Delivery no.:3.5a1
[Model Predictive Control (MPC)-based control algorithm for the smart buildings-PowerFlexHouses at PowerLabDK]

Photo: By & Havn / Ole Malling

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Preface

EnergyLab Nordhavn – New Urban Energy Infrastructures is an exciting project which will continue until the year of 2019. The project will use Copenhagen's Nordhavn as a full-scale smart city energy lab, which main purpose is to do research and to develop and demonstrate future energy solutions of renewable energy.
The goal is to identify the most cost-effective smart energy system, which can contribute to the major climate challenges the world are facing.

Budget: The project has a total budget of DKK 143 m (€ 19 m), of this DKK84 m (€ 11 m) funded in two rounds by the Danish Energy Technology Development and Demonstration Programme (EUDP).

Forord

EnergyLab Nordhavn er et spændende projekt der løber til og med 2019. Projektet vil foregå i Københavns Nordhavn, og vil fungere som et fuldskala storbylaboratorium, der skal undersøge, udvikle og demonstrerer løsninger for fremtidens energisystem.
Målet er at finde fremtidens mest omkostningseffektive energisystem, der desuden kan bidrage til en løsning på de store klimaudfordringer verden står overfor nu og i fremtiden.

Budget: Projektets totale budget er DKK 143 mio. (EUR 19 mio.), hvoraf DKK 84 mio. (EUR 11 mio.) er blevet finansieret af Energiteknologisk Udviklings- og Demonstrationsprogram, EUDP.

Disclaimer

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List of Abbreviations

ADSM	active demand side management
BAS	building automation systems
BEMS	building energy management systems
CTSM	Continuous Time Stochastic Modelling
DERs	distributed energy resources
DM	decision making
DSO	distribution system operator
DSR	demand side resources
ELN	EnergyLab Nordhavn
EMPC	Economic Model Predictive Control
EMS	energy management systems
EV	electric vehicles
FPGA	Field- Programmable Gate Array
HP	heat pump
HVAC	heating, ventilation and air-conditioning
LTI	Linear Time Invariant
MPC	model predictive control
PID	Proportional-Integral-Differential
PLC	programmable logic controller
PLDK	PowerLabDK
PRBS	pseudo random binary signal
PV	photovoltaic
RC	resistance capacitance
RMI	remote method invocation
SDE	stochastic differential equations
TSO	transmission system operator
WP	work package

Executive Summary

Because of the delay on building recruiting and construction, the data (both forecast and measurement) and models are not available for the task 3.5-model predictive control (MPC)-based building energy management systems (BEMS). The MPC-based controller architecture and algorithm design had been conducted by using the PowerFlexHouses on PowerLabDK (PLDK) (http://www.powerlab.dk/Facilities/PowerFlexHouses).

This report delivered by CEE, DTU Electro mainly describes a prototype implementation of economic MPC for PowerFlexHouse3 and a preliminary guideline for Work Package 3 (WP3) of EnergLab Nordhavn (ELN) project - Smart Energy buildings. It includes a short introduction on the buildings' role in future energy systems and the state-of-the-art building energy management system in Section 1. In Section 2 we briefly introduce MPC and its evolution. How to design the architecture of MPC controller is provided in Section 3. Then, the challenges of implementation MPC are discussed in Section 4. In Section 5, some results and analysis of implement the Economic MPC controller for PowerFlexHouse3 on PLDK-SYSLAB test platform are shown. Finally, conclusion is drawn in Section 6, followed by the discussion on the future work.

Resumé

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1. Introduction

1.1 Buildings' role in future energy systems

Buildings are the largest energy consuming sector and account for almost 40% of society's energy demand [1] . The thermal mass of buildings is "for free" and can provide a very large possibility for flexibility. Therefore, buildings play a key role in the green transition and smart buildings can extend beyond the buildings themselves when they act as flexible components in a diverse energy systems. To fulfil the 2050 energy target in Denmark, on one hand, buildings needs to improve their energy efficiency; on the other hand, thermal capacity of the buildings can be used to become a flexible power consumer that can actively take part in the future energy systems.

1.2 Smart energy system and flexibility

A smart energy system is a cost-effective, sustainable and secure energy system in which renewable energy production, infrastructures and consumption are integrated and coordinated through energy services, active users and enabling technologies (See Figure 1). This integration requires more flexibility in the entire energy system, and it will challenge the existing energy (electricity, heat, transportation and gas) infrastructure and its control systems with more complicated dynamics and uncertain problems [2].

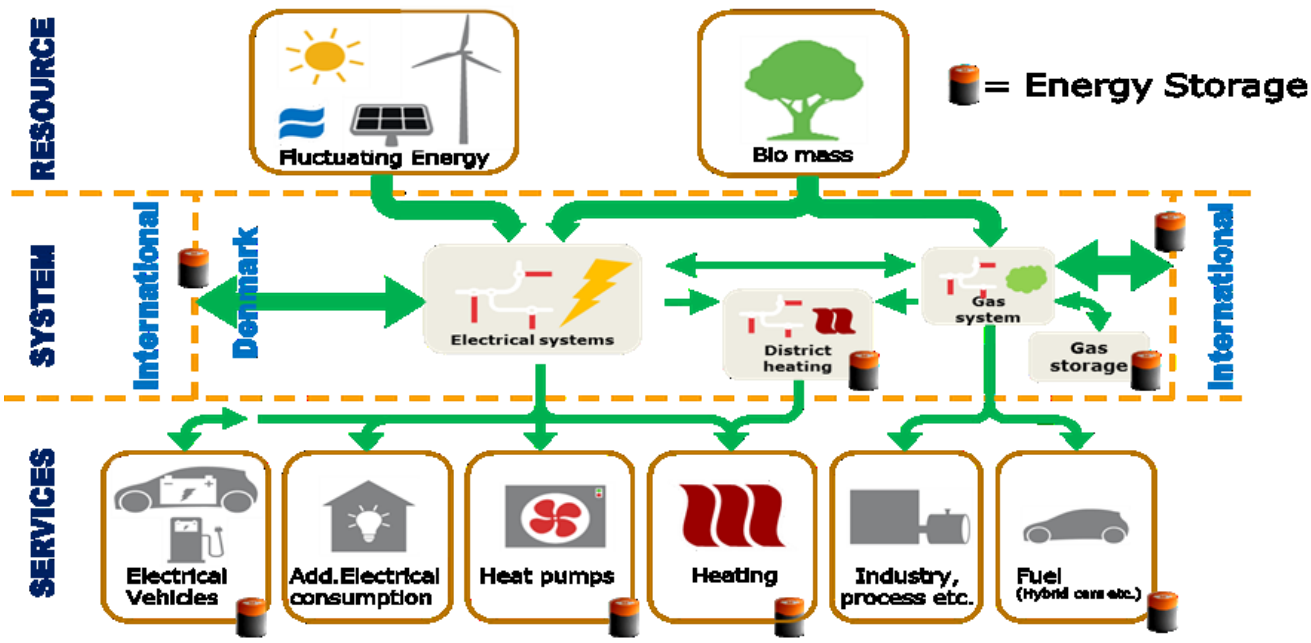


Figure 1 Overview of a future Danish smart energy system [3]. The orange-and-grey cylinders indicate technologies and subsystems with storage-alike cross-sectoral flexibility options.

Flexibility is understood as the ability of a system to respond to variability and uncertainty at different time scales and different locations. In energy system operation and dispatch planning, flexibility is of importance and has a significant commercial value. Today, the Distributed Energy Resources (DERs) in the energy system need better control and management to get their value maximized; in addition, flexibility at the demand side provides opportunities at the end user level to smooth out the peak demand which will have major impact on system reliability and generation cost [4]. The buildings can provide flexibility such as:

Demand-side flexibility: DER owners who are able to regulate the generation/demand at their premises can offer their flexibility by participating in various demand response/demand-side management. The corresponding mechanisms include automated load control by system operators; smart grid and smart metering and various tariff schemes. Although demand-side flexibility is relatively inexpensive, it requires verifiability of demand-side resources, aggregation schemes, and regulatory support etc.

Thermal energy storage-enabled flexibility: The heating, ventilation and air-conditioning (HVAC) system of a building is used to keep the indoor climate within comfortable limits and there are many possibilities to introduce thermal energy storage. Some of the most widely used storage techniques today, such as domestic hot water stores or larger (water) tanks used together with solar collectors or boilers [5].

1.3 Building Energy Management System (BEMS)

It is believed that most buildings are not operated as efficiently as they could be. In general, there are two approaches to achieve energy savings: by installing more energy efficient equipment in buildings, or by managing energy consumption in an efficient way via the building automation systems (BAS) with advanced control algorithms to provide ancillary services for energy systems.

In recent years, there are two main research trends in the advanced control for buildings: One is the learning based approaches such as fuzzy techniques, genetic algorithms etc. The other is the Model based predictive control (MPC) [6]. This report will focus on the MPC-based BEMS.

The reasons why MPC is an efficient approach to manage the portfolio of energy usage in buildings are [6]:

- can take into account stochastic properties of random disturbance variables (e.g. weather forecast, occupancy profiles); thus it adjusts control actions appropriately;
- is able to deal with variable energy price that can be easily included into the formulation of an optimization problem;

- can handle minimization of the energy peaks and thus shift energy loads within certain time frame (beneficial because of both the possibility of tariff selection and lowering operational costs);
- can be formulated in a distributed manner and thus the computational load can be split among several optimization solvers;
- can utilize the thermal mass of a building in a better way compared to the conventional control strategies (e.g. Proportional-Integral-Differential (PID), weather compensated or rule based control).

1.4 Scope and utilization of this report

Because of the delay on building recruiting and construction, the data (both forecast and measurement) and models are not available for the task 3.5-model predictive control (MPC)-based building energy management systems (BEMS). The MPC-based controller architecture and algorithm design had been conducted by using the PowerFlexHouses on PowerLabDK (PLDK) (http://www.powerlab.dk/Facilities/PowerFlexHouses).

The remaining of this report is organized as follows: in Section 2 we briefly introduce MPC and its evolution. How to design the architecture of MPC controller is provided in Section 3. Then, the challenges of implementation MPC will be discussed in Section 4. In Section 5, some results and analysis of implement the MPC controller for PowerFlexHouse3 on PLDK-SYSLAB test platform are shown. Finally, conclusion is drawn in Section 6, followed by the discussion on the future work.

It is important to realize that the MPC-based BEMS described as such in this report will continue to evolve also after the finalization of this document. Thus, the scope of the document is limited to serving, only the Work Package 3 (WP3) of EnergLab Nordhavn (ELN) project - Smart Energy buildings, as a prototype implementation of economic MPC for PowerFlexHouse3 and a preliminary guideline for work related. The document cannot be used to determine anything about decisions and rationales which fall beyond its scope.

2. MPC and its evolution

2.1 Traditional model predictive control

As shown in Figure 2, actually, the traditional MPC refers to a class of control algorithms that optimize a sequence of adjustments for manipulated variable to keep the reference trajectory over a future time horizon, using a process model to forecast the process behaviour in the same time horizon, based on a linear or quadratic objective function, which is subject to equality or inequality constraints.

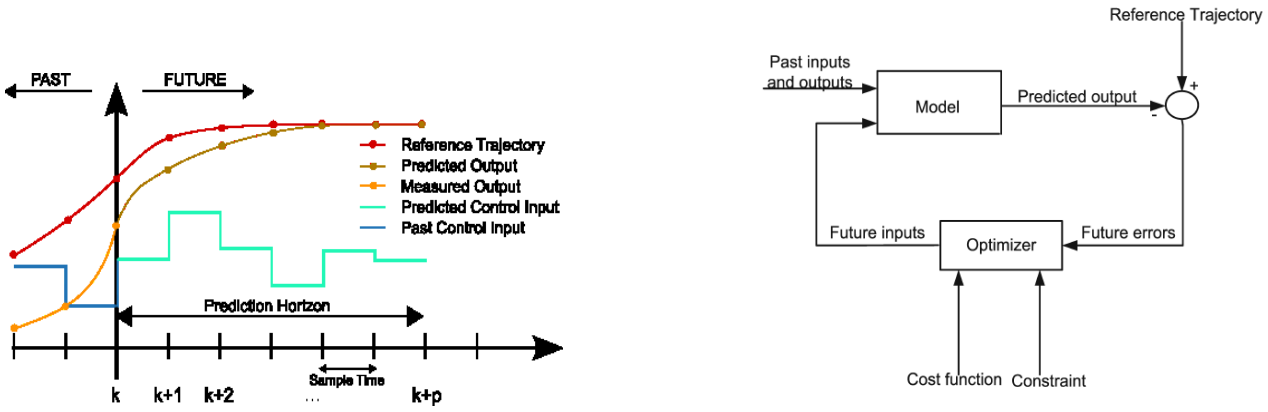


Figure 2. Main principle of MPC

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 [7]. 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 [8].

Recently, MPC has drawn the attention of the energy 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 [9][10][11].

2.2 Economic model predictive control (EMPC)

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 [12][13]. It is designated as an economic MPC (EMPC), which always copes with dynamically changing energy prices. Figure 3 shows the difference between the traditional MPC and EMPC. 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]. While in traditional tracking control, the objective is to minimize the error between a reference trajectory and the measured output (to maintain the process variables around a few desired steady states.) EMPC enables to define temperature bands or comfort zones realized by output constraints. The same as traditional MPC, at each step, a look-ahead finite-horizon optimal control problem in EMPC is solved, but only the first step of control sequences is implemented.

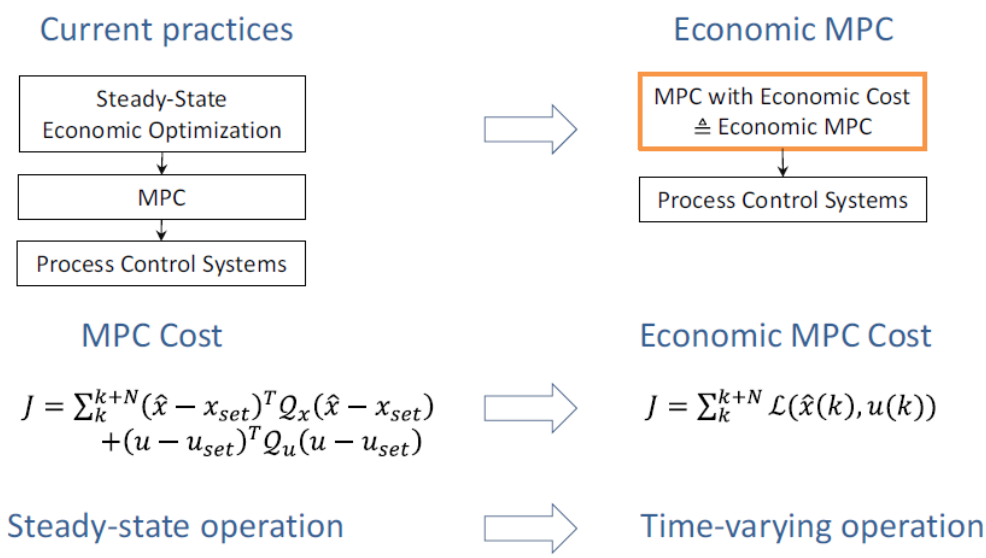


Figure 3. The difference between traditional MPC and EMPC

In addition, the hard constraints can be changed to the soft constraints to ensure feasibility in the linear optimization by adding a term to the cost function that penalizes constraint violation to obtain better controller performance. It was also proved that any stabilizable system can be asymptotically stabilized with soft constraints and state feedback [15]. The EMPC problem with soft constraints (grey coloured) can be expressed as linear program in the following form:

$$\min_{\{u_k, V_{k+1}\}_{k=0}^{N-1}} \phi = \sum_{k=0}^{N-1} c_k' u_k + \sum_{k=1}^{N} \rho V_k \qquad \text{(1a)}$$

subject to:

$$x_{k+1} = Ax_k + Bu_k + E\omega_k \qquad k=0, 1,\ldots, (N-1) \qquad \text{(1b)}$$

$$y_k = Cx_k + v_k \qquad k=1, 2,\ldots, N \qquad \text{(1c)}$$

$$u_{\min} \le u_k \le u_{\max} \qquad k=0, 1,\ldots, (N-1) \qquad \text{(1d)}$$

$$\Delta u_{\min} \le \Delta u_k \le \Delta u_{\max} \qquad k=0, 1,\ldots, (N-1) \qquad \text{(1e)}$$

$$z_k^{\min} \le y_k \le z_k^{\max} \qquad k=1, 2,\ldots, N \qquad \text{(1f)}$$

$$s_k^{\min} \le y_k - v_k \le s_k^{\max} \qquad k=1, 2,\ldots, N \qquad \text{(1g)}$$

$$v_k \ge 0 \qquad k=1, 2,\ldots, N \qquad \text{(1h)}$$

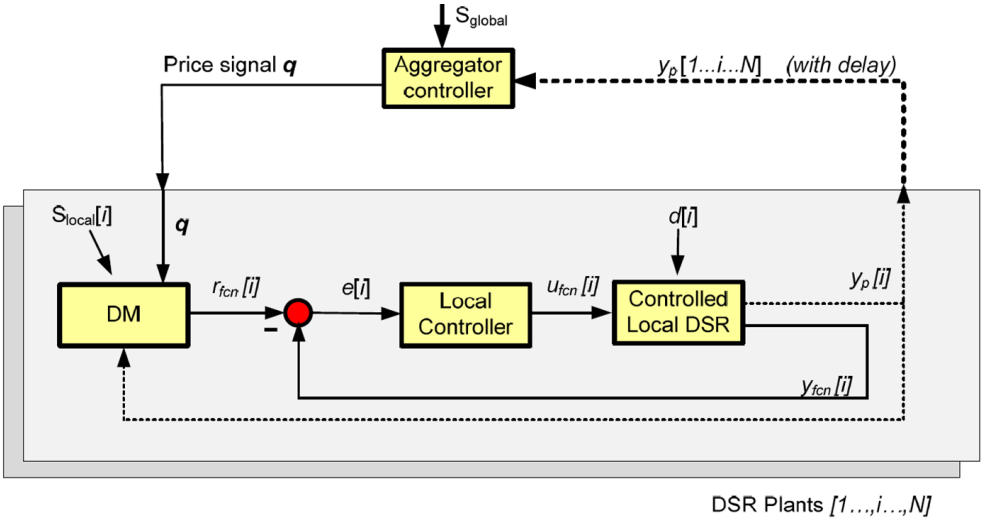
where $\boldsymbol{x_k}$ is the state vector; $\boldsymbol{u_k}$ is the manipulated input vector; $\boldsymbol{w_k}$ is the process noise; $\boldsymbol{y_k}$ is the measurement vector; $\boldsymbol{\rho}$ is the cost of breaking the constraints and $\boldsymbol{v_k}$ is the vector of slack variables.

2.3 Control strategies: indirect control and direct control

The control of demand side resources (DSR) to provide various power system services can be classified into two different types in the ways the final control element is activated. They are

- Indirect control (See Figure 4)
- Direct control (See Figure 5)

Based on the decision-making (DM) intelligence location, direct and indirect controls can be autonomous or centralised control.



(DSR=demand side resources; DM= decision making)

Figure 4. Indirect control [16]

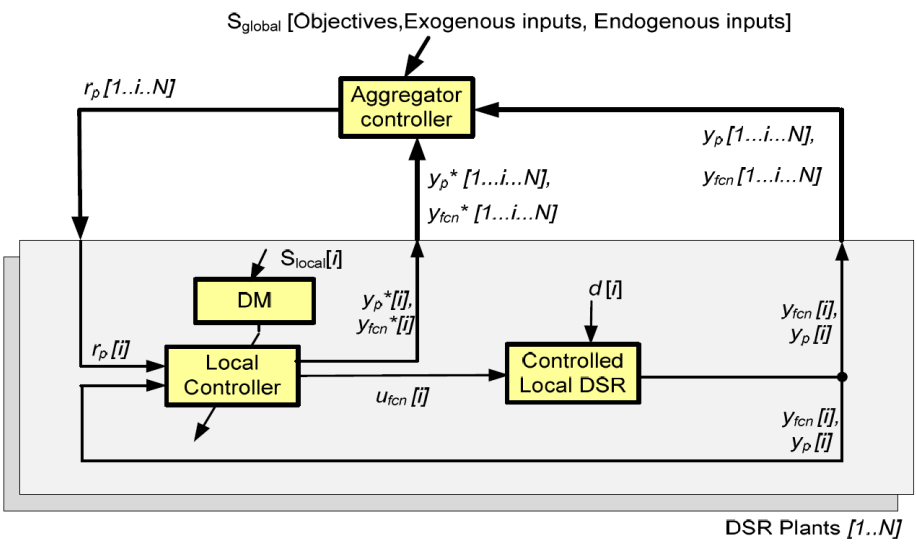


Figure 5. Direct control [16]

2.3.1 Indirect control

In indirect control the signal for control could be the electricity price or the variation in the service set points; for example, variations in the temperature set points of a room heater. The controller for the load is not obliged to react to the signal [17]. The indirect control becomes nondeterministic due to the local decision making ability of the controller [16][17]. The intelligence for decision-making is distributed and final control option is limited to then local control. The indirect control method is not intended for critical power system services [18]. The control decision on signal can be taken by a central controller that has the information of the device consumption, operational status, their service set points and flexibility. In the case of distributed controllers, the control signal (namely, the power price) is broadcast to all consumers [16][17]. Electricity price based indirect control has gained increased interest in recent years [19]. The controllable price-elastic flexibility with consumer consumption on price based indirect control is observed with varying prices [20]. The indirect control can be of interest to the electricity retailer to maximize revenue, or it can be of interest to the aggregator to deliver power service [21].

2.3.2 Direct control

In domestic sector, the loads that have higher power-flexibility for example water heaters, and air conditioners are utilised for direct load control. It is by sending a specific signal or command to the load controller or even controlling the load directly through a unidirectional or bidirectional communication link. If a unidirectional link is used for communication, the load or the load controller has to oblige to the command. The bidirectional communication link facilitates an acknowledgement by the load or the load controller and has the freedom of deciding load curtailment. The command signal can be initiated by the Distribution System Operator (DSO) or by an aggregator, who bridges the gap between the consumer and the DSO. There are four load control schemes based on the type of information exchange between the two parties as following [22]:

- Shift in time of operation, which is suitable for load of non-interruptible type, for example washing machines and dishwashers.
- Reduction in power consumption, which is suitable for the loads that can reduce their power consumption and extend their duration of operation, for example room heaters or water heaters.
- Schedule of power consumption with a time series of allowable power consumption and its duration.
- Direct power control, which can alter the power consumption.

2.3.3 MPC control strategy

From the system control point of view, the price-based indirect control (See Figure 4), where a price signal from market, is broadcast to a large number of demand side resources (DSRs) to encourage end-users to change their power consumption from the peak to off-peak time. This can be considered as an EMPC strategy. The other one is the direct control (See Figure 5), where a centralized controller—or coordinator/aggregator—is directly controlling a number of DSRs by sending a reference set point for requested power consumption or generation to each of them. This strategy can be considered as the traditional MPC.

3. Architecture design for MPC

3.1 MPC-based controller for a large scale system

Figure 6 illustrate four different MPC architectures. Decentralized architectures where the control (input *u*) and the controlled (output *y*) variables are grouped into disjoint sets. These sets are then coupled to produce non-overlapping pairs for which local regulators are designed to operate in a completely independent fashion. In distributed control structures, it is assumed that some information is transmitted among the local controllers (MPC1 & MPC2), so that each one of them has some knowledge on the behaviour of the others. A two-level hierarchical control structure is highlighted in this report- an MPC algorithm at the higher level coordinates the actions of local MPCs [23].

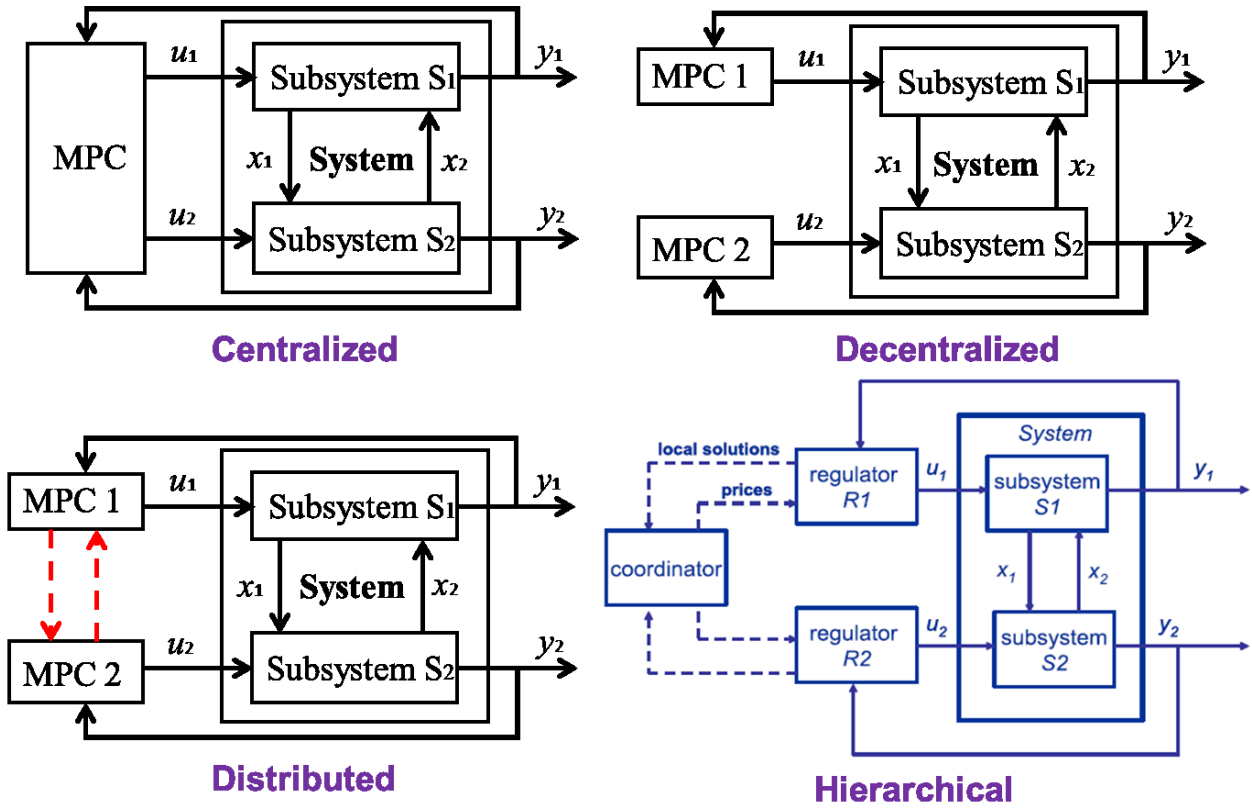


Figure 6 Four different architectures of MPC controllers for a large scale system

3.2 Hierarchical MPC for the ELN demonstration buildings

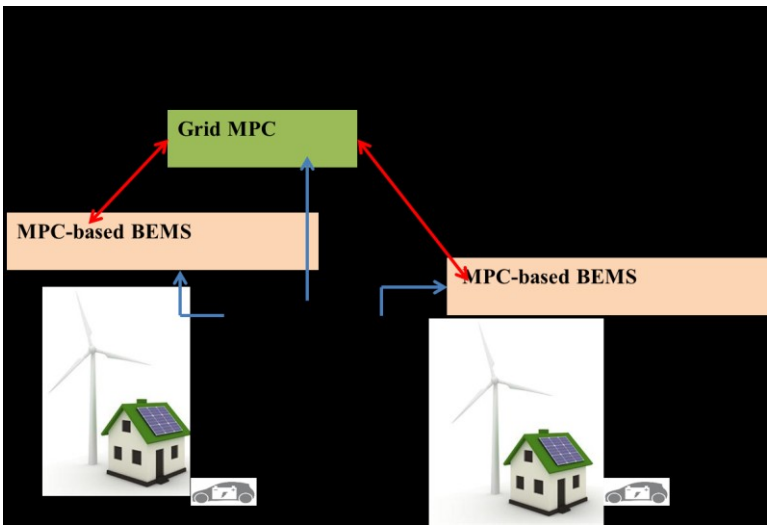


Figure 7 Two-level hierarchical MPC

Figure 7 shows a two-level hierarchical MPC, which takes both the low voltage distribution grid and the building domains into account. For each building, a separated MPC-based Building Energy Management System (BEMS) controller is designed and it aims at the local optimization for the whole building and determines the set points for the low-level

(rooms or zones) controllers, such as PID/PI controller (See Figure 8) . At the top of the hierarchy in the Figure 7, the Grid MPC controller aims to optimize the whole 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, energy price or load) should be considered for all the MPC controllers at different levels.

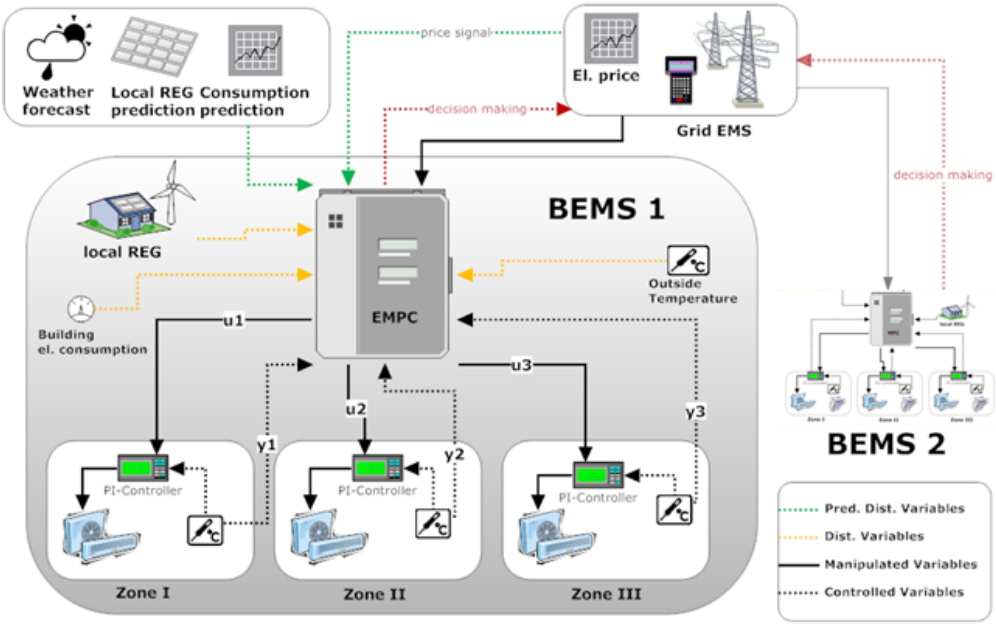


Figure 8 MPC-based BEMS

The research presented in this report 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.

4. Challenges of MPC implementation for active smart buildings

According to our experience on the implementation of MPC, it presents considerable challenges in data analysis, modelling, hardware and communication, optimization technique and state estimation, etc. The investigations on these challenges are summarized in the following sub-sections.

4.1 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 energy 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). For example, currently, the available time interval of the electricity price signals from Nordpool market [24] is hourly based; while the available weather forecast data are in 10-15 minutes interval.

For the building data management, it is important to focus on the data worth collecting, the analysis worth sharing, and analytical tools for the coordination control on DERs. This is a time-consume and important preparation for the modelling and EMPC controller design. The data (both forecast and measurement) for MPC-based controller development can be found in Appendix 8.1.

4.2 Control-oriented modelling

When large measurement data sets are available, a purely statistical approach for creation of a building model is preferred. EMPC inherently requires an appropriate model of the controlled plant, which is then used for the computation of the optimal control inputs. The relevant dynamic behaviour of the buildings for the active demand side management (ADSM) control tasks can be divided into the thermal dynamics (room temperatures, thermal capacities, heat inputs and losses) as well as the relevant building resources to provide corresponding services, such as heating, cooling, lighting, ventilation, photovoltaic (PV) systems or storage (batteries and electric vehicles). 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 EMPC controller, the building thermal models should have the ability to be adjusted at least with the season's change. According to the application needs, models with different fidelity and mathematical properties will be used, based on a combination of physics-based approaches and data-driven approaches.

Normally, it is much more suitable to use Linear Time Invariant (LTI) models for the MPC controller design. This results in 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 [25]:

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 much complicate 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 signal (PRBS) [41]. 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.

[26][27][28] show that using grey-box modelling, together with resistance capacitance (RC) networks based on the principle of thermal dynamics, to build control-oriented models, is an effective approach for the modelling of the thermal dynamics of the buildings. RC networks (see the example in the section 5.3) use lumped capacitance and resistance in an analogy electric circuit to represent the thermal elements of a building. The resultant models can be transformed into state-space forms, which are available for the implementation of an EMPC.

4.3 Hardware and communication

At present, to implement EMPC in active smart buildings, the common practice is to connect an external MPC computational core with the building's automation system (BAS), as shown in Figure 9. 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 EMPC to Chips", for example, integration of EMPC into the Programmable Logic Controller (PLC) [29][30] or Field- Programmable Gate Array (FPGA) [31][32], which has been widely investigated in BAS as field controllers.

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

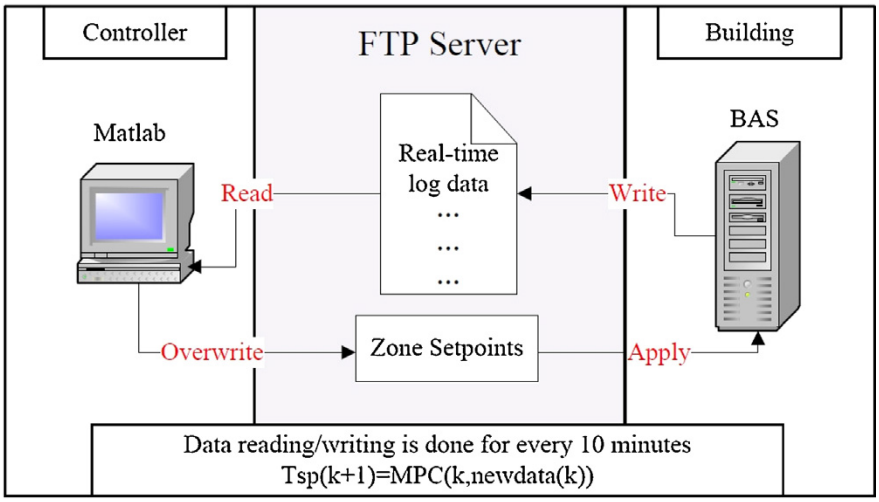


Figure 9 MPC-based BEMS developed in MATLAB integrated into a BAS

4.4 Objective function & Multi-objective optimization

Optimization is an indispensable part of EMPC functionality, wherein it is applied towards the economic optimization and constraint handling objectives. The objective function of EMPC 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 EMPC, 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 [33]. 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 (e.g. soft constraints) to recover online from the infeasibility. The existing recovery techniques are based on the priorities of the constrained and controlled variables [34] [35].

4.5 State Estimation

In EMPC for ADSM, besides potentially modelling errors and disturbances as occupation, open windows or high wind speed affect the thermal dynamics of the buildings. In order to achieve offset free control for the EMPC a proper disturbance model is needed. [36] found that a number of integrating disturbances equal to the number of measured states are sufficient to reach offset free control. In addition, 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 the above two cases, a Kalman filter is the solution to the central state estimation problem in EMPC, which can be used to estimate the current state of the building and the estimation is used as initial/ current state for control [11] [37].

5. EMPC strategies for PowerFlexHouse3 on SYSLAB platform

5.1 SYSLAB platform

Figure 10 SYSLAB platform

DTU Elektro, Risø campus has established a flexible platform for research in advanced control systems and concepts, power system communication and component technologies for distributed power systems-SYSLAB. It is built around a small power grid with renewable (wind, solar) and conventional (diesel) power generation, battery storage, and various types of consumers [38]. Currently components on the SYSLAB platform are listed as following (See Figure. 10):

- Gaia wind turbine (11 kW)

- Aircon wind turbine (10 kW)
- Diesel generator set (48 kW/60kVA)
- Solar panels (7 kW+10kW+10kW)
- Vanadium battery (15 kW/120kWh)
- Capacitor bank (46 kVAr)
- Back-to-back converter (30 kW/45kVA)
- Dump load (78kW)
- Office/Residential buildings-PowerFlexHouse1, 2 & 3
- Plug-in hybrid car (9 kWh)
- Pure EV (16 kWh)

The SYSLAB facility is spread across multiple locations at Risø DTU as shown in Figure 10. Its backbone is formed by a 400V grid with several busbars and substations. A central crossbar switch with tap-changing transformers enables meshed operation and power flow control. All components on the grid – generators, loads, storage systems, switchgear – are automated and remote controllable. Each component is supervised locally by a dedicated controller node. The node design combines an industrial PC, data storage, measurement and I/O interfaces, backup power and an Ethernet switch inside a compact, portable container. All nodes are interconnected via redundant high speed Ethernet, in a flexible setup permitting on-line changes of topology and the simulation of communication faults. The whole system can be run centrally from any point on the network, or serve as a platform for fully decentralized control. All SYSLAB controller nodes run the SYSLAB software stack. This is a modular framework for developing distributed control systems for power systems. It is written in the Java (TM) programming language. Each physical SYSLAB component is controlled by a software module designing on one of the SYSLAB nodes. Distributed controllers can control these components by using one of the supported types of communication. The one most used is the Java RMI (Remote Method Invocation) system [11].

One of the components on the SYSLAB grid is a small, intelligent office building and two residential buildings-PowerFlexHouses. Each room the PowerFlexHouses is equipped with a motion detector, temperature sensors, light switches, window and door contacts and actuators. A meteorology mast outside of the buildings supplies local environmental measurements of ambient temperature, wind speed, wind direction, and solar irradiation. The electrical load of the building consists of heating, lighting, air-conditioning, a hot-water supply and various household appliances, such as a refrigerator and a coffee machine. All individual loads in the building are remote-controllable from a central building controller. The controller software runs on a Linux-based PC. It is written in Java (TM) and is based on the SYSLAB software stack. The controller software consists of several modules working together. The hardware module collects data from the sensors and sends commands to the actuators. It does this via serial port (communication with the

meteorology mast), modbus (switchboard instruments), and wireless transceivers (Enocean and infrared). The database module collects all sensor measurements and all commands sent to the actuators for further analysis. Another module collects data from external sources: the Nord Pool power price, the local weather forecast data, and some state information from the Danish power system. Finally, the controller module supports the development of any kind of controller algorithm for the PowerFlexHouses. The controller is able to communicate with the SYSLAB grid through its own node computer (See Figure. 11). Information can also flow in the other direction, for example providing the power system controller with the expected near-future behaviour of the building loads.

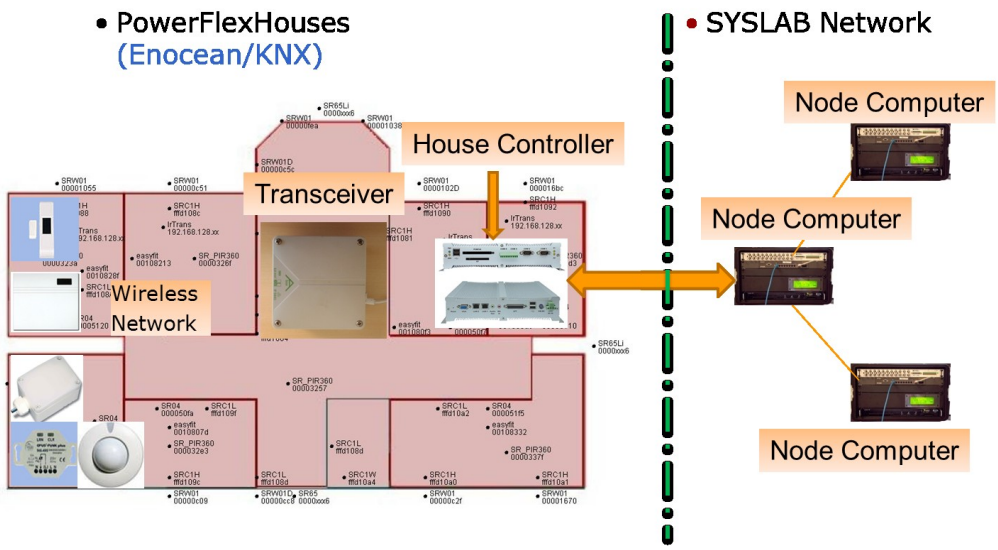


Figure 11 Communication between PowerFlexHouses and SYSLAB

5.2 PowerFlexHouse3

The PowerFlexHouse3 (See Figure 12) is a 150 m^2 3-floor house built in 1954 [39]. The outer walls of the house are brick constructed with a layer of insulation between them and the roof is tile. All sensors (temperature, motion and contacts, etc.) in PowerFlexHouse3 support KNX standard communication. There are four types of water-based heating radiators in the building [40]. In the basement there are three radiators of 2.708 kW total power; in the first floor there are 6 radiators of 6.138 kW total power and in the second floor there are 2 radiators of 2.198 kW total power. The total power consumption of the heating radiators is around 11 kW and they can be remotely controlled via electro-valves. The detailed structure and the location of sensors and actuators in PowerFlexHouse3 can be found in Appendix 8.2.

(a) Back facade (b) Front facade

Figure 12. A residential building-PowerFlexHouse3.

5.3 Control-oriented modelling-PowerFlexhouse3

The heat flow in PowerFlexHouse3 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, in PowerFlexHouse3, each floor is considered as a single room where all the radiators are grouped as one input for each floor. The building'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 (RC-network). In such an RC-network, 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 13. The heat transfer model takes measured disturbances namely the solar irradiance P_s (kW/m^2), the ambient temperature T_a (˚C) and the earth temperature T_{earth} (˚C) into consideration. Ventilation does not directly cause heat transfer, but due to mass transfer heat is transferred. It is considered the wind speeds up to 5m/s in the thermal resistance of the building walls as shown in [41] and high wind speeds are considered as a noise term. This approximation is invalid for higher wind speeds where it becomes non-linear [42]. The heat flux (u_iP_{hi}) coming from the heaters in each floor is the controlled input in the model. The solar irradiation goes through the windows directly into the rooms and is described in the model as (Aw_iP_s).

The first-order heat dynamics for the PowerFlexHouse3 are represented by the stochastic differential equations (SDEs) (2a) - (2c) for the floors, and equations (2d) - (2f) for the building envelopes, respectively, where t is the time. The term σ_i $d\omega_i/d_t$ represents the process noise; where ω_i are standard Wiener processes with the variances σ_i. Table 1

presents the relevant parameters and variables, regarding the characteristics of the building illustrated by Figure 13 and equations (2a) to (2f).

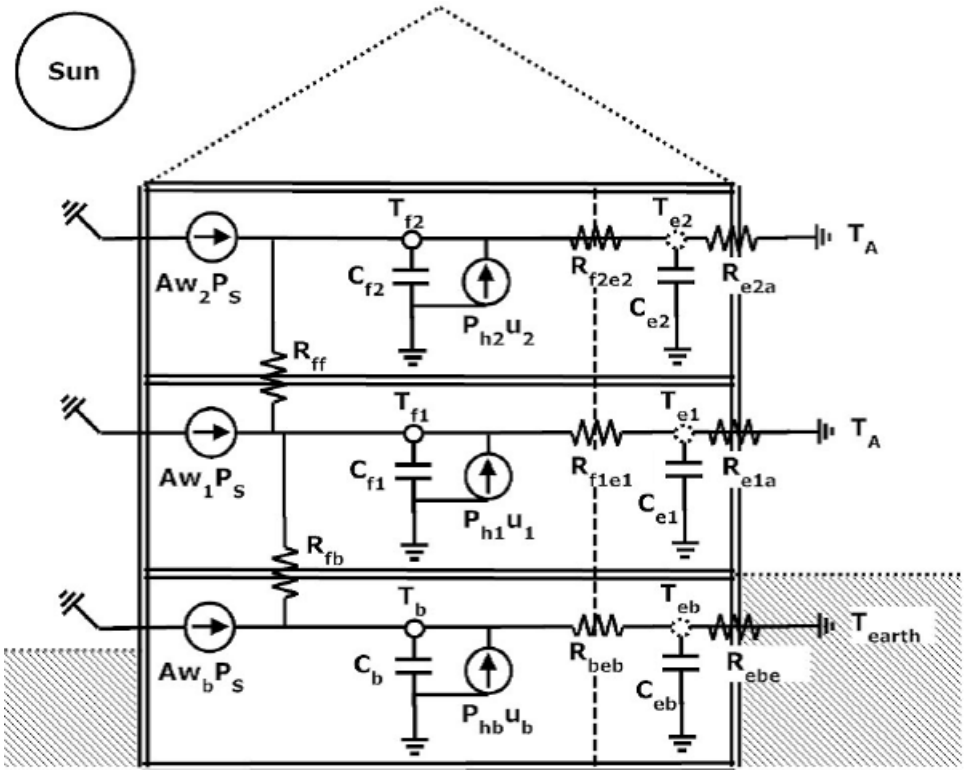


Figure 13. Heat dynamics RC-network of the PowerFlexHouse3.

$$\frac{dT_{f1}}{dt}=\frac{1}{R_{ff}C_{f1}}(T_{f2}-T_{f1})+\frac{1}{R_{fb}C_{f1}}(T_b-T_{f1})+\frac{1}{R_{f1e1}C_{f1}}(T_{e1}-T_{f1})+\frac{P_{h1}u_1}{C_{f1}}+\frac{Aw_1P_s}{C_{f1}}+\sigma_{f1}\frac{dw_1}{dt} \tag{2a}$$

$$\frac{dT_{f2}}{dt}=\frac{1}{R_{ff}C_{f2}}(T_{f1}-T_{f2})+\frac{1}{R_{f2e2}C_{f2}}(T_{e2}-T_{f2})+\frac{P_{h2}u_2}{C_{f2}}+\frac{Aw_2P_s}{C_{f2}}+\sigma_{f2}\frac{dw_2}{dt} \tag{2b}$$

$$\frac{dT_b}{dt}=\frac{1}{R_{fb}C_{fb}}(T_{f1}-T_b)+\frac{1}{R_{beb}C_{fb}}(T_{eb}-T_b)+\frac{P_{hb}u_b}{C_{fb}}+\frac{Aw_bP_s}{C_{fb}}+\sigma_b\frac{dw_b}{dt} \tag{2c}$$

$$\frac{dT_{e1}}{dt}=\frac{1}{R_{e1a}C_{e1}}(T_a-T_{e1})+\frac{1}{R_{f1e1}C_{e1}}(T_{f1}-T_{e1})+\sigma_{e1}\frac{dw_1}{dt} \tag{2d}$$

$$\frac{dT_{e2}}{dt}=\frac{1}{R_{e2a}C_{e2}}(T_a-T_{e2})+\frac{1}{R_{f2e2}C_{e2}}(T_{f2}-T_{e2})+\sigma_{e2}\frac{dw_2}{dt} \tag{2e}$$

$$\frac{dT_{eb}}{dt}=\frac{1}{R_{ebe}C_{eb}}(T_{earth}-T_{eb})+\frac{1}{R_{beb}C_{eb}}(T_b-T_{eb})+\sigma_{eb}\frac{dw_b}{dt} \tag{2f}$$

Table 1 Model parameters of PowerFlexHouse3

Symbols	Physical meaning	Estimation value
T_{f1}, T_{f2}, T_b	Temperature in floor 1, floor 2 and basement	-
T_{e1}, T_{e2}, T_{eb}	Envelope temperature in floor 1, floor 2 and basement	-
T_{earth}, T_a	Earth and ambient temperature	-
P_{h1}, P_{h2}, P_{hb}	Radiator power in floors (kW)	-
P_S	Solar irradiation (kW/m^2)	-
u_i	Control inputs	-
Aw_b	Window area in basement (m^2)	0.2110
Aw_1	Window area in floor 1 (m^2)	0.8915
Aw_2	Window area in floor 2 (m^2)	0.1526
C_{f1}	Heat capacity in floor 1 (kJ/kgK)	1.0466×10^4
C_{f2}	Heat capacity in floor 2 (kJ/kgK)	3.5417×10^3
C_b	Heat capacity in basement (kJ/kgK)	3.6410×10^3
C_{e1}	Heat capacity in floor 1 building envelope (kJ/kgK)	2.0929×10^4
C_{e2}	Heat capacity in floor 2 building envelope (kJ/kgK)	1.6307×10^4
C_{eb}	Heat capacity in basement building envelope (kJ/kgK)	2.0860×10^4
R_{ff}	Thermal resistance between floor 1 and 2 (K/kW)	4.249
R_{fb}	Thermal resistance between floor 1 and basement(K/kW)	3.7129
R_{e1a}	Thermal resistance between floor 1 envelope and ambient (K/kW)	13.934
R_{e2a}	Thermal resistance between floor 2 envelope and ambient (K/kW)	24.562
R_{ebe}	Thermal resistance between basement envelope and earth (K/kW)	15.546
R_{f1e1}	Thermal resistance between floor 1 and its envelope (K/kW)	0.65327
R_{f2e2}	Thermal resistance between floor 2 and its envelope (K/kW)	3.6202
R_{beb}	Thermal resistance between basement and its envelope (K/kW)	3.0275

The parameters of the SDEs were estimated using a PRBS which provides the flexibility to extend the model up to several states as stated in [43]. PRBS is a deterministic random signal with white noise characteristics sent to the controllable inputs of the plant, namely the heaters in each floor. Measurement data of the ambient temperature, solar irradiation, floor temperatures, wind speed and direction were taken in a 3-week experimental set in spring 2013 [44]. All inner doors were assumed to be opened whilst all windows and doors to the outside were considered to be closed. The parameter estimation, whose values are presented in Table 1, was realized using maximum likelihood estimation with CTSM-R [45], a software tool for estimating embedded parameters in a continuous time stochastic state space model, developed at DTU Department of Applied Mathematics and Computer Science. From this process the estimated values, the corresponding standard error, the value of the t-statistic and associated probabilities for testing the validation of the

parameters are calculated to assure the accuracy and reliability of the parameters' evaluation. Actually, a simple model that only includes one state variable-the indoor temperature of different floors, was also built and validated [46]. As shown in the equations (2a)-(2f), the model provides a more detailed knowledge of the dynamics of the building by augmenting the state space with the introduction of the envelope temperature. Adding the external envelope of the building, a heat capacity [C_{e1} C_{e2} C_{eb}] is also formed giving increased inertia to the heat dynamics of the building. Comparing with the simple [T_{f1} T_{f2} T_b] model, the [T_{f1} T_{f2} T_b T_{e1} T_{e2} T_{eb}] model shown in equations (2a)-(2f) can describe the heat dynamics of the building much better. The detailed description of building's models and the models' validation for PowerFlexHouse3 can be found in the reference [46].

5.4 EMPC controller

According to the national statistics, due to cold climates in the Nordic countries, space heating accounts for more than 60% of all energy use in buildings. The main objective of the developed EMPC controller is to realize the load shifting by using heating radiators in the PowerFlexhouse3. That is to say, to decrease peak load, reduce energy costs, and improve building thermal comfort, the other impactors, such as the windows area, solar irradiation, building envelope and heat capacity in different floors, etc., which have strong influence on the interior thermal behaviour, are also considered in the sub-section 5.3. The detailed parameters are listed in Table 1.

5.4.1 EMPC formulation

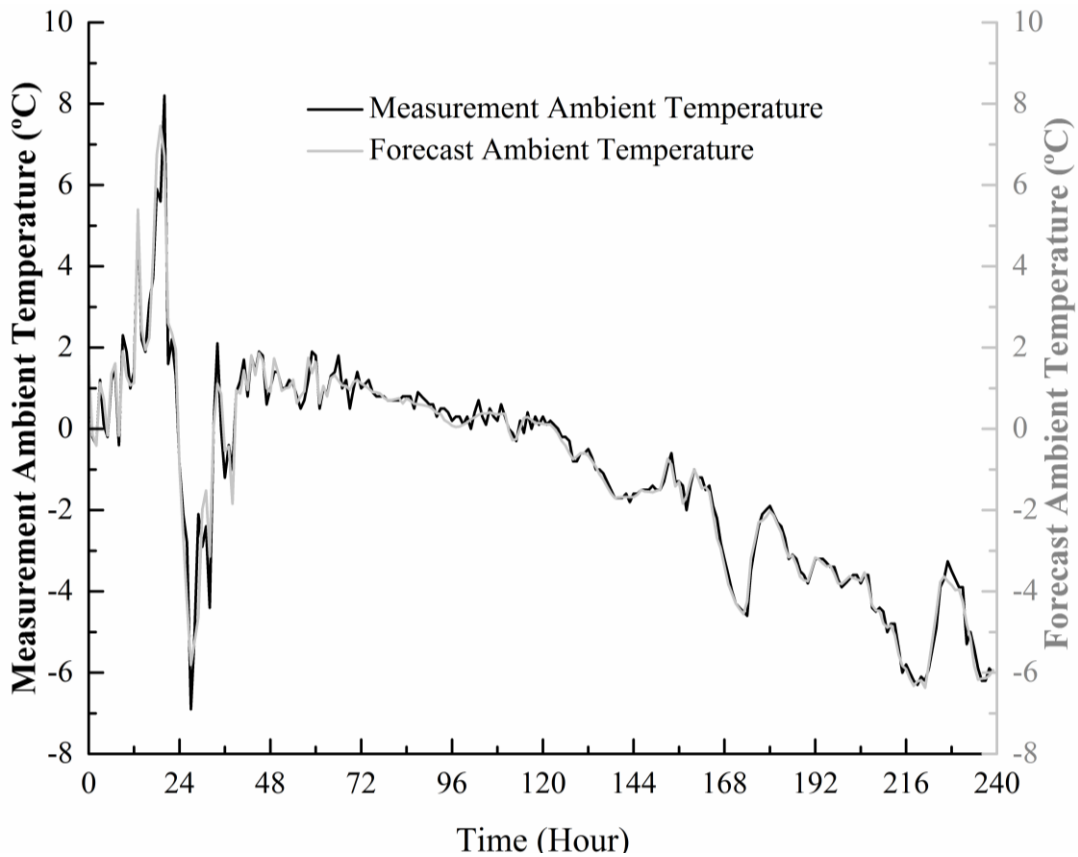
In the pilot testing study, the objective function was formulated as (1a), where c' is a vector with the price signals broadcasted by an aggregator, central controller or a power provider, u_k is the optimized power consumed by the radiators in order to heat the PowerFlexHouse3 and N is the length of the prediction horizon (for example 12 hours). The index k stands for the iteration in the prediction horizon.

Concerning the bound constraints, the radiators are only able to give off a certain amount of heat, therefore the solution is subject to (1d); an output (inside temperature) constraint is required, which is defined by (1f); The output constraints and represent the predefined limits of the comfort temperature bands in the zones and can be set independently for each zone. For example, the residential building PowerFlexHouse3 has requirements on the inside temperature from 21˚C to 23˚C during 8:00-19:00. According to [47] based on ISO 7730 a bandwidth of operative temperature in regular buildings from 21˚C to 23 ˚C reach 90% acceptability from the inhabitants in winter, whereas a temperature band from 19 ˚C to 25 ˚C is for 70% acceptance. It is assumed that the average temperature and in the same way the comfort zone can be softly lowered during the night by 1˚C. (See the low/high temperature reference curves in the Figure 18, 20 and 22).

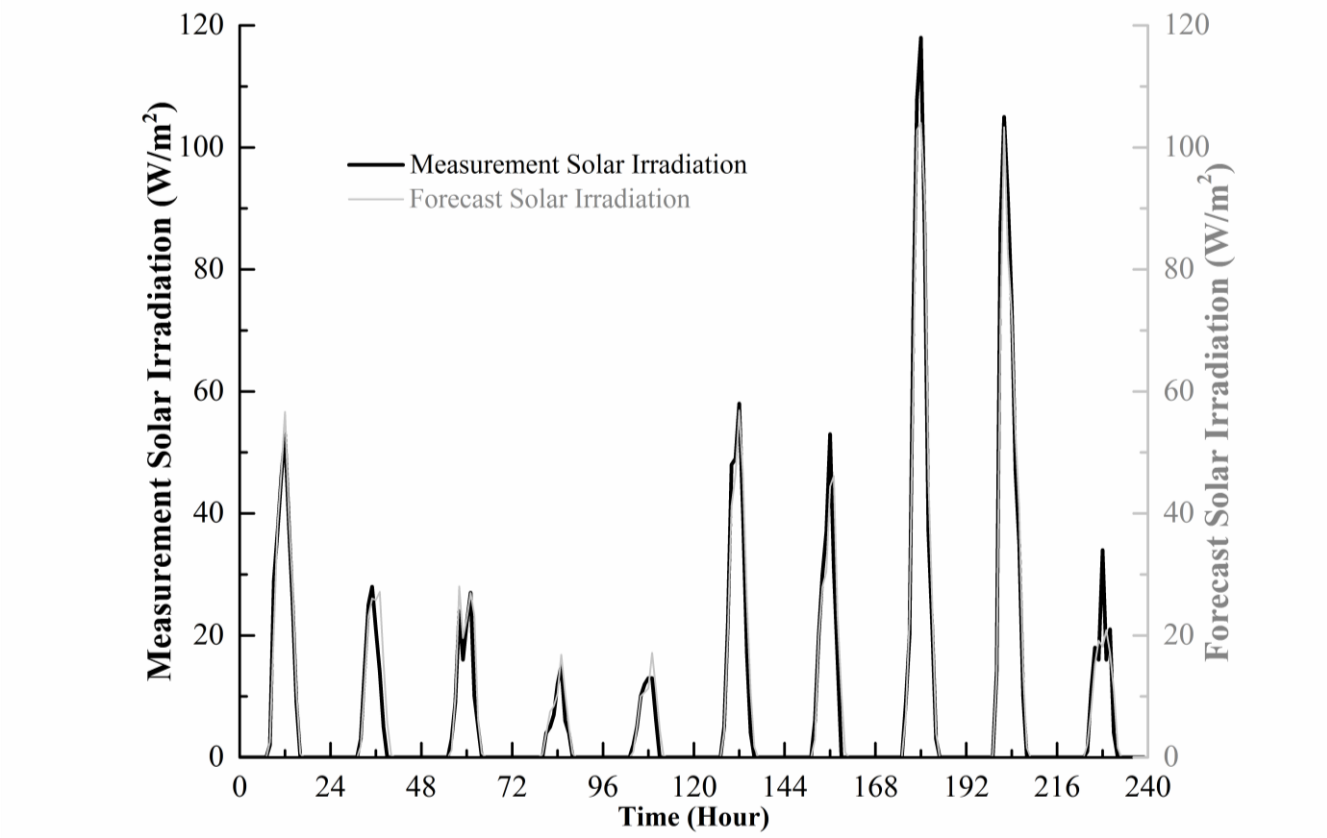
The model formulated in equations (2a)-(2f) and the parameters estimated and presented in Table 1 were used as the constraints presented in equations (1b) and (1c).

5.4.2 *Input data and State Estimation*

The proposed EMPC controller considers electricity prices, ambient temperature and solar irradiation data for the predictions. The input data were taken from 17. 01. 2014 until 26. 01. 2014 a total of 10 days. The dynamic price signals were obtained from the Nord Pool spot DK1 market [24]. The local forecast data of the ambient (outdoor) temperature T_a and the solar irradiation P_s are updated twice a day for the next 48 hours, which are provided by the meteorology group in the Wind Energy Division at DTU Risø campus. The maximum relative error between the actual measurement and the forecast data of the wind and solar irradiation are 8.7% and 7.9% respectively during the 10 days' test period (See Figure 14). Therefore, we concluded that the local weather forecast data are available to be integrated into the EMPC control strategy. Otherwise, to overcome a bigger weather forecast error, the weather actual measuring data (ambient temperature and solar irradiation, etc.) could be integrated with the prediction model for the building indoor air temperature, and verifies the predictive values. Then we could use the process's real-time output (the actual measuring inside air temperature) and model's (previous) predictive output to structure one model output feedback correction.



(a) Forecast ambient temperature (grey) and actual measuring ambient temperature (black)



(b) Forecast solar irradiation (grey) and actual measuring acutal measuring solar irradiation (black)

Figure 14. Comparison between the weather forecast data and actual measuring weather data

In addition, because of the model's uncertainty and disturbances such as building occupation, open windows or high wind speed, as shown in Figure 15, the developed model without any observer implementation is not capable to precisely predict the future behavior of the residential building. There were big errors between the actual temperature measurement and model's calculation for the first floor's temperature in Figure 15. Moreover, not all states of the control model can be measured (for example the envelop temperature of the building), and state estimation is a required step in MPC scheme. The state estimation problem boils down to examining the past monitoring data and reconciling these measurements with the model to determine the most likely value of the state at the current time. To diminish their impacts and increase the model's accuracy, for linear models, the optimal state estimation problem has an offline well known solution, one stationary Kalman filter can be introduced and its impact can be observed in Figure 16 [37].

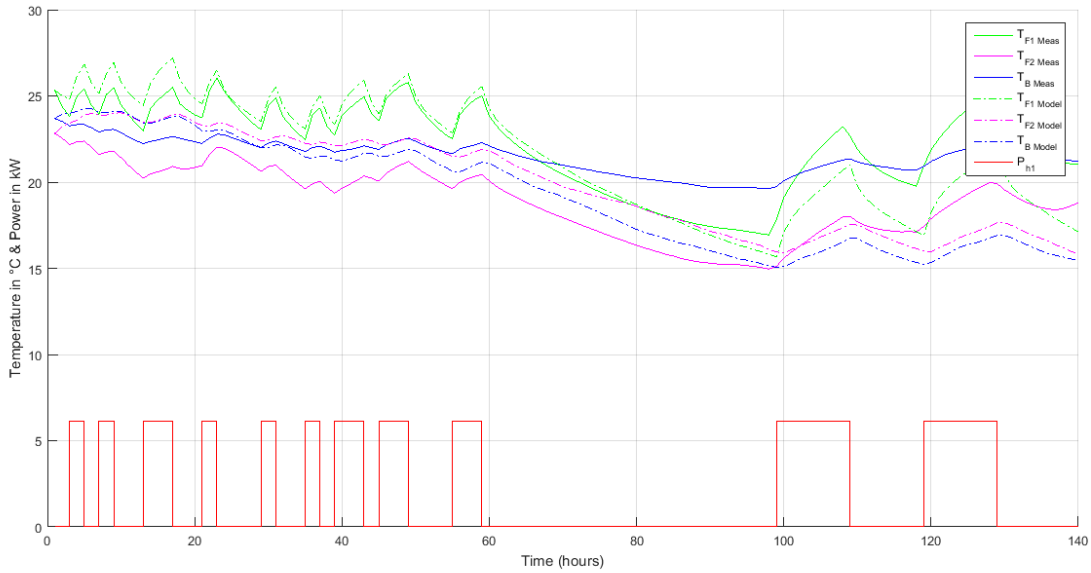


Figure 15. Comparison of discrete thermal model temperatures and temperature measurements from PowerFlexHouse3 with respect to the heater in the 1st floor. The red line shows the heating power in the 1st floor (P_{max} = 6.138kW).

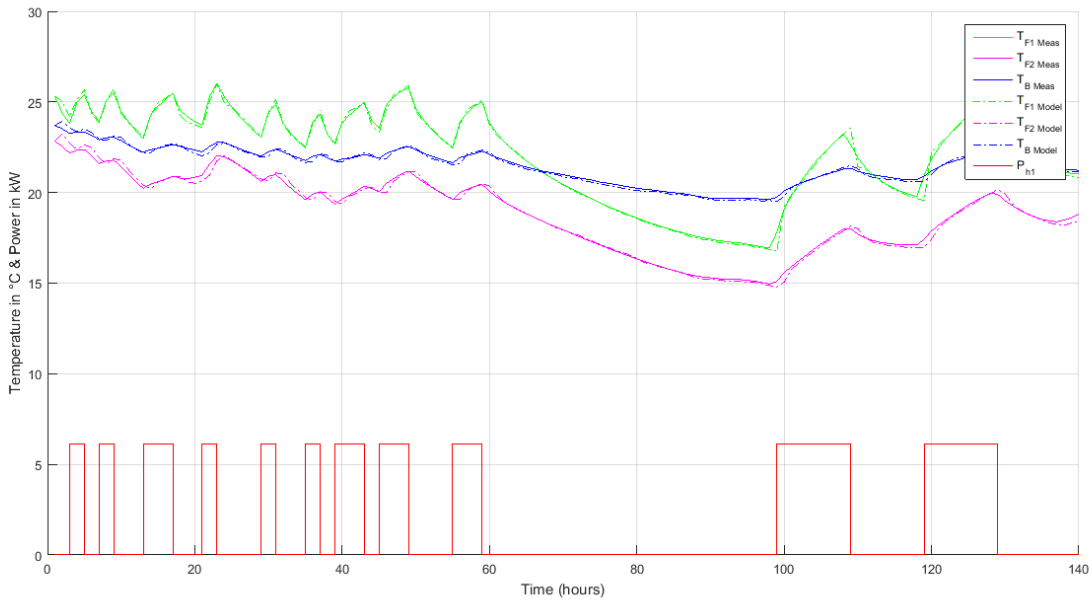


Figure 16. Comparison of discrete thermal model temperatures with stationary Kalman filter and temperature measurements from PowerFlexHouse3 with respect to the heater in the first floor. The red line shows the heating power in the 1st floor (P_{max} = 6.138kW).

5.4.3 Results analysis and discussion

Figure 18, Figure 20 and Figure 22 demonstrate the good performance of the inside temperature of 3 different floors in PowerFlexHouse3 during the test period. The inside temperatures are controlled in the reference band following the comfort pattern with the predictive occupancy. Figures 17, 19 and 21, show 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 **Fejl! Henvisningskilde ikke fundet.**. The radiators in PowerFlexHouse3 as shown in Figure 17, Figure 19 and Figure 21, even if work during the daytime, they all occurred when there is a lower price during the daytime. The results further illustrate that EMPC control strategy can achieve energy savings by shifting load from on-peak to off-peak period.

In addition, it can be observed in Figure 17 that the temperature of the first floor is much more variable than the other floors' temperature. On the one hand, there are six radiators on first floor which can be operated; on the other hand, the first floor has a strong thermal interaction 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 [48]. 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.

In order to compare the controller performance in terms of energy costs, a scenario is implemented where the investigated building is equipped with traditional set point based thermostatic controllers namely PID controller. Due to the fact that the EMPC normally does not trace a fixed reference temperature trajectory, two reference scenarios are proposed. In the so called PID low temperature scenario the lower band temperature is continuously traced for all zones. In the PID average temperature scenario the controllers reference temperature is the average comfort zone temperature. Both scenarios fulfil the temperature specification but they differ in terms of provided heat. For these two reference scenarios, the simulations were conducted under the same conditions as EMPC running. In other words, for each control strategy listed in Table 2, PID low/average controllers were simulated in the same test period of EMPC controller, with the same weather and energy prices input data. In Table 2, the results of the scenarios' analysis are presented by electricity costs in EUR for the designed controllers (i.e. PID low/average and EMPC controllers), the corresponding energy consumption can be expressed in kWh and the relative energy costs, which is the ratio between the electricity costs and the energy

consumption. It is obviously that the electricity cost and energy consumption of the PID low controller are much lower than those of the PID average controller because of its lower set points for the reference temperature. Comparing with the two reference scenarios (PID low/average), EMPC controller demonstrates that its energy consumption (and the provided heat) increases with the EMPC prediction horizon. Both the costs of electricity and the relative cost of EMPC controller firstly decrease with the prediction horizon increases and reach the minimum with the prediction horizon N = 5 hours. The results also illustrate that the importance on how to tune the prediction horizon, which will play a great influence on the EMPC controller performance.

Although the electricity cost of EMPC controller are not much significant when compared them with the PID solutions, the main achievement of EMPC controller is to demonstrate that buildings can provide "flexibility" services to the energy systems. As illustrated in Figures 17, 19 and 21, it is notable that the energy consumptions occur mainly at the low energy prices periods, characterizing a high share of renewables (wind) in the grid, for example, according to the data provided by Energinet.dk [49] and Nordpool DK East market, the correlation between wind power penetration and a day-ahead electricity spot price is shown in Figure 23. It is obviously that, for DK-East market where the test site-DTU Risø campus is located, the higher the wind power penetration, the lower the day-ahead hourly electricity spot price during the test period from January 17, 2014 to January 26, 2014. In one word, the proactive feature of EMPC is a must for the future smart energy systems.

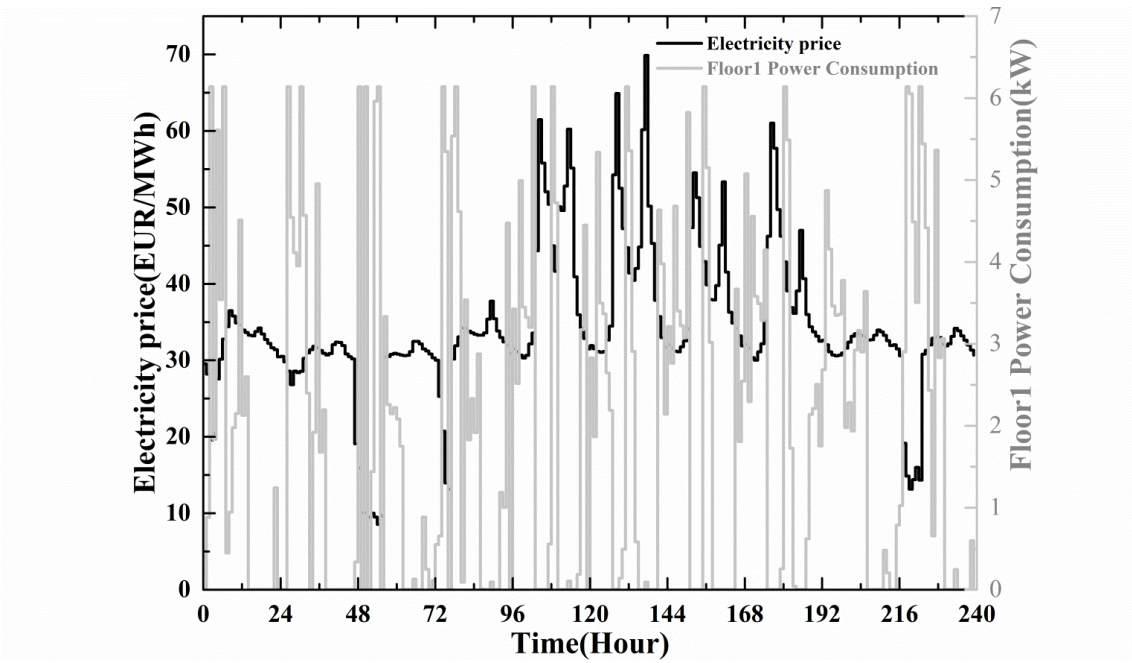


Figure 17. EMPC with prediction horizon N= 5 hours: the optimized predictive power consumption on the first floor of PowerFlexHouse3 (the black curve is the corresponding varying electricity price).

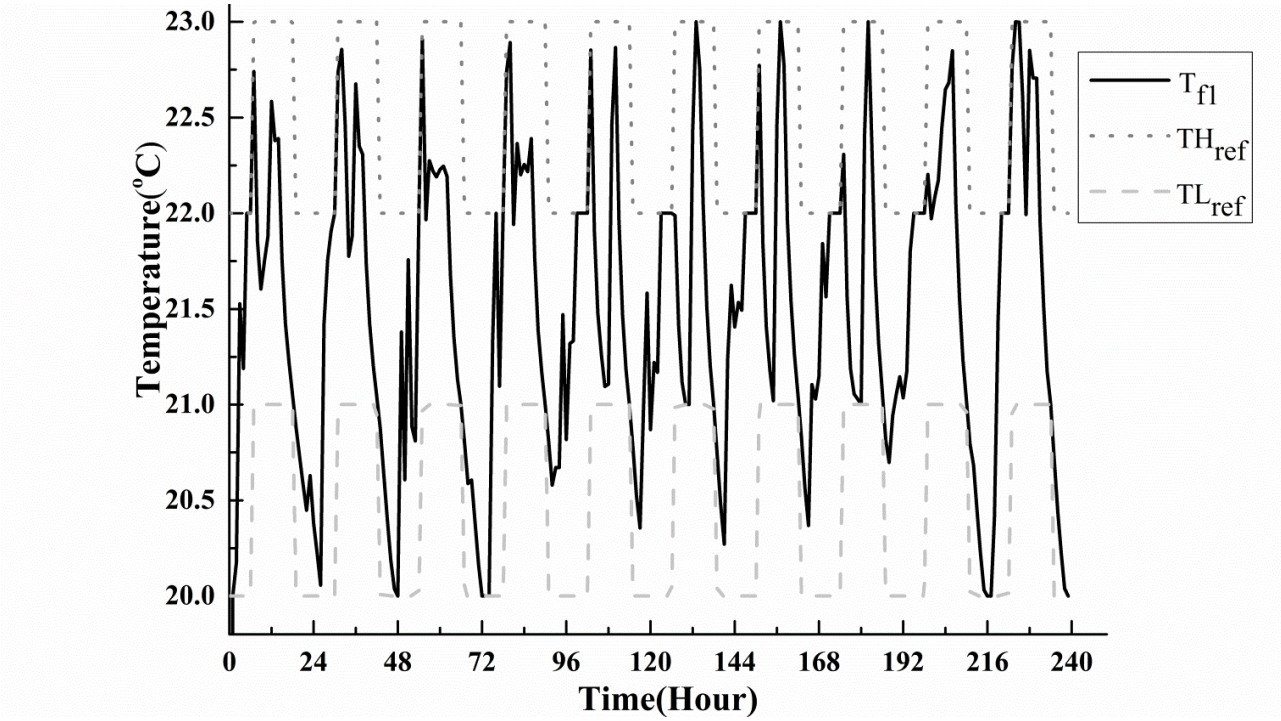


Figure 18. EMPC with prediction horizon N= 5 Hours: the first floor inside temperature of PowerFlexHouse3 related to the optimized the power consumption shown in Figure 17.

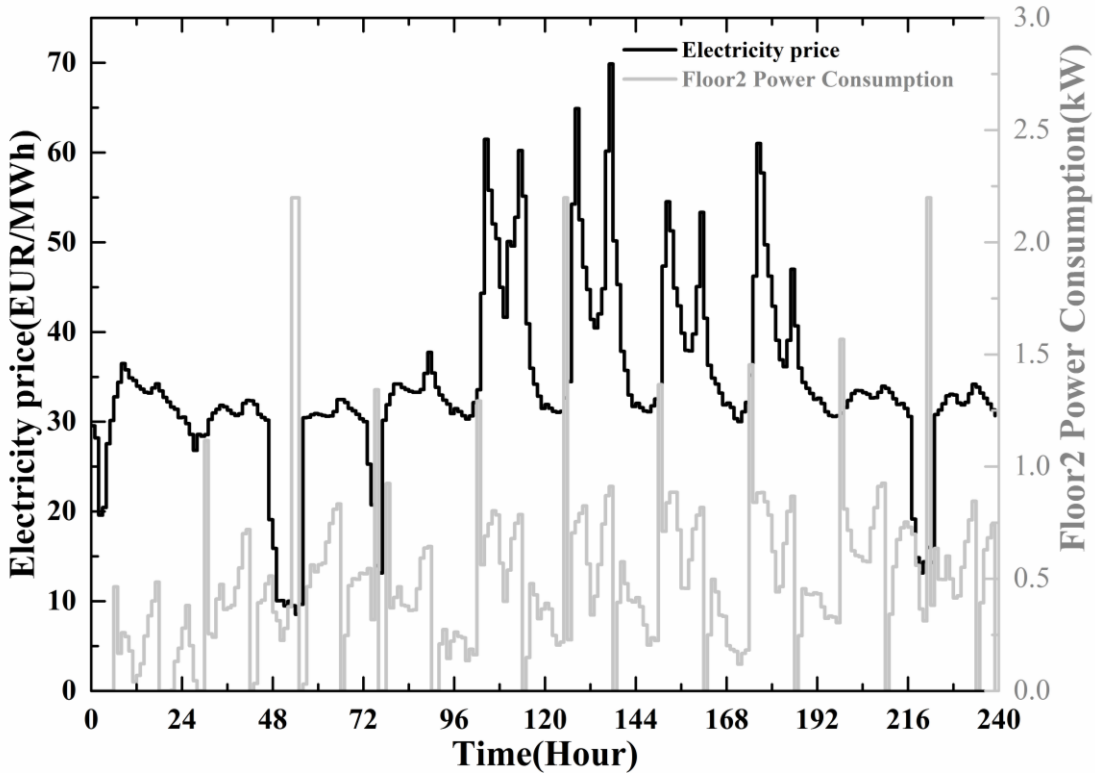


Figure 19. EMPC with prediction horizon N= 5 hours: the optimized predictive power consumption on the second floor of PowerFlexHouse3 (the black curve is the corresponding varying electricity price).

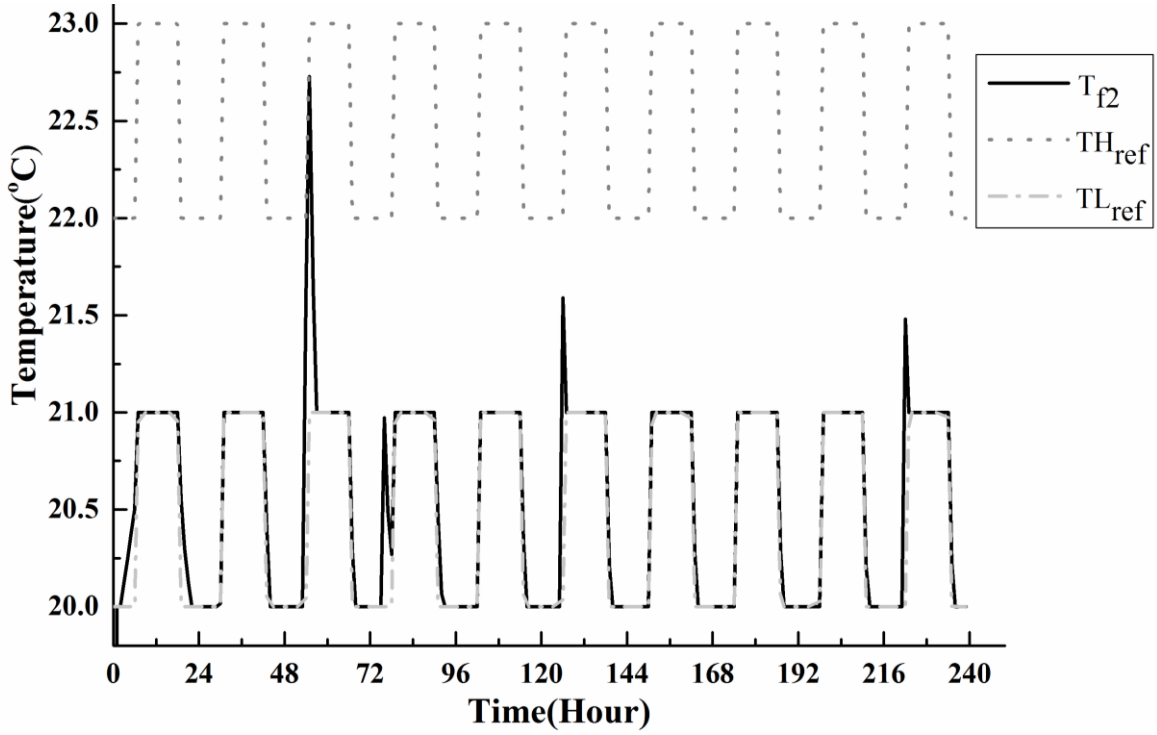


Figure 20. EMPC with prediction horizon N= 5 hours: the second floor inside temperature of PowerFlexHouse3 related to the optimized the power consumption shown in Figure 19.

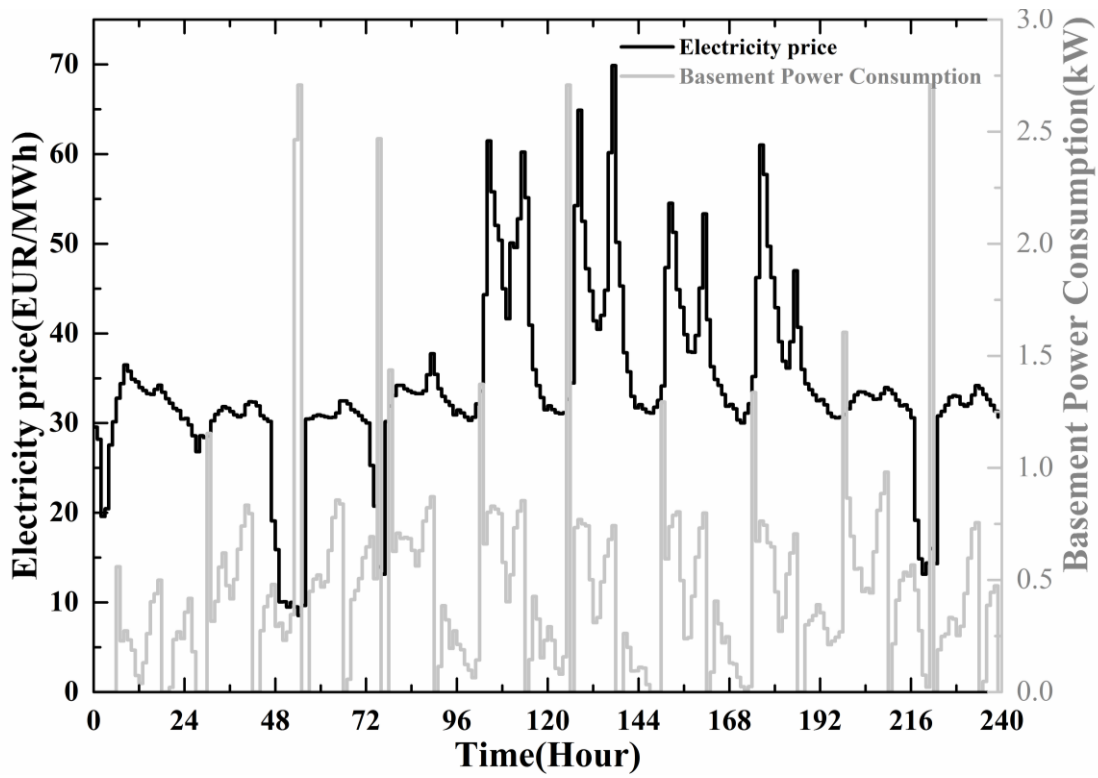


Figure 21. EMPC with prediction horizon N= 5 hours: the optimized predictive power consumption in the basement of PowerFlexHouse3 (the black curve is the corresponding varying electricity price).

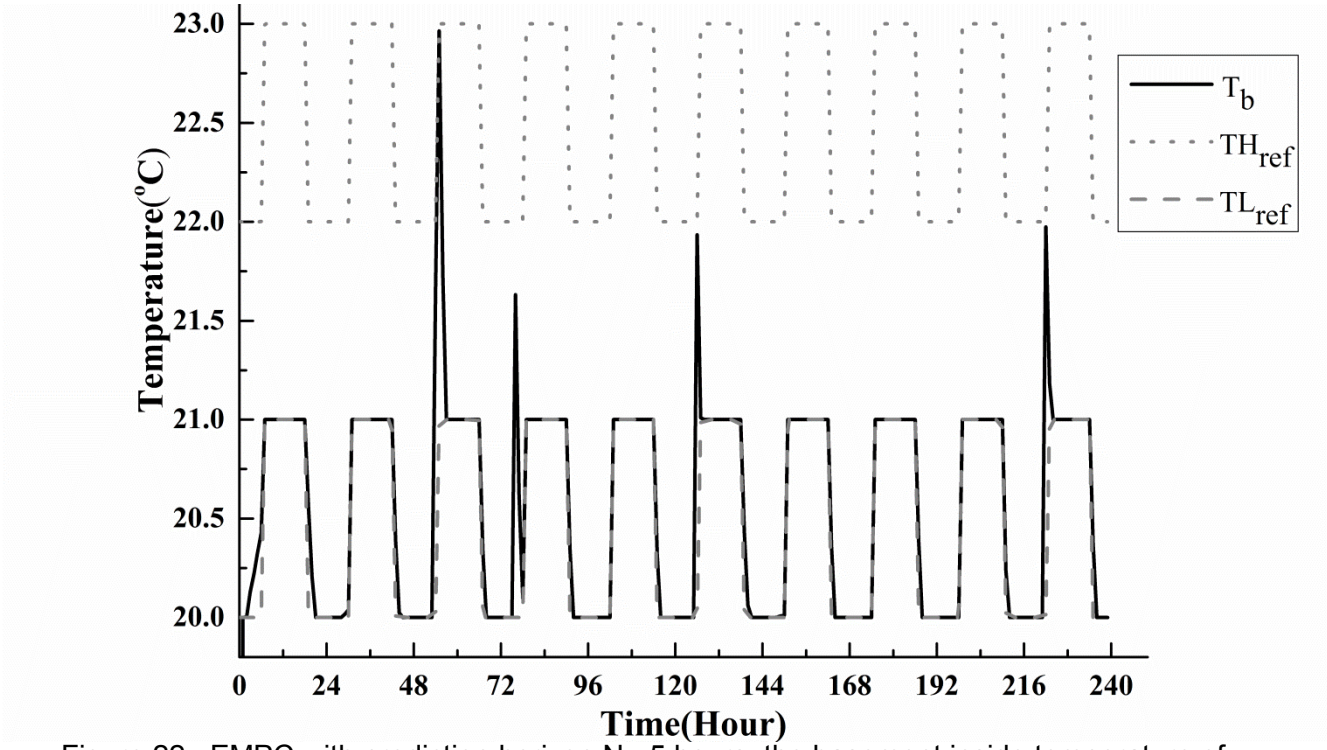


Figure 22. EMPC with prediction horizon N= 5 hours: the basement inside temperature of PowerFlexHouse3 related to the optimized the power consumption shown in Figure 21.

Table 2 Electricity costs and energy consumption for 10 days in January 2014

		Electricity Costs in EUR (for 10 days)	Energy Consumption in kWh	Relative Costs in EURcent/kWh
PID low		23.15	684.1	3.38
PID average		25.35	742.4	3.41
EMPC with Prediction Horizon N =	1	23.61	687.4	3.43
	2	23.24	689.1	3.37
	3	22.83	691.6	3.30
	4	22.53	699.5	3.22
	5	**22.49**	**706.7**	**3.18**
	6	22.72	710.5	3.20
	7 ...	23.13 …	713.7 …	3.24 …
	12 …	23.91 …	727.1 …	3.23 …
	24	24.03	729.4	3.29

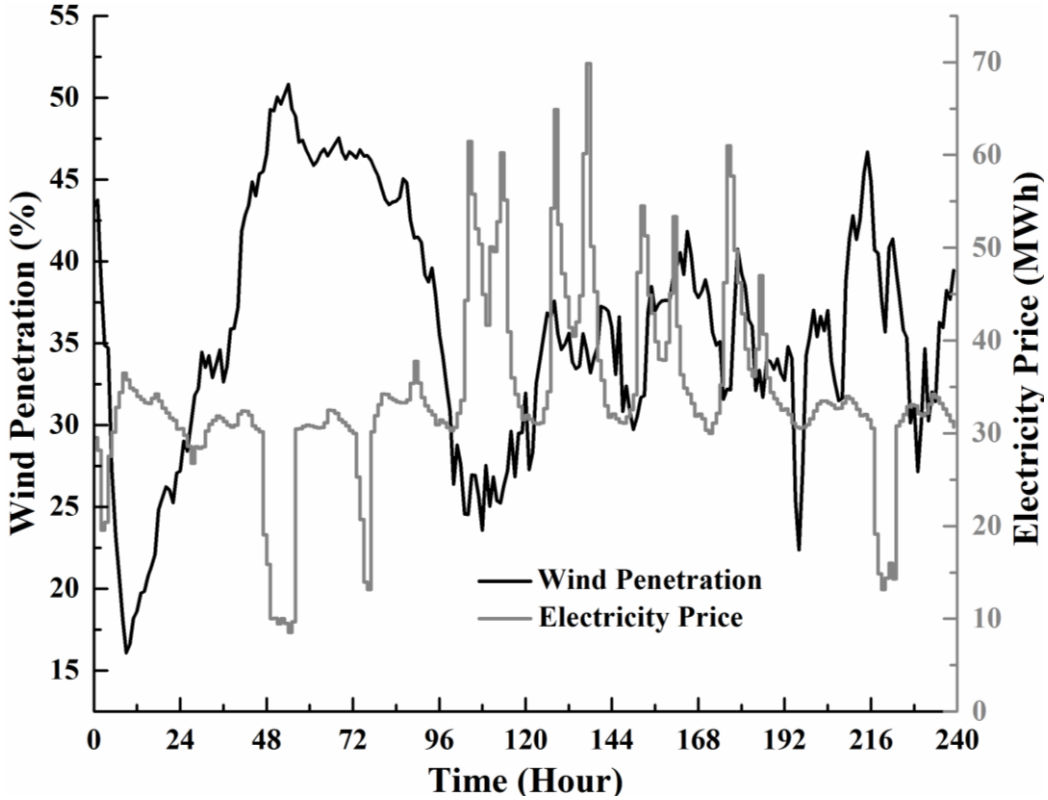


Figure 23. Hourly electricity spot price and wind power penetration during the test period for DK-East

6. Conclusions and future work

In summary, to harness the full potential of the increased share of renewables, energy must be used more efficiently, effectively, and intelligently. Flexible consumption and smart energy systems must be developed with correlative dependence and interplay to meet the challenge of integrated fluctuating RESs. Buildings play a crucial role in this process, especially for buildings with large thermal storage capacity.

The pilot testing study demonstrated that EMPC implementation for active buildings is effective and attractive; but there are still some challenges, such as big data and modelling, hardware and communication, multi-objective optimization and state estimation, which need to be effectively handled in practice.

The future work will focus on adaptive and distributed MPC for buildings integrated into smart energy systems, including the adaptive models and comfort bands for the different seasons and user behaviour. In addition, how to best achieve the coordination between the widely used low-level control loops (switch/PID controller) and the top-level MPC-based energy management systems should also be considered.

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8. Appendix

8.1 Appendix 1- Data needed for MPC controller development

Measurement data delivered

Description	Unit	Resolution	Frequency	Avaliability	Communication protocol(s)	Security requirements	Ownership	Comments
Voltage L1	V	0,1 V	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Voltage L2	V	0,1 V	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Voltage L3	V	0,1 V	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Aperage L1	A	0,01 A	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Aperage L2	A	0,01 A	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Aperage L3	A	0,01 A	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Elec. Power Total Active	W	0,1 W	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Elec. Power Total Reactive	W	0,1 W	1 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Elec. Active Energy Total	kWh	1 W	5 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Elec. Active Energy Total	kWh	1 W	5 min	1 min	Modbus RTU / ZigBee			All apartements, 1 each
Heat Power	W	0,1 W	1 min	1 min	Mbus ???			Depends on meter
Heat Temperature Forward	°C	0,1 °C	1 min	1 min	Mbus ???			Depends on meter
Heat Temperature Return	°C	0,1 °C	1 min	1 min	Mbus ???			Depends on meter
Heat Flow	1 l/s	1 l/s	1 min	1 min	Mbus ???			Depends on meter
Heat Energy total	kWh	1 W	5 min	1 min	Mbus ???			All apartements, 1 each
Hot water Flow	l/s	1 l/s	1 min	1 min	Mbus ???			Depends on meter
Hot water Temperature	°C	0,1 °C	1 min	1 min	Mbus ???			Depends on meter
Hot Water Energy total	kWh	1 W	5 min	1 min	Mbus ???			All apartements, 1 each
Heat. Valve 1	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Heat. Valve 2	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Heat. Valve 3	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Heat. Valve 4	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Heat. Valve 5	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Heat. Valve 6	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Heat. Valve 7	%	0,1 %	1 min	1 min	KNX			All apartements, 1 each
Ventilation 1	??	??	??	??	KNX			All apartements, 1 each
Ventilation 2	??	??	??	??	KNX			All apartements, 1 each
Ventilation 3	??	??	??	??	KNX			All apartements, 1 each
Ventilation 4	??	??	??	??	KNX			All apartements, 1 each
Ventilation 5	??	??	??	??	KNX			All apartements, 1 each
Ventilation 6	??	??	??	??	KNX			All apartements, 1 each
Ventilation 7	??	??	??	??	KNX			All apartements, 1 each
Ventilation 8	??	??	??	??	KNX			All apartements, 1 each
Ventilation 9	??	??	??	??	KNX			All apartements, 1 each
Ventilation 10	??	??	??	??	KNX			All apartements, 1 each
Room temperature Mid. 1	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Mid. 2	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Mid. 3	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Mid. 4	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Mid. 5	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Mid. 6	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature High. 1	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature High. 2	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature High. 3	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Low. 1	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Low. 2	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
Room temperature Low. 3	°C	0,1 °C	1 min	1 min	KNX			All apartements, 1 each
In wall temperature	°C	0,1 °C	1 min	1 min	KNX			Selected apartements, 1 or more
Room Humidity 1	%RH	0,1 %RH	1 min	1 min	KNX			All apartements, 1 each
Room Humidity 2	%RH	0,1 %RH	1 min	1 min	KNX			All apartements, 1 each
Room Humidity 3	%RH	0,1 %RH	1 min	1 min	KNX			All apartements, 1 each
Room Humidity 4	%RH	0,1 %RH	1 min	1 min	KNX			All apartements, 1 each
Room CO2 1	ppm	1 ppm	1 min	1 min	KNX			All apartements, 1 each
Room CO2 2	ppm	1 ppm	1 min	1 min	KNX			All apartements, 1 each
Room Light 1	Lux	1 lux	1 min	1 min	KNX			All apartements, 1 each
Room Light 2	Lux	1 lux	1 min	1 min	KNX			All apartements, 1 each
Room Light 3	Lux	1 lux	1 min	1 min	KNX			All apartements, 1 each
Room Light 4	Lux	1 lux	1 min	1 min	KNX			All apartements, 1 each
Occupancy 1	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Occupancy 2	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Occupancy 3	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Occupancy 4	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Occupancy 5	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Occupancy 6	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Door open 1	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Door open 2	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Window open 1	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Window open 2	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Window open 3	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Window open 4	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Window open 5	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Window open 6	Bool	-	1 min	1 min	KNX			All apartements, 1 each
Blind 1	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Blind 2	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Blind 3	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Blind 4	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Blind 5	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Blind 6	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Dimmer 1	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Dimmer 2	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Dimmer 3	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Dimmer 4	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Dimmer 5	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Dimmer 6	%	1 %	1 min	1 min	KNX			All apartements, 1 each
Weather, wind speed	m/s	0,1 m/s	1 min	1 min				3, 2 buildings + 1 metrologic station
Weather, wind direction	0-360	0,1	1 min	1 min				3, 2 buildings + 1 metrologic station
Weather, sun	Lux	1 lux	1 min	1 min				3, 2 buildings + 1 metrologic station
Weather, temperature	°C	0,1 °C	1 min	1 min				3, 2 buildings + 1 metrologic station
Weather, humidity	%RH	0,1 %RH	1 min	1 min				3, 2 buildings + 1 metrologic station
Weather, pressure	pa	1	1 min	1 min				3, 2 buildings + 1 metrologic station

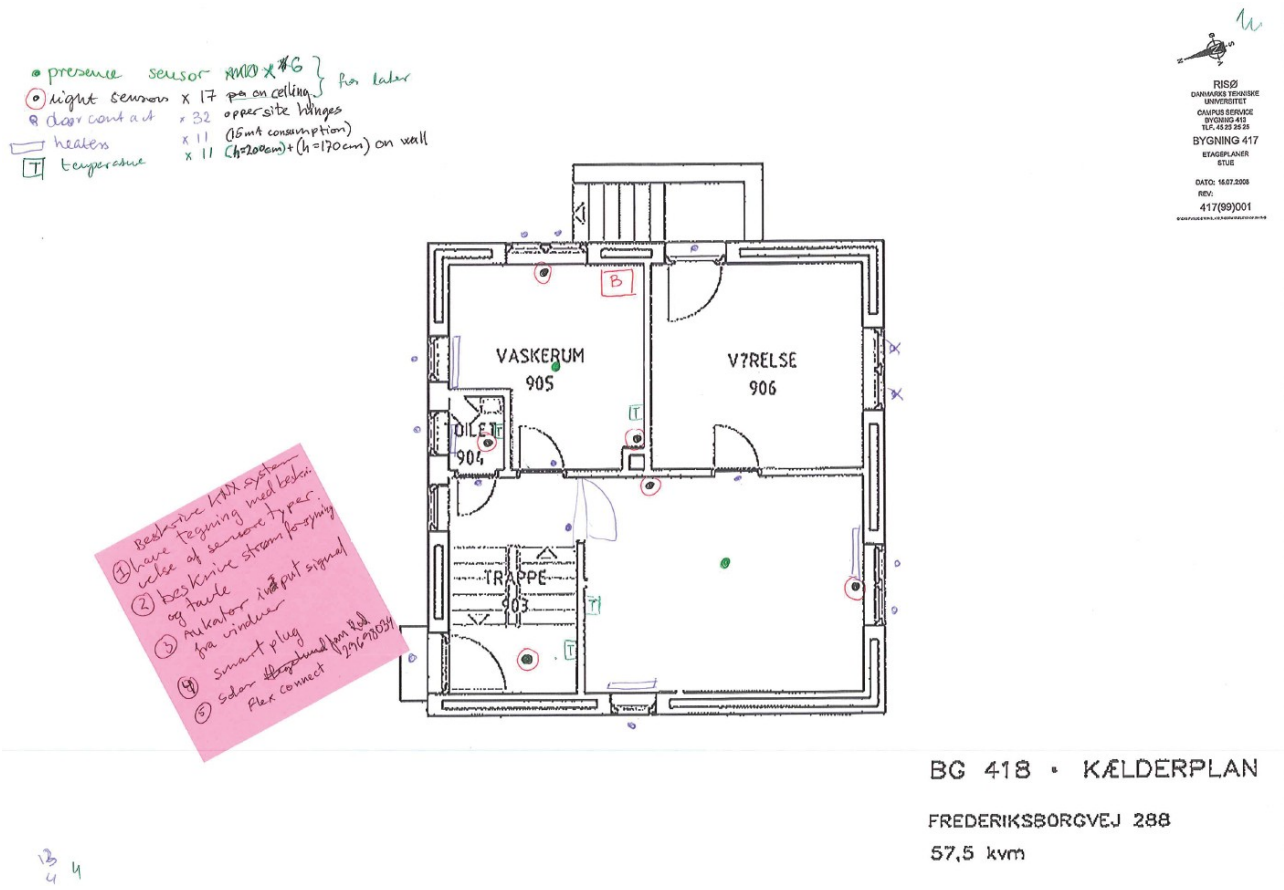
Measurements data needed

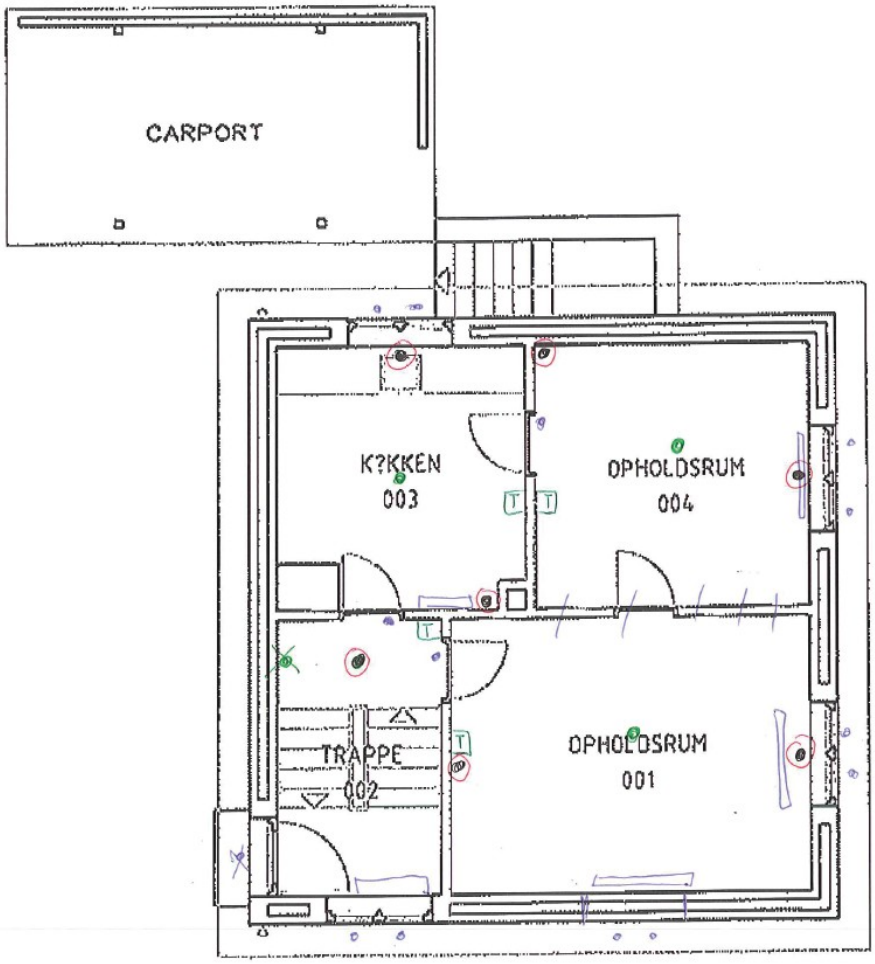
Description	Units	Resolution	Frequency	Avaliability	Use	Comments
Voltage at appartment (3 phase)	V	0,1 V	5 min	24 hours	For experiment x	Example
Measurement data needed by T3.5						
Frequency at appartment	HZ	0.01HZ	1 min	24 hours	for grid-MPC T3.5	If Grid-MPC is needed
PVs power output?(Active/reactive)	W	0.1W	1 min	24 hours	for T3.5 MPC Controller	if CIS installation with PVs
PV AC voltage	V	0.1V	1 min	24 hours	for T3.5 MPC Controller	if CIS installation with PVs
PV AC current	A	0.01A	1 min	24 hours	for T3.5 MPC Controller	if CIS installation with PVs
PV DC voltage	V	0.1V	1min	24 hours	for T3.5 MPC Controller	if CIS installation with PVs
PV DC current	A	0.01A	1 min	24 hours	for T3.5 MPC Controller	if CIS installation with PVs
PV cell temperature	°C	0.1°C	1 min	24 hours	for T3.5 MPC Controller	if CIS installation with PVs
Switches on lighting(dim/blind)	Bool		1 min	24 hours	for T3.5 MPC Controller	If switches are installed
Actuators for Electricity radiator	Bool		1 min	24 hours	for T3.5 MPC Controller	If electricity space heating is used

Forecast data

Forecast data needed for Task 3.5						
Wind speed	m/s	0.01	5 min.- 1 hour	15 minutes?	for T3.5 MPC Controller	Depending on DMI data source
Wind direction	deg.	0.1	5 min.- 1 hour	15 minutes?	for T3.5 MPC Controller	Depending on DMI data source
Solar irradiation	w/m^2	0.1	5 min.- 1 hour	15 minutes?	for T3.5 MPC Controller	Depending on DMI data source
Ambient temperature	°C	0.1	5 min.- 1 hour	15 minutes?	for T3.5 MPC Controller	Depending on DMI data source
Electricity price	DKK(EUR) /MWh	0.01	5 min. -1 hour	1 hour (Nordpool)	for T3.5 MPC Controller	Ecogrid-EU- CEE Pierre Pinson- 5 minutes market can be used??
Heating price					for T3.5 & WP10 Danfoss DH	If there is ? Constant in whole year
Relative humidity	%	5 min.~ 1 hour	5 min. -1 hour	15 minutes?	for T3.5 MPC Controller	optinal
Load	MW	5 min.~ 1 hour	5 min. -1 hour	5 minutes??	for T3.5 MPC Controller	Connection with WP6: PhD student: Guillaume le Ray's work
Solar power output?(Active/reactive)	kW/MW	5 min.~ 1 hour	5 min. -1 hour	1-5 minutes??	for T3.5 MPC Controller	If CIS installation of PVs
			(Note: The purple colored parameters can be optional.)			

8.2 Appendix 2- PowerFlexHouse3 structure and location of the sensors and actuators





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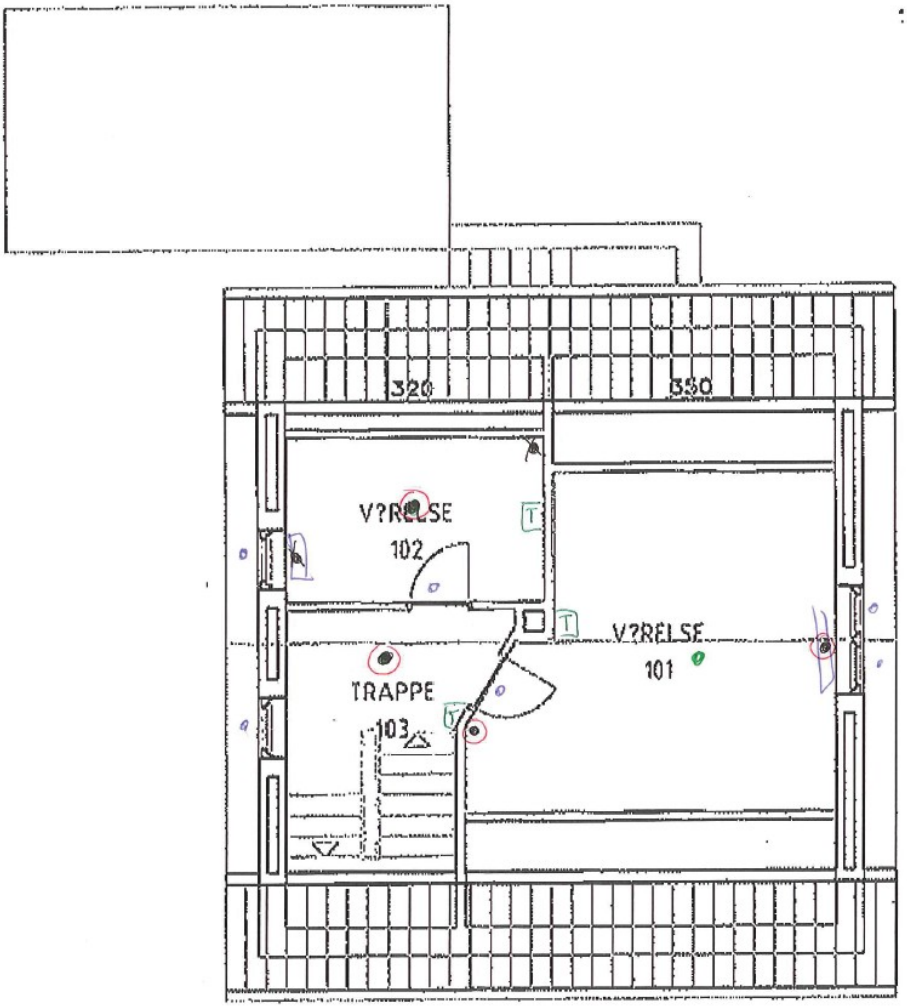
BG 418 • STUEPLAN

57,5 kvm + CARPORT 11,7 kvm



BG 418 - TAGPLAN

44,3 kvm