bP_s + \sigma_b\frac{dw_b}{dt} \quad (3)$$

*Table 1: Physical meaning for the symbols*

| SYMBOLS | PHYSICAL MEANING |
|---|---|
| $T_{f1}$ ,$T_{f2}$, $T_b$ | Temperature [°C] for each floor |
| $T_{earth}$ | Earth temperature [°C]( as a constant of 7°C during the test ) |
| $C_{f1}$ ,$C_{f2}$, $C_b$ | Heat capacity for each floor (including indoor air, interior walls and furniture, etc.) [kJ/°C] |
| $R_{ff}$ | Thermal resistance between the 2nd and 1st floor [°C/kW] |
| $R_{fb}$ | Thermal resistance between the 1st floor and basement [°C/kW] |
| $R_{fa}$ | Thermal resistance between the 2nd, 1st floor and the ambient [°C/kW] |
| $R_{fba}$ | Thermal resistance between the basement and the ambient [°C/kW] |
| $A_{w1}$ ,$A_{w2}$, $A_{wb}$ | Effective window area in each floor [$m^2$] |
| $P_s$ | Solar irradiation [$W/m^2$] |
| $Ph_1$,$Ph_2$,$Ph_b$ | Radiator power for each floor [kW] |
| $\mu_i$ | Inputs(power inputs of heaters) |
| $\sigma_{fi}$ | Gaussian white noise for each floor |
| $w_1$,$w_2$,$w_b$ | A standard Wiener Process for each floor |

### Objective functions and constraints

In the two case studies, the objective function was formulated as (4), where *c'* is a vector with the price signals broadcasted by an aggregator, central controller or a power provider, $\mu_k$ is the planed power consumed by the radiators order to heat the PowerFlexhouses and $N$ is the length of the prediction horizon (for example 12 hours). The index $i$ represents the radiators, and the index $k$ stands for the iteration in the prediction horizon. The initial state of the controller in the two case studies is the same of 19°C.

$$J = \min \sum_{i=1}^{h} \sum_{k=0}^{N-1} C_i(\mu_k)_i \qquad (4)$$

Concerning the bound constraints, the radiators are only able to give off a certain amount of heat, therefore the solution is subject to (5):

$$\mu_{\min} \le \mu_k \le \mu_{\max} \qquad k = 0,1,2......N-1 \qquad (5)$$

An output constraint is required, which is defined by (6),

$$Z_k^{\min} \le y_k \le Z_k^{\max} \qquad k = 1,2......N \qquad (6)$$

where $Z_k^{\min}$ and $Z_k^{\max}$ define a comfort band, within which the room temperature $y_k$ must be kept for different users. For example, the office building-PowerFlexhouse1 from 8:00-20:00 the inside temperature should be controlled between 20°C and 22°C; while the residential building PowerFlexhouse3 has slack requirements on the inside temperature during 8:00-16:00 assuming that there is no occupantcy during this period.(See the low/high temerature reference curves in the Figure 7 and Figure 10).

### Data and Results

The MPC scheme test occurred from January 18 to 25, 2014, 168 hours in total. The weather forecast data were provided by the Wind Department, DTU Risø campus (See Figure 6). The price signals were obtained from the Nord Pool spot DK1 market [35]. The results of PowerFlexhouse1 were shown in Figures 7-9. Figures 10-11 present the results of PowerFlexhouse3.

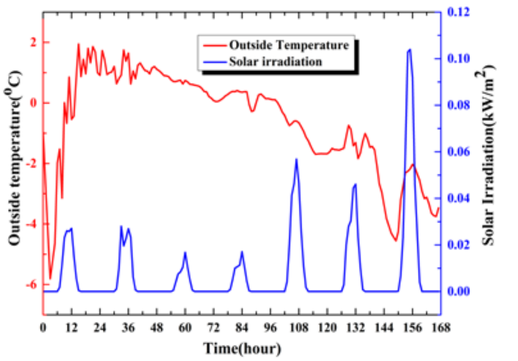


*Figure 6: Weather forecast data*

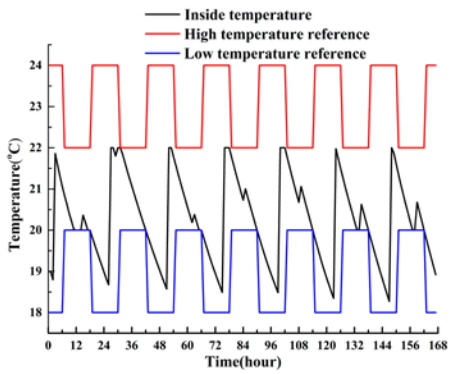


*Figure 7: Inside temperature performance with MPC scheme during a week.*

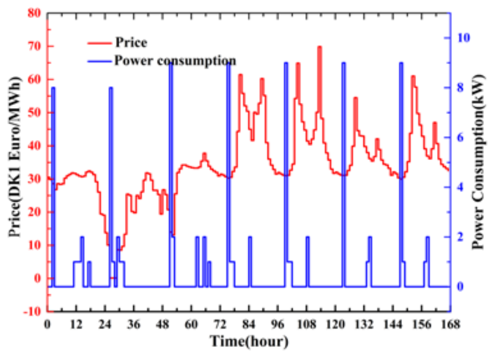


*Figure 8: Optimized power consumption(blue) vs power price signals(red) .*

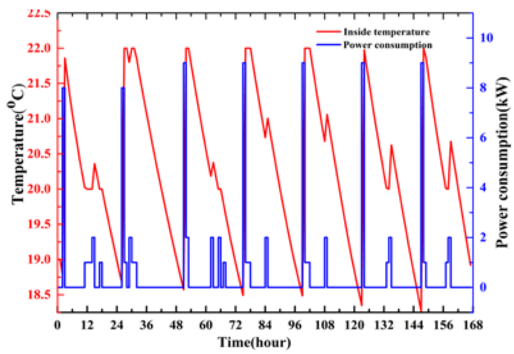


*Figure 9: Optimized power consumption(blue) vs inside temperature(red) .*

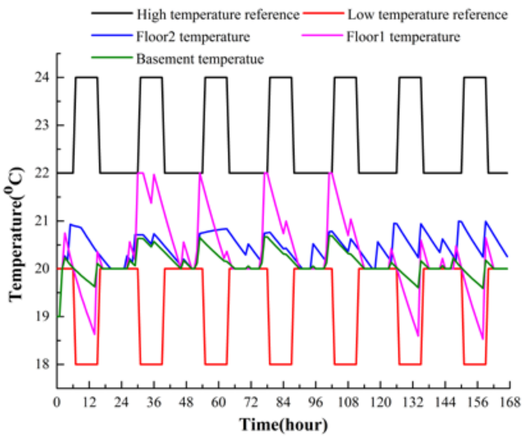


*Figure 10: Inside temperature performance of the different floor in PowerFlexhouse3.*

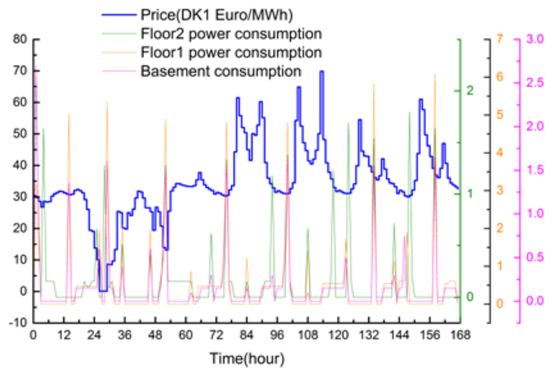


*Figure 11: Optimized power consumption of the different floor in PowerFlexhouse3 vs power price signals(blue).*

## RESULTS ANALYSIS AND DISCUSSION

Figure 7 and Figure 10 demonstrate the good performance of the inside temperature in PowerFlexhouses during the test period. The inside temperatures are controlled in the reference band following the different comfort pattern with the predictive occupancy. In the office building-PowerFlexhouse1, Figure 8 shows that the heaters are always working during the deep night to preheat the building, because the much lower power spot price always happened during 22:00-6:00 in Denmark [21]. The radiators in PowerFlexhouse3 as shown in Figure 10, even if work during the daytime, they all occurred when there is a lower price during the daytime. The results further illustrate that MPC control strategy can achieve energy savings by shifting load from on-peak to off-peak period. Moreover, the user behaviour of the office building and residential building shows that it is necessary to investigate the effect of having a synergy between office and dwellings close together. As offices tends to have an energy demand during the daytime and dwellings during evening, early morning and weekends.

In addition, it can be observed in Figure 10 that the temperature of the first floor is much more variable than the other floors' temperature. On one hand, there are six radiators on first floor which can be operated; on the other hand, the first floor has a strong thermal interactions among the basement and the second floor. To some large scale applications, the thermal interactions between neighbouring zones/building blocks can not be negligible, such that we need to use the decentralized MPC or distributed MPC. At the same time, for large multi-zone buildings, even simple mathematical models describing the building's thermal dynamics can result in a long computation time for the optimal control inputs, in particular when a centralized MPC approach is considered. An alternative consists in using a distributed MPC [36]. By using distributed MPC, the overall computation time can be significantly reduced; meanwhile, the robustness of the whole control system can be increased. However, this solution completely depending on the communication support and how good the sub-optimal performance is.

## CONCLUSION

In summary, ADSM should be established, in particular for buildings with large thermal storage capacity, in order to enable more use of renewable energy in power system. Our experience demonstrated that MPC implementation for ADSM is effective and attractive; but there are still some challenges in big data and modelling, hardware, multi-objective optimization and state estimation, which need to be further handled in practice.

The future work will focus on distributed MPC and how to best achieve the coordination between low-level control loops (switch/PID controller) and the top-level MPC-based EMS for ADSM.

## ACKNOWLEDGEMENT

This work is supported by the International Network Programme, Energy Management Systems for Active Distribution Network (EMS4ADGrids) project grant by the Danish Agency for Science, Technology and Innovation (No. 4070-00023B).

## REFERENCES

[1] Danish Energy Agency, Energy Policy in Denmark, December, 2012. [Online]. Available: http://www.ens.dk/en/info/publications/energy-policy-denmark

[2] The International Renewable Energy Agency (IRENA), Renewable Energy Prospects: China, November 2014.[Online]. Available: http://irena.org/remap/IRENA_REmap_China report_2014.pdf

[3] P. Palensky, D. Dietrich, Demand Side Management: Demand response, intelligent energy systems, and smart loads, IEEE Transactions on Industrial Informatics (vol.7, No. 3, 2011) 381-388.

[4] M. Castillo-Cagigal, E. Caamaño-Martín, D. Masa-Bote, A. Gutiérrez, F.Monasterio-Huelin, and J. Jiménez-Leube, PV self consumption optimization with storage and Active DSM for the residential sector", Solar Energy,(vol. 85, issue 9, 2011) 2338-2248.

[5] Y. Zong, D. Kullmann, A. Thavlov, O. Gehrke, and H.W. Bindner, Active load management in an intelligent building using model predictive control strategy, in Proc. 2011 PowerTech Conf. pp. 1700589.

[6] G. Papagiannis, A. Dagoumas, N. Lettas, and P. Dokopoulos, Economic and environmental impacts from the implementation of an intelligent demand side management system at the European level, Energy Policy , (vol. 36, issue 1, 2008) 163-180.

[7] G. Strbac, Demand side management: benefits and challenges, Energy Policy, (vol.36, issue 12, 2008), 4419-4426.

[8] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. M. Scokaert, Constrained model predictive control: stability and optimality, Automatica 36, (2000), 789–814.

[9] B. C. Ding, Modern predictive control, chapter 1. CRC Press, 2010, United States.

[10] R. Scattolini, Architectures for distributed and hierarchical model predictive control-A review, Journal of process control 19,(2009) 723-731.

[11] Otomega B, Marinakis A, Glavic M, Cutsem TV. Use of model predictive control for experimental microgrid optimization, Applied Energy 115, (2014), 37-46.

[12] Y. Ma, G. Anderson, and F. Borrelli, A distributed predictive control approach to building temperature regulation, Proc. 2011 American Control Conf. pp.2089-2094.

[13] Chen Chen, Jianhui Wang, Yeonsook Heo, and Kishore, S, MPC-based appliance scheduling for residential building energy management controller , IEEE Transactions on Smart Grid, (volume: 4 , issue: 3, 2013), 1401 – 1410.

[14] Y. Ma, F. Borrelli, B. Hencey, B. Coffey and P. Haves, Model predictive control for the operation of building cooling systems, IEEE Trans. Control Systems Technology Mar. 2011, pp. 1-8.

[15] Samuel Prívara, ZdenekVána, Jirí Cigler, Frauke Oldewurte and Josef Komárek, Role of MPC in building climate control, Proc. 21st European Symposium on Computer Aided Process Engineering - ESCAPE 21, Porto Carras Resort, Chalkidiki, Greece, May 29 - June 1, 2011, pp 728-732.

[16] Xiaojing Zhang, Georg Schildbach, David Sturzenegger, and Manfred Morari, Scenario-based MPC for energy efficient building climate control under weather and occupancy uncertainty, 2013 European Control Conference (ECC), July 17-19, 2013, Zürich, Switzerland.

[17] P.Morosan, R.Bourdais, D.Dumur,and Jean Buisson, Building temperature regulation using a distributed model predictive control, Energy and Buildings 42(2010) 1445-1452.

[18] G. Ripaccioli, D. Bernardini, S. DiCairano, A. Bemporad, and I. Kolmanovsky, A stochastic model predictive control approach for series hybrid electric vehicle power management, 2010 IEEE American Control Conference (ACC), pp.5844–5849.

[19] T. G. Hovgaard, S. Boyd, Lars F.S. Larsea and J. B. Jørgensen, Nonconvex model predictive control for commercial refrigeration, International Journal of Control, Published online: 26 Jan 2013

[20] M. U. Kajgaard, J. Mogensen, A. Wittendorff, A. T. Veress, and B. Biegel, Model predictive control of domestic heat pump, 2013 American Control Conference (ACC)Washington, DC, USA, June 17-19, 2013.

[21] Yi Zong, Daniel Kullmann, Anders Thavlov, Oliver Gehrke and Henrik Bindner, Application of Model Predictive Control for active load management in a distributed power system with high wind penetration", IEEE Transactions on Smart Grid, (volume 3, issue: 2, 2012) 1055-1062.

[22] J. Široký, F. Oldewurtel, J. Cigler, and S. Prívara, Experimental analysis of model predictive control for an energy efficient building heating system, Applied Energy 88, (2011) 3079-3087.

[23] Henrik Madsen, Statistical Modelling of Physical Systems-An introduction to Grey Box modelling, [Online]. Available:

http://iiesi.org/assets/pdfs/101_madsen_4.pdf.

[24] A. Thavlov, Dynamic Optimization of Power Consumption, Chapter 4. Master thesis. Kongens Lynby 2008.

[25] B. Huyck, L. Callebaut, F. Logist, H. J. Ferreau, M. Diehl, J. De Brabanter, J. Van Impe, and B.De Moor, Implementation and experimental validation of classic MPC on Programmable Logic Controllers, Control Automation (MED), 20th Mediterranean Conference on, 2012, pp. 679–684.

[26] A. Syaichu-Rohman and R. Sirius, Model predictive control implementation on a programmable logic controller for dc motor speed control, 2011 International Conference on Electrical Engineering and Informatics,17-19 July 2011, Bandung, Indonesia.

[27] K.V. Ling, S.P. Yue and J.M. Maciejowski, A FPGA implementation of model predictive control, Proceedings of the 2006 American Control Conference Minneapolis, Minnesota, USA, June 14-16, 2006, pp. 1930-1935.

[28] N.Yang, D.Li, J.Zhang,and Y.Xi, Model predictive controller design and implementation on FPGA with application to motor servo system, Control Engineering Practice 20 (2012) 1229–1235.

[29] Vada J, Slupphaug O, Foss BA. Infeasibility handling in linear MPC subject to prioritized constraints. In: PeprintsIFAC'99 14th world congress. 1999.

[30] W. Wojsznis, A. Mehta, P. Wojsznis, D. Thiele and T. Blevins, Multi-objective optimization for model predictive control, ISA Transactions 46 (2007) 351–361.

[31]PowerLabDK, [Online]. Available: http://www.powerlab.dk/Facilities/PowerFlexHouses

[32] OIS House Location, [Online]. Available https://www.ois.dk/default.aspx , 2014.

[33] SMU. [Online]. Available http://smu.edu/geothermal/heatloss/heatloss.html.

[34] K. Tsapralidis, Modelling, identification and control for heat dynamics of a three-storey brick house, Master thesis, Technical University of Denmark, Kgs. Lyngby-2014.

[35]The Nord Pool spot market, [Online] available: http://www.nordpoolspot.com/Market-data1/Elspot/Area-Prices/SYS1/Hourly/?view=table

[36] P. D. Moroçan, R. Bourdais, D. Dumur, and B. J., A distributed MPC strategy based on Benders' decomposition applied to multi-source multi-zone temperature regulation, Journal of Process Control, (vol. 21, no. 5, 2011) 729–737.