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Optimal building operation exploiting thermal inertia and battery storage in a dynamic pricing environment

Master Thesis
PSL1226

EEH – Power Systems Laboratory
Swiss Federal Institute of Technology (ETH) Zurich

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Zurich, October 22, 2012
Abstract

In this thesis, in order to investigate the potential of Demand Side Management (DSM) in smart buildings, a residential building equipped with PV panels, batteries, controllable and uncontrollable loads is modeled. To manipulate the behavior of buildings in a grid-friendly manner, dynamic price signals are used as the incentive mechanisms for the building controller. Model Predictive Control (MPC) is used to incorporate the dynamic price signals in the formulation of the optimization problem. Rule Based Control (RBC) is used as benchmark such that the results of MPC can be compared and therefore the economic benefit for end-user consumers participating in DSM schemes can be verified. The simulation results are analyzed to determine the impacts of MPC not only on the overall system but also on each component.

From a power system perspective, understanding the controllability of the loads is necessary to achieve a successful DSM. The developed system is analyzed with two types of dynamic prices, day-ahead price signals and real-time price signals. Through the analysis, the capability of scheduling loads for the system in advance is examined, and the flexibility of real-time adjustment for the system is studied.
Acknowledgements

This work was conducted at the Power System Laboratory (PSL), within the Department of Information Technology and Electrical Engineering (D-ITET) at the Federal Institute of Technology Zurich (ETH Zurich).

I would like to express my greatest thanks to Evangelos Vrettos for his commitment to supervise me in this thesis. I appreciate his guidance, motivation and inspiration. He is always willing to help me and share his valuable advices. I am also very grateful to Stephan Koch, who also supervises me at the later stage of the thesis. It was always helpful to hear his advises from his impressive expertise. My grateful thanks also go to Frauke Oldewurtel for her kindness and her support. I would like to also thank Andreas Ulbig for providing the price data. I also wish to thank Prof. Dr. Andersson for giving the opportunity to write my thesis at PSL.

My sincere thanks also go to my friends ShuTing Wang, YiCheng Ng and Martin Pfeiffer for their support at the final stage of the thesis. I also would like to thank my colleagues Abhishek Rohatgi, Marina Katsampani, Jun Kono, Moonjo Kang and Farid Comaty. It was a pleasure to work with them in the same office.

Finally, I would like to extend my thanks to my family, especially my parents, without whom my entire academic studies and this thesis would not have been possible.
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<th>Description</th>
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<tbody>
<tr>
<td>COP</td>
<td>Coefficient of Performance</td>
</tr>
<tr>
<td>DSM</td>
<td>Demand Side Management</td>
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<tr>
<td>EEX</td>
<td>European Energy Exchange</td>
</tr>
<tr>
<td>EWH</td>
<td>Electric Water Heater</td>
</tr>
<tr>
<td>KiBaM</td>
<td>Kinetic Battery Model</td>
</tr>
<tr>
<td>LBNL</td>
<td>Lawrence Berkeley National Laboratory</td>
</tr>
<tr>
<td>MHC</td>
<td>Moving Horizon Control</td>
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<tr>
<td>MPC</td>
<td>Model Predictive Control</td>
</tr>
<tr>
<td>MPPT</td>
<td>Maximum Power Point Tracking</td>
</tr>
<tr>
<td>NOCT</td>
<td>Normal Operating Cell Temperature</td>
</tr>
<tr>
<td>NPV</td>
<td>Net Present Value</td>
</tr>
<tr>
<td>PV</td>
<td>PhotoVoltaic</td>
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<tr>
<td>RBC</td>
<td>Rule Based Control</td>
</tr>
<tr>
<td>RES</td>
<td>Renewable Energy Source</td>
</tr>
<tr>
<td>RHC</td>
<td>Receding Horizon Control</td>
</tr>
<tr>
<td>SIA</td>
<td>Schweizerische Ingenieur und Architektenverein</td>
</tr>
<tr>
<td>SOC</td>
<td>State of Charge</td>
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<td>TABS</td>
<td>Thermally Activated Building System</td>
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</table>
List of Symbols

$A_{\text{tank}}$  EWH surface area [m$^2$]
$c$  Battery capacity ratio [-]
$C$  Building thermal capacity [J/(kg ·K)]
$G_s$  Standard direct radiation [W/m$^2$]
$k$  Battery rate constant [1/h]
$K_{ij}$  Heat transfer coefficient [W/m$^2$·K]
$P_{\text{Ba}}$  Charging (positive) or discharging (negative) battery power [kW]
$q$  Thermal power [kW]
$Q$  Thermal energy [kWh]
$Q_{\text{Ba},0}$  Total energy in the battery in the beginning of the time step [kWh]
$Q_{\text{Ba1},0}$  Available energy at the beginning of the time step [kWh]
$Q_{\text{Ba2},0}$  Bound energy at the beginning of the time step [kWh]
$Q_{\text{Ba}}$  Total energy in the battery at the end of the time step [kWh]
$Q_{\text{Ba1}}$  Available energy at the end of the time step [kWh]
$Q_{\text{Ba2}}$  Bound energy at the end of the time step [kWh]
$Q_{\text{Ba,max}}$  Maximum battery energy capacity [kWh]
$T_{\text{Air}}$  Ambient temperature [K]
$T_{\text{cell}}$  Cell temperature [K]
$T_{\text{room}}$  Room temperature [C]
$T_{\text{tank}}$  Tank temperature [C]
$T_{\text{NOCT}}$  Normal operating cell temperature [C]
$T_s$  Standard temperature [C]
$W_D$  Water withdraw rate [l/s]
$\rho$  density [kg/l]
$\Delta t$  Duration of a simulation time step [s]
Chapter 1

Introduction

1.1 Motivation

One of the most critical challenges of this century is the increasing consumption of fossil energy and the associated impact on climate change. The utilization of renewable energy sources (RES) can be a possible solution to this major challenge. In many countries a lot of efforts have been dedicated to low-carbon electricity generation by increasing share of electricity generated from RES such as wind and solar. Especially after Fukushima Daiichi nuclear disaster, there is a tendency to consider a more ambitious plan relying completely on RES around the world. A concluded has stated that the potential of RES is sufficient to meet the world’s electricity demand [1].

However, a high share of RES causes great challenges to power systems. Currently, power systems are highly dependent on dispatchable power plants. Since most of the RES are intermittent in nature, their controllability is limited and at times they may fail to cover the demand. Therefore, operating power systems in order to achieve a continuous balance between energy supply and demand becomes a dynamic optimization problem that is oriented toward demand side management (DSM) or energy storage. Since residential and commercial buildings are responsible for more than 40% of all the energy consumption across Europe and half of this energy goes to space heating and domestic hot water, which are controllable loads [2], building automation presents significant potential for energy balancing in DSM. In this context, price signals are used as the control mechanisms to manipulate the behavior of building system, because an economic inventive for consumers can shift their electricity demand to low-price time intervals. Therefore, from a power system perspective, the price-control approaches can be used for peak shaving and load shifting applications.
1.2 Objectives

In this work, we focus on local perspectives of DSM and we investigate operating policies for a typical residential building is investigated. To explore the controllability of buildings and their reaction to dynamic electricity prices in smart buildings, a comprehensive building system equipped with controllable loads, uncontrollable loads, energy storage and local generation is developed. Based on the developed system, the objectives of this thesis are outlined in the following:

- In order to incorporate the incentive mechanisms for consumers, it is crucial to verify the promising public acceptance of DSM. Therefore, an objective to derive the optimal operating policy for smart buildings participating in DSM is imposed in this study such that the economic benefit is maximized for the consumers. In addition, based on different control strategies, the results and the behavior of the building system are analyzed and the benefits of end-consumers are inspected by comparing the electricity costs.

- Another objective of this study is to quantify the flexibility of building system brought by price signals. From an electricity network perspective, it is important to know the controllability of loads in smart buildings such that an appropriate price schedule can be decided in advance. Hence, the effect of variable prices on the electrical consumption of individual buildings is analyzed.

- Besides the capability to shape an appropriate demand profile via pre-defined electricity prices, it is also important for power system to assess the flexibility of demand resources in order to make real-time adjustments for unexpected changes. Thereby, analyzing the influence of real-time price signals on energy consumption is an essential step to quantify the flexibility of system via real-time price control.

1.3 Structure

In Chapter 2, two building control concepts are presented. The first one is the current control practice, while the second one is an advanced predictive control strategy that derives the upper performance bound for the building.

Chapter 3 describes the building component modeling as well as the data and assumptions that are chosen to represent a realistic residential building. Subsequently, the simulation software, which is capable of solving the dynamic problem, is presented and the overall picture of the system setup is illustrated.
In Chapter 4, the developed state space dynamic model for the whole building is presented. In addition, the implementation of the control strategies, including objective function formulation and problem constraints, is explained.

Chapter 5 demonstrates the simulation results, including annual profiles and weekly profiles of the system, together with an explicit discussion for each component such that the system behavior can be understood. Furthermore, a comparison between the results of two control strategies is presented and discussed.

Chapter 6 presents the results of a sensitivity analysis over three important parameters, namely prediction horizon of the optimization problem, building internal heat gains and shape of day-ahead price signal. The effect of these parameters on system performance is concluded based on the sensitivity analysis results.

In Chapter 7, the analysis of real-time price control is presented. Similar to Chapter 6, sensitivity analysis is made based on different sensitivity parameters such that the real-time response of system can be investigated. The results are provided with the discussion of the system flexibility and controllability.

Chapter 8 concludes this thesis and points the possible future work.
Chapter 2

Control algorithms

This chapter introduces two control strategies that are compared in the study: Rule-Based Control (RBC) and Model Predictive Control (MPC). RBC is a common control practice nowadays for building automation and is therefore used as a benchmark. To examine the potential improvement of building behavior, MPC is the control strategy under investigation. The implementation of MPC modeling with cost function and constraints is detailed in Section 4.4. Both control concepts are presented below.

2.1 Rule-based control

RBC is the current control method in building automation systems. Algorithms with rules of the kind “if condition then action” is the standard procedure used in RBC. The conditions and actions are usually defined by numerical values (e.g., temperature thresholds). A brief RBC for heater is given as an example in Algorithm 1. The choices of rules and the associated parameters have significant influence on the performance of RBC. RBC could be very sophisticated for a more complex building to ensure an energy efficient system. Many studies show that there is significant potential for advanced control regarding energy efficiency [3]. Nevertheless, the current study places emphasis on shifting energy. Thus, a basic RBC in terms of rules is used as benchmark in this study and the associated algorithm is only based on system states.
Algorithm 1: Example: rule-based heater control

**Data:** room temperature

**if** temperature < bottom threshold **then**
| turn on heater;

**else if** temperature > top threshold **then**
| turn off heater;

**else**
| no action;

**end**

2.2 Model predictive control

MPC, also referred to Receding Horizon Control (RHC) or Moving Horizon Control (MHC), is an advanced method of process control developed in 1980s [4] and was firstly applied to slow process industries such as chemical plants and oil refineries. It has been investigated and extended over the years in diverse fields for faster dynamic systems.

MPC is an optimization algorithm based on a sequence of future control inputs that minimizes a predefined cost function. At time $t$ or at step $k$ (after discretization), the current plant is optimized over a finite time horizon by minimizing the cost function subject to some given constraints. In most cases, some constraints will be imposed on state, input and output signals, which are restricted by physical properties, safety issues and economical reasons. After the solution of the optimization problem, only the first step of the optimal control sequence is applied to the plant. The optimization is then shifted to the next time step while the prediction horizon keeps receding in the future. Generally, the results of MPC are not optimal solution to the control problems, but it has given very good approximation to the real solution [5].

![Schematic representation of discrete MPC](image-url)
Chapter 3

Simulation Environment

This chapter describes all components in a Matlab-based system model for simulating a smart building. First, we develop first principles models for system components including single rooms in a simplified building, a heat pump, a lead-acid battery, a thermal tank storage, and a photovoltaic system. Second, the assumptions and external parameters, including a real-time end-user electricity price profile, weather data, domestic water usage, and electricity profile, will be presented. Finally, the overall relation and interaction among various system components is illustrated.

3.1 System components

3.1.1 Building model

To simulate the building energy consumption, a method of stacking single rooms and building zones on top of each other is commonly used [6]. This method is introduced in the system to examine the thermal behavior of a single room. A simplified model of the room is adopted from the work within the OptiConrol project [7], [8]. The original model was validated and compared with TRNSYS\(^1\) and the thermal dynamics of the model was found to match the relevant response of a building adequately [9], [10].

Furthermore, an additional water supply system is integrated into the original room model as TABS\(^2\) in order to capture the actual dynamics between the water heating system and the room temperature [11], [12]. Instead of a direct heating power to the floor slab, the heating power is supplied to the water supply system. The water supply system is based on the model from [11]. In addition to the floor heating system, several adoptions have

\(^{1}\text{TRNSYS = Transient system simulation tool, a commercial software widely used to simulate the behavior of buildings and HVAC systems.}\)

\(^{2}\text{TABS = Thermally activated building system, i.e. the building is implemented with heating and cooling system by embedded tube-systems inside the floor, wall, or ceiling.}\)
been made for the goal of this study, which is to investigate the controllability of buildings. The building model is simplified from a bilinear system to a linear model by eliminating blind positioning, cooling tower and natural ventilation. To focus on the potential of shifting energy, heating/cooling mechanical ventilation and electric lighting are also excluded from the original model. Further details on the experimental setup can be found in Section 4.1.

The room can be seen as a circuit of first-order transient systems, where the nodes are the states \( X \), representing the temperatures in the room, walls, floor, water or ceiling. The concept of the heat transfer for each node is illustrated in Figure 3.1 and the heat transfer equation is defined as:

\[
\frac{dQ}{dt} = K_{ij} \cdot (X_i - X_j) + K_{jk} \cdot (X_k - X_j)
\]

\[
\Rightarrow \quad \frac{dQ}{dX_j} = \frac{1}{C_j} \cdot \frac{dX_j}{dt} = K_{ij} \cdot (X_i - X_j) + K_{jk} \cdot (X_k - X_j) \quad (3.1)
\]

where \( t \) denotes the time, \( X_i, X_j \) and \( X_k \) are the temperatures in states \( i, j \) and \( k \) respectively, \( Q \) denotes the thermal energy, \( C_j \) is the thermal capacitance of state \( j \), and \( K_{ij} \) is the heat transfer coefficient between states \( i \) and \( j \). The heat transfer coefficient \( K_{ij} \) depends on the cross sectional area.
CHAPTER 3. SIMULATION ENVIRONMENT

of heat transmission and on the properties of materials \( i \) and \( j \). Equation 3.1 is applied for each node, i.e. its state of the thermal model. The 14 first order differential equations for 14 states (nodes) are used to obtain the state space representation of the system as follow:

\[
\dot{x} = A \cdot x + B_u u + B_v v
\]  

(3.2)

where \( A \) is the dynamic matrix that consists of zeros, \( K_{ij}, K_{jk} \) and \( C_j \). \( x \in \mathbb{R}^n \) is the state, \( u \in \mathbb{R}^m \) is the input, \( v \in \mathbb{R}^p \) is the disturbance at time step \( k \), and matrices \( A, B_u, B_v \) are of appropriate sizes.

3.1.2 Heat pump model

Due to the large number of heat pump users and its increasing trend in Switzerland [13], the influence of heat pump implementation is to be investigated. Hence, a heat pump is assumed in the system to provide heating power for the heating water system in 3.1.1. The selected type of the heat pump model is air-to-water, which extracts heat from ambient air to refrigerant and then the heat is released to water from refrigerant. The principle of the heat flow is illustrated in Figure 3.2). Generally, a heat pump consists of a compressor, a condenser, an evaporator and an expansion valve. However, the system is only interested in the amount of thermal energy that can be provided with an unit energy of electricity at certain ambient temperature. Therefore, the heat pump model is simply an equation to express the Coefficient of Performance (COP), which is given as:

\[
COP = \frac{P_{th}}{P_{el}}
\]  

(3.3)

Through the COP, the electricity required for the certain amount of thermal energy, which supplies to the water system, is calculated. Owing to the characteristic of heat pumps, the COP is dependent on the supply water temperature and the ambient temperature. However, the system becomes nonlinear when the heat pump power, which is a system input, is to be optimized. Since the providing thermal power depends on COP, which depends on the supply water temperature, which is a system state, and therefore on the thermal power itself, the optimization problem is nonconvex and thus convergence to the global solution is not guaranteed. This non-convex optimal control problem has drawn much attention for a long time (see [14],[15],[12],[16]). According to [17], linearizing the heat pump model by using a predefined COP profile while using a soft constraint to penalize the square of heat pump electric power consumption, results in a solution that is only 0.1% worse than the optimal solution obtained by the nonlinear problem. The same simplification with a predefined COP equation from [17] is used for this heat pump model.
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Figure 3.2: Schematic representation of heat pump’s principle [13].

With such a simplification, a fixed value for supply water temperature is required to calculate the predefined COP profile. The fixed value is a steady state temperature of the supply water. To obtain the steady state temperature, Equation 3.2 is used by setting the derivatives to zero as follow:

\[ 0 = A \cdot x + B_u u + B_v v \]  

(3.4)

However, there are 14 first order differential equations in Equation 3.4 with the 14 states, the input and the disturbance, which are 16 unknowns in total. Therefore, the steady state of the system is calculated beforehand by assuming room temperature, \( T_{room} \), remains unchanged for the prediction horizon and with a given mean disturbance, \( v_{avg} \):

\[ 0 = A \cdot x_{SS} + B_u u_{SS} + B_v v_{avg} \]

\[ x_{SS} = [T_{room}, x_{2,SS}, \cdots, x_{14,SS}]^T \]

where \( x_{SS} \) is the steady state, \( u_{SS} \) is the steady state input, and \( x_{14,SS} \) is the steady state supply water temperature \( T_{w,s,SS} \), which is estimated for each prediction horizon in order to calculate the predefined COP profile for MPC controller. The COP at the given steady state supply water temperature \( T_{w,s,SS} \) is defined as [17]:

\[
COP = COP_0 + c_1 \cdot T_{amb} + c_2 \cdot T_{w,s,SS}
\]

(3.5)

where \( COP_0 \) denotes the constant term in linear fit for COP, \( c_1 \) is the coefficient for COP source temperature dependency, and \( c_2 \) is the coefficient for COP supply temperature dependency (See Appendix A.1 for the values of \( COP_0, c_1 \), and \( c_2 \)).
3.1.3 Electric water heater model

An Electric Water Heater (EWH) is used for simulating domestic hot water usage. The EWH is modeled as a thermally stratified water tank with ten water layers and the model is adopted from [18]. The heat transfer equation of each layer in EWH is defined as [18]:

\[
\frac{\partial T}{\partial t} = -v \cdot \frac{\partial T}{\partial y} + \alpha \epsilon_{\text{eff}} \cdot \frac{\partial^2 T}{\partial y^2} - h \cdot (T - T_{\text{amb}}) + \dot{Q}(t) \tag{3.6}
\]

where \( t \) denotes time, \( \alpha, h \) and \( v \) are the thermal diffusivity of water, the heat loss coefficient of EWH and the water withdraw rate, respectively, \( \epsilon_{\text{eff}} \) accounts for turbulent mixing at the tank inlet (\( \epsilon_{\text{eff}} = 1 \) for laminar flow and \( \epsilon_{\text{eff}} >> 1 \) for turbulent flow) and \( \dot{Q} \) is the heating element power, which is placed at the third layer of EWH. The second-order, three level finite difference Crank-Nicolson scheme from [19] is used to numerically solve Equation 3.6 such that numerical diffusion and inaccuracy that are inherent in first-order upwind differencing schemes are avoided.

However, Equation 3.6 does not account for natural convection. Natural convection is the effects of buoyancy and viscous friction. Due to the dependence of buoyancy on the temperature of each layer, the problem becomes nonlinear if natural convection is taken into account as the temperatures of EWH are the system states. Owing to the nonlinearity, the optimization problem is nonconvex. Hence, the buoyancy effect, denoted as \( B \), is divided into two parts in this study. The first part is a division term that distributes the electric power over the layers of EWH, while the second part of the buoyancy effect is a correction procedure executed after MPC controller generates the optimal input each time. The flow chart in Figure 3.3 shows the principle of the control algorithm and how the buoyancy effect is implemented in EWH. It has been verified in [18] that the simulation of EWH model matches the experimental data from the Lawrence Berkeley National Laboratory (LBNL).

![Figure 3.3: Schematic representation of the control algorithm for EWH](image-url)
3.1.4 Lead-acid battery model

Considering the real-time price scenario as well as the characteristic of intermittent PV power, a battery would be helpful to balance and optimize the system operation. Thus, a lead-acid battery model incorporated into the system.

For modeling lead-acid batteries, it is common to use the Kinetic Battery Model (KiBaM) [20], [21], [22]. The principle of KiBaM can be described as a two-well capacity (see Figure 3.4). The first well is the available capacity and the second one well is the bound capacity. KiBaM comprises five sub-models which are capacity, voltage, charge transfer, battery losses and battery life sub-models. Because this study places emphasis on the dynamics between battery power and state of charge, the battery voltage and the battery life model are not included in the simplified model. Due to this simplification, the capacity, charge transfer and losses sub-models are adopted without relying on the voltage model. The total battery capacity is given by: [22]:

\[ Q_{Ba} = Q_{Ba1} + Q_{Ba2} \]  \hspace{1cm} (3.7)

where \( Q_{Ba1} \) and \( Q_{Ba2} \) are the available and the bound charges at the end
of a time interval $\Delta t$, which are given by [22]:

$$Q_{Ba1} = Q_{Ba1,0} \cdot e^{-k \cdot \Delta t} + \frac{(Q_{Ba,0} \cdot k \cdot c - P_{Ba}) \cdot (1 - e^{-k \cdot \Delta t})}{k} - \frac{P_{Ba} \cdot c \cdot k \cdot \Delta t - 1 + e^{-k \cdot \Delta t}}{k}$$ (3.8)

$$Q_{Ba2} = Q_{Ba2,0} \cdot e^{-k \cdot \Delta t} + Q_{Ba,0} \cdot (1 - b) \cdot (1 - e^{-k \cdot \Delta t}) - \frac{P_{Ba} \cdot (1 - b) \cdot (k \cdot \Delta t - 1 + e^{-k \cdot \Delta t})}{k}$$ (3.9)

where $c$, $k$ and $P_{Ba}$ are the capacity ratio of the battery, the rate constant of the battery and the battery power, respectively. $Q_{Ba,0}$, $Q_{Ba1,0}$ and $Q_{Ba2,0}$ correspond to the total, the available and the bound charges at the beginning of a time step.

The charge transfer model calculates the maximum charge and discharge power at each charging or discharging time interval $\Delta t$, which are given by [22]:

$$P_{Ch_{Ba},\text{max}} = -k \cdot c \cdot Q_{Ba,\text{max}} + k \cdot Q_{Ba1,0} \cdot e^{-k \cdot \Delta t} + Q_{Ba,0} \cdot k \cdot c \cdot (1 - e^{-k \cdot \Delta t}) \frac{1 - e^{-k \cdot \Delta t} + c \cdot (k \cdot \Delta t - 1 + e^{-k \cdot \Delta t})}{1 - e^{-k \cdot \Delta t} + c \cdot (k \cdot \Delta t - 1 + e^{-k \cdot \Delta t})}$$ (3.10)

$$P_{Dis_{Ba},\text{max}} = \frac{k \cdot Q_{Ba1,0} \cdot e^{-k \cdot \Delta t} + Q_{Ba,0} \cdot k \cdot c \cdot (1 - e^{-k \cdot \Delta t})}{1 - e^{-k \cdot \Delta t} + b \cdot (k \cdot \Delta t - 1 + e^{-k \cdot \Delta t})}$$ (3.11)

Battery losses are essential during optimization process. According to KiBaM, the losses are based on voltage equations which are omitted in the simplified model. Thus, an aggregate efficiency coefficient is used for the battery losses. Here different coefficients are used for charge and discharges efficiencies. The round-trip efficiency is given by:

$$\eta_{rt}^{Ba} = \eta_{ch}^{Ba} \times \eta_{dis}^{Ba}$$ (3.12)

where $\eta_{ch}^{Ba}$ and $\eta_{dis}^{Ba}$ are the battery efficiencies for charge and discharge, respectively. Even though battery life sub-model is not included in the model, capacity of the battery is set to be above 40% due to battery life time issues. Detailed values of battery parameters are provided in Appendix A.4.

### 3.1.5 Photovoltaic model

A grid-connected photovoltaic (PV) module is modeled in order to investigate the performance of adopting local generation into the system. The PV model is parametrized based on the commercial product BP 3160 photovoltaic module. The associated parameters have been verified with experimental data in [23]. The model is equipped with the maximum power point
tracking and the power is formulated as [24]:

\[ P_{\text{mppt}} = I_{\text{mppt}} \cdot V_{\text{mppt}} \cdot N_{\text{PV}} \]  

(3.13)

where \( N_{\text{PV}} \) is the number of panels. \( I_{\text{mppt}} \) and \( V_{\text{mppt}} \) are maximum power point tracking current and the maximum power point tracking voltage of the PV panel and are computed as:

\[ I_{\text{mppt}} = I_{\text{mps}} \cdot \frac{G}{G_s} \cdot (1 + \Delta I_{\text{mps}} \cdot (T_{\text{cell}} - T_s)) \]  

(3.14)

\[ V_{\text{mppt}} = V_{\text{mps}} \cdot (1 + \Delta V_{\text{mps}}(T_{\text{cell}} - T_s)) + K_1 \cdot V_{\text{th}} \cdot \ln\left(\frac{G}{G_s}\right) \]  

\[ + K_2 \cdot (V_{\text{th}} \cdot \ln\left(\frac{G}{G_s}\right))^2 \]  

(3.15)

\[ V_{\text{th}} = \frac{A \cdot k \cdot T_{\text{cell}}}{q} \]  

(3.16)

where \( G, I_{\text{mps}} \) and \( V_{\text{mps}} \) are the solar irradiation, the peak power current and voltage, respectively. \( \Delta V_{\text{mps}}, \) and \( \Delta I_{\text{mps}} \) are the temperature effects on peak power voltage and current, respectively. \( K_1 \) and \( K_2 \) are constant coefficients. \( G_s, T_s, A, k \) and \( q \) are the standard temperature, the standard irradiation, the diode ideality factor, the Boltzman constant and the charge of an electron, respectively. An approximate expression for calculating the cell temperature \( T_{\text{cell}} \) is given by [25]:

\[ T_{\text{cell}} = T_{\text{Air}} + G \cdot (T_{\text{NOCT}} - 20) \]  

(3.17)

where \( T_{\text{NOCT}} \) represents the normal operating cell temperature of the panel and \( T_{\text{Air}} \) denotes the ambient temperature. The detailed parameters in equation 3.14-3.17 are provided in Appendix A.3.

3.2 Assumptions and external parameters

Buildings are influenced by a variety of disturbances, including weather, internal gains due to occupants and equipment, as well as human behavior. Since the current study focuses on the deterministic case to determine the upper bound of potential improvement with the proposed method, perfect knowledge is assumed for future forecasts. In addition, a dynamic price signal and a day-night tariff are incorporated into the system in order to examine the effect of changes in electricity prices.

3.2.1 Weather data

In the system, the weather has direct influence on the COP of heat pump, the temperatures in building and the generated PV power. The weather
data is hourly weather measurements of the year 2007 which is obtained from MeteoSwiss. The measured data is also used as the prediction data, which means that a perfect weather prediction is available in MPC. The data comprises the outside air temperature and the incoming solar radiation, which are shown in Figure 3.5 and Figure 3.6. Fluntern, Zurich was chosen as the measurement location for this study.

![Figure 3.5: Annual profile of ambient temperature.](image1)

![Figure 3.6: Annual profile of solar radiation.](image2)

3.2.2 Internal gains

The heat gains that are released from occupants (people) or equipment (e.g., refrigerators, televisions) are known as internal gains. The assumed values of internal gains are based on the Swiss standard SIA, and the weekly profiles are shown in Figure 3.7. The assumption that the profile is the same for every week over the simulation year is made. During weekdays from 7am to 6pm occupants were assumed to be outside of the room; hence, the internal gains due to occupants were set to zero, and the internal gains due to equipment are set to smaller values.
CHAPTER 3. SIMULATION ENVIRONMENT

3.2.3 Domestic water consumption

A predefined profile of daily water draw schedule is used to simulate the hot water demand of EWH. The probability profile was developed by [26], which is shown in Figure 3.8. According to [27], an average hot water usage for a 5-people household, including dishwasher, clothes washer and shower, is 468.4 liters per day. Since a 3-people family is assumed in this study, a daily hot water demand of 280 liters per day is used as the water withdraw for EWH.

3.2.4 Electricity profile

To investigate a more comprehensive building system, the electricity consumption of non-controllable loads (e.g., lighting, televisions, ovens) is included in the study by using real measurements from [28]. The measurements include electricity profiles for different loads (e.g., microwaves, refrigerators, stoves), for the time period of 18 April 2011 to 24 May 2011, with a time resolution of one second. However, some data are missing in the measurement period which makes the data discontinuous. Thereby, week-long measurements, from 10am 21 April to 9am 28 April, is adopted and used as the weekly electricity profile in the simulation, which is assumed to be the same for all weeks through the year. While this assumption is reasonable for most non-controllable loads such as television and oven, this is not the case for lighting, which is of course season dependent. Figure 3.9 shows the adopted profile from Monday to Sunday with an hourly time step.
3.2.5 End-user price signals

A building with PV and storage can in principle sell energy back to the grid. In this section, we define the investigated scenarios for buying and selling electricity prices. For buying price, two different cases are considered:

1. A time-varying, hourly-based end-consumer tariff.
2. A high/low tariff, also labeled peak/offpeak and day/night tariff.

The time-varying tariff is based on the Swiss EPEX spot market prices of the year 2009 [29]. Regarding to day/night tariff, the existing tariff from Elektrizitätswerk der Stadt Zürich (ewz) is used here. Week-days tariff (Mon.-Sat. 6h-22h CHF0.185/kWh) are about double of the prices as during night time and on Sundays as well as on public holidays (Mon.-Sat. 22h-6h, Sun. 0h-24h CHF0.095/kWh) [29].

Four scenarios for selling energy back to the grid and the respective price have been considered:

1. No feed-in tariff.
2. Selling price is equal to the buying price, both for battery and PV.
3. Selling price is constant but lower to buying price, both for battery and PV.
4. Selling price is equal to the buying price for battery. The energy produced by PV is sold at a constant feed-in tariff of 40Rp/kWh\(^1\).

All the scenarios above have been investigated in this study. However, the results of different selling scenarios are found as the system components behave independently as a decoupled system during optimization process. For the constant high feed-in tariff, the result of PV system is found to

\(^1\)A high price of incentive is assumed if Switzerland plans to switch from nuclear to renewable electricity.
always sell the energy back to grid. For the same dynamic feed-in tariff as buying, the optimization result would be same as a decoupled system. A theory can easily explained with a small example as shown in Figure 3.10. Two different strategies, storing solar energy and not storing solar energy, result in a same amount of profit. Thus, only the scenario without feed-in tariff is considered through the simulation.

![Comparison between two strategies at the same buying and selling price. Left: battery stores PV energy and sells at a higher price. Right: battery stores grid energy and sells at a higher price.](image)

**Figure 3.10:** Comparison between two strategies at the same buying and selling price. Left: battery stores PV energy and sells at a higher price. Right: battery stores grid energy and sells at a higher price.

### 3.3 Overview of system setup

A network diagram in Figure 3.11 illustrates an overview of the connected system. All the components explained above with interactions between all components are shown in the diagram. These components can be categorized into five groups: generation, electric storage, thermal storage, usage and disturbance, as shown in Table 3.1. Four scenarios with different combinations of building, PV system and battery are simulated through this thesis work and each scenario is examined with both price scenarios: the time-varying tariff and high/low tariff. Table 3.2 lists an overview of the system combinations.

<table>
<thead>
<tr>
<th>Category</th>
<th>Components</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generation</td>
<td>Grid, PV system</td>
</tr>
<tr>
<td>Electric storage</td>
<td>Battery</td>
</tr>
<tr>
<td>Thermal storage</td>
<td>Building, Electric water heater</td>
</tr>
<tr>
<td>Usage</td>
<td>Water withdraw, Uncontrollable load</td>
</tr>
<tr>
<td>Disturbance</td>
<td>Internal gains, Weather</td>
</tr>
</tbody>
</table>
Table 3.2: Overview of system combinations of building, PV, battery and tariff type.

<table>
<thead>
<tr>
<th>Case</th>
<th>Building</th>
<th>PV system</th>
<th>Battery</th>
<th>Tariff type</th>
</tr>
</thead>
<tbody>
<tr>
<td>I-A</td>
<td>✓</td>
<td></td>
<td></td>
<td>time-varying</td>
</tr>
<tr>
<td>II-A</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>time-varying</td>
</tr>
<tr>
<td>III-A</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>time-varying</td>
</tr>
<tr>
<td>IV-A</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>time-varying</td>
</tr>
<tr>
<td>I-B</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>high/low</td>
</tr>
<tr>
<td>II-B</td>
<td>✓</td>
<td></td>
<td>✓</td>
<td>high/low</td>
</tr>
<tr>
<td>III-B</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td>high/low</td>
</tr>
<tr>
<td>IV-B</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>high/low</td>
</tr>
</tbody>
</table>
CHAPTER 3. SIMULATION ENVIRONMENT

Figure 3.11: Schematic representation of the connected system with each components and actuators.
Chapter 4

System setup and component modeling

4.1 System model

In order to estimate and control the dynamics of the building system, a model of a connected system in the building is needed. The system model comprises the components described in Section 3.1 and the parameters explained in Section 3.2. The system dynamics is described as:

\[ x_{k+1} = Ax_k + B_u u_k + B_v v_k \] (4.1)

where \( x_k \in \mathbb{R}^n \) is the system state representing the temperatures in the electric water heater, states of battery charge and the temperatures in the walls, room, floor and ceiling. \( u_k \in \mathbb{R}^m \) is the system input at time step \( k \). \( v_k \in \mathbb{R}^p \) is system the disturbance at time step \( k \) including weather and internal gains. Details of the state, input and disturbance of the system dynamics can be found in Appendix B. The matrices \( A, B_u, B_v \) are of appropriate sizes. The states of room temperature \( T_{\text{room}} \), tank temperature \( T_{\text{tank}} \) and battery capacity \( Q_{\text{Ba}} \) are constrained to lie within upper and lower bounds as follow:

\[
\begin{align*}
21 & \leq T_{\text{room},k} \leq 23 \text{ [°C]} \\
55 & \leq T_{\text{tank},k} \leq 70 \text{ [°C]} \\
2 & \leq Q_{\text{Ba},k} \leq 5 \text{ [kWh]} \\
T_{\text{room},k} & = x_{k,15} \\
T_{\text{tank},k} & = \frac{x_{k,2} + \cdots + x_{k,11}}{10} \\
Q_{\text{Ba},k} & = x_{k,13} + x_{k,14}
\end{align*}
\] (4.2)
CHAPTER 4. SYSTEM SETUP AND COMPONENT MODELING

The inequality constraints on the inputs are given as follows:

\[ 0 \leq u_{k,i}, i \in [1, \cdots, 19] \]
\[ 0 \leq u_{k,1} + u_{k,2} + u_{k,3} \leq P_{\text{EWH}}, P_{\text{EWH}} = 4.1 \]
\[ 0 \leq u_{k,8} + u_{k,10} + u_{k,11} \leq P_{\text{HP}}, P_{\text{HP}} \in [0, 2] \]
\[ 0 \leq u_{k,3} + u_{k,4} + u_{k,7} + u_{k,8} + u_{k,16} = P_{\text{Dis}}^{k} \leq P_{\text{Dis}, \text{max}, k} \]
\[ 0 \leq u_{k,5} + u_{k,6} = P_{\text{Ch}, \text{max}, k}^{k} \]
\[ 0 \leq u_{k,12} \leq P_{\text{SLB}, \text{SLB}} \in [0, 4] \]
\[ 0 \leq u_{k,13} \leq P_{\text{SLB}, \text{SLB}} \in [0, 4] \]
\[ 0 \leq u_{k,14} \leq P_{\text{rad}}, P_{\text{rad}} \in [0, 2] \]
\[ 0 \leq u_{k,2} + u_{k,6} + u_{k,9} + u_{k,10} + u_{k,17} \leq P_{\text{PV}, k} \]

with equality constraints defined as:

\[ u_{k,15} = \text{COP} \times (u_{k,8} + u_{k,10} + u_{k,11}) \]
\[ u_{k,18} = u_{k,12} + u_{k,13} + u_{k,14} - u_{k,16} - u_{k,17} \]
\[ u_{k,19} = P_{\text{PV}, k} - u_{k,2} - u_{k,6} - u_{k,9} - u_{k,10} - u_{k,17} \]
\[ 0 = \min(P_{\text{Ch}, \text{max}, k}^{k}, P_{\text{Dis}, \text{max}, k}^{k}) \]
\[ P_{\text{UC}, k} = u_{k,7} + u_{k,9} + u_{k,20} \]

where \( P_{\text{EWH}}, P_{\text{HP}}, P_{\text{SLB}}, P_{\text{SLB}} \) and \( P_{\text{rad}} \) are the maximum EWH power, the maximum heat pump power, the maximum slab cooling power, the maximum slab heating power and the maximum radiator power, respectively. \( P_{\text{Ch}, \text{max}, k}^{k}, P_{\text{Dis}, \text{max}, k}^{k}, P_{\text{UC}, k} \) and \( P_{\text{PV}, k} \) are the maximum battery charge power, the maximum battery discharge power, total uncontrollable load and generated PV power at time step \( k \), respectively.

4.2 Radiator

Due to the goal of this thesis: investigate the flexibility of the building system via price signals, the current study focuses on exploiting the capability of shifting energy. Therefore, it is important to realize the potential of shifting energy on each actuator and hence analysis comparing the heating controllability of radiator (direct to room node) and heat pump (through floor water system) is made. The results of the analysis indicate that radiator is incapable to respond to price signal compared to heat pump. Consequently, the radiator is eliminated in the system while keeping only the heat pump for the heating actuator. An example of the analysis is provided in Appendix C.
CHAPTER 4. SYSTEM SETUP AND COMPONENT MODELING

4.3 Seasonal setting

Figure 4.1 shows the annual evolution of room temperature without heating or cooling power and a horizontal line at 24°C. In order to have a more realistic control algorithm, cooling power is eliminated in winter time while heating power is eliminated in summer time. Without such a seasonal setting, heating and cooling power might happen in same day. Hence, a seasonal setting where heating power and cooling power can only be used in winter and summer, respectively, is applied for both control strategies.

4.4 MPC formulation

For the MPC approach, the state, the input and the weather and internal gains in (4.1) during the prediction horizon \( N \in \mathbb{N}_+ \) are defined as:

\[
\mathbf{x} := [x_0^T, \ldots, x_N^T]^T \in \mathbb{R}^{(N+1)n}
\]

\[
\mathbf{u} := [u_0^T, \ldots, u_{N-1}^T]^T \in \mathbb{R}^{Nm}
\]

\[
\mathbf{v} := [v_0^T, \ldots, v_{N-1}^T]^T \in \mathbb{R}^{Np}
\]

and prediction dynamics matrices \( \mathbf{A} \), \( \mathbf{B}_u \) and \( \mathbf{B}_v \) such that

\[
\mathbf{x} = \mathbf{A} \mathbf{x}_0 + \mathbf{B}_u \mathbf{u} + \mathbf{B}_v \mathbf{v}
\]

with the constraints on inputs \( \mathbf{u} \) and states \( \mathbf{x} \) over the prediction horizon \( N \) are

\[
\mathbf{S} \mathbf{u} \leq \mathbf{s} \quad \text{(4.5)}
\]

\[
\mathbf{A} \mathbf{G} \mathbf{x} \leq \mathbf{g} \quad \text{(4.6)}
\]

All the inputs \( u \) can vary under the constraints defined in (4.3) and (4.4). The optimal control input \( u \) over the prediction horizon \( N \) is determined by
minimizing the objective function, which is defined as:

\[
J(x_0, u) = S_0 \cdot \sum_{k=0}^{N-1} c_k^T \cdot u_{\text{grid},k} + S_1 \cdot \sum_{k=0}^{N-1} u_{\text{HP},k}^T \cdot Q \cdot u_{\text{HP},k} \n\]

\[
+ S_2 \cdot \sum_{k=1}^{N} (T_{\text{room}} - T_{\text{ref}})^2
\]

(4.7)

where \(S_0, S_1, S_2\) are the gains of each penalty term. \(u_{\text{grid},k}\) and \(u_{\text{HP},k}\) denote the power from grid and the heat pump power, respectively, and are of the form:

\[
u_{\text{grid},k} = \begin{bmatrix} u_{k,1} & u_{k,5} & u_{k,11} & u_{k,18} & u_{k,20} \end{bmatrix}^T
\]

(4.8)

\[
u_{\text{HP},k} = \begin{bmatrix} u_{k,8} & u_{k,10} & u_{k,11} \end{bmatrix}^T
\]

(4.9)

with \(Q\) used as penalty matrix for heat pump power formulated as:

\[
Q = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}
\]

In objective function, in addition to a monetary term, there are additional penalties for heat pump power and room temperature. Regarding to heat pump power, the penalty is used to approximate the nonlinearity of heat pump (See Section 3.1.2). Figure 4.2 shows the heat pump power profile with and without the penalty present in objective function. Another penalty for room temperature is used as a softened constraint such that the result of MPC can be compared with RBC in a fair way. The reference temperature of the temperature penalty is set to be 22°C, as shown in Figure 4.3.
Figure 4.3: Schematic representation of a reference line for MPC controller.
Chapter 5

Simulation results

The simulation results are demonstrated in this chapter. First, this chapter starts with annual time series of the system states, including EWH temperature, battery state of charge and room temperature, as well as power profiles of the system. Second, results of each component are shown in more detail by weekly profiles. Finally, the total electricity cost and the total energy consumption with RBC and MPC will be compared.

5.1 Annual profiles

Figure 5.1 shows the annual profiles of the system, including price signal, battery SOC, EWH temperature, room temperature, overall power and PV power. Battery SOC is maintained between 40% and 100% as mentioned in Section 3.1.4. The average temperature of EWH fluctuates between 55°C and 70°C as constrained. The room temperature lies within 21°C and 23°C throughout the simulation, with one exception, as highlighted in the graph, where the temperature exceeds 23°C in the 98th day. This exception is caused by the seasonal setting where cooling is not yet activated during the 98th day. The room temperature in summer time is found to track 22°C better than in winter time. This is because the heat pump power, which is supplied to the heating water, has slower dynamics compared to the cooling power, which is a direct power to the room floor. PV production is higher in summer due to higher irradiance levels.
Figure 5.1: Annual profiles of price signal, battery state of charge, EWH temperature, room temperature, system total power and generated PV power [Case IV-A].
5.2 Building

In order to highlight the difference in system performance in summer and in winter, a weekly profile for each season is presented below. The room temperature and heat pump power profiles of the first week in winter time are shown in Figure 5.2 while the profiles of the 30th week in summer time are shown in 5.3.

5.2.1 Influence of internal gains

During weekdays the temperature fluctuates between 21.5°C and 22.5°C for both cases. This is because the room temperature is significantly influenced by internal gains as internal gains are different during day time and night time. Lower values of internal gains lead to a decline in temperature during day time, while higher values of internal gains increase temperature during night time. Since the internal gains for weekends are set to be the high values as night time, the room temperature keeps increasing over the weekend such that no heating power is required in winter, while during summer time the system requires more cooling power over the weekend.

5.2.2 Heating and cooling power

It can clearly be seen that the heat pump power is higher than cooling power. This can be attributed to the higher difference between the room temperature and the ambient temperature in winter than in summer. Hence, in order to keep the system balanced and maintain the room temperature in a desired range, a higher power is necessary for the system in winter.

Besides the magnitude of the power, it is noteworthy that the heating power responds better to price signals than cooling power. As shown in Figure 5.2, the heat pump power varies with low price time intervals. Moreover, the price signals have less influence on cooling power. Since the floor heating water system with its thermal inertia acts as a big capacity bank such that heating power can be shifted with less influence on the room temperature. In addition, the system tends to increase the cooling power when the room temperature steps over 22°C. This is because an aggregate objective function is used in MPC to track 22°C over the time. Consequently, the best cooling moment in order to track the room temperature at 22°C happens when the room temperature intercepts 22°C.
CHAPTER 5. SIMULATION RESULTS

Figure 5.2: Profiles of the 1st week, including price signal (top), room temperature along with ambient temperature (middle) and heat pump power (bottom) [Case IV-A].

Figure 5.3: Profiles of the 30th week, including price signal (top), room temperature along with ambient temperature (middle) and cooling power (bottom) [Case IV-A].
CHAPTER 5. SIMULATION RESULTS

5.3 Battery

Figure 5.4 shows the battery SOC profile with the associated power profile along with the price signals of the first week. In general, the battery sustains a charge-discharge cycle per day. It be observed that the system tends to charge battery from the grid during the low price time intervals and discharge to the system during the high price time intervals. Furthermore, charging power of the battery always decreases after a period of time. The decreasing behavior of the charging power is caused by the rate constant in KiBaM. As note that the battery SOC is seldom charged to 100%. There are two possible reasons for this: First, the charging power is limited by the rate constant. Second, the time interval of low price is short such that charging power has to be stopped before SOC reaches 100%.

![Figure 5.4: Profiles of the 1st week, including price signal (top), battery SOC (middle) and battery power (bottom) [Case IV-A].](image)

5.4 Electric water heater

Figure 5.4 shows the evolution of EWH average temperature with the associated power profile along with the price signal of the first week. Similarly to battery, the system tends to increase the temperature of EWH during the low price time intervals. It is interesting to note that during the third day of the week, a higher power is executed due to a greater price difference. Moreover, it can be found that the system also has the tendency to avoid the peak price of each day. For example, during the sixth day, the temperature is higher before and after the peak price happens.
5.5 PV

PV power utilization for the summer and winter weeks are shown in Figure 5.6 and Figure 5.7, respectively. It is clear that the generated PV is higher in summer time such that it can provide its excessive power to battery. Besides supplying power to battery, power to electric water heater and uncontrollable load accounts for the biggest share of generated PV power, as shown in both figures.
CHAPTER 5. SIMULATION RESULTS

5.6 Operation cost and energy consumption

In this section, the comparisons between the benchmark (RBC) and the performance bound (MPC) with different prediction horizons (4 hr, 8 hr, 16 hr, 20 hr and 24 hr) are presented. First, results for time-varying tariff are presented and compared. Then, results for high/low tariffs are also presented.

5.6.1 Case A: time-varying tariff

The comparisons for time-varying tariff between the benchmark and the performance bound are presented in Tables 5.1 - 5.6. Each table comprises annual electricity costs and energy consumption in 6 different cases. When comparing the scenarios without PV system (I-A, II-A), electricity cost is decreased by 10% to 14% when controlling via MPC controller, except the case with 4 hours of prediction horizon. This is because peak prices can
not be forecasted by MPC with 4 hours of prediction horizon from the low price time intervals. Hence, a limited decrease of electricity cost is induced. Regarding to energy consumption, it can be seen that no certain decreasing or increasing trend occurs in the case of MPC controller, since there is no penalization for total energy consumption in the objective function.

Additionally, when comparing the scenarios with PV system (III-A, IV-A), 17% to 22% decrease of electricity cost is caused by MPC controller with more than 8 hours of prediction horizon while electricity cost with 4 hours of prediction horizon is only reduced by 12%. For energy consumption, the system tends to consume less energy with MPC controller because more generated PV energy is utilized when prediction is available.

Furthermore, it is clear that a battery can help the system to reduce electricity cost when comparing case I and case II or case III and IV. However, it is interesting to note that employment of battery increases energy consumption up to 3% because of energy losses during charging and discharging.

5.6.2 Case B: high/low tariff

Tables 5.7 - 5.12 show the comparisons for high-low tariff between the benchmark and the performance bound. Annual electricity cost and energy consumption are shown in each table. Similar results are found in both scenarios for high-low tariff and time-varying tariff. For example, electricity cost is also decreased due to MPC controller and prediction horizon of 4 hours has limitation on the improvement as well. MPC controller also is able to utilize more generated PV energy such that electricity cost is reduced by another 10% and less energy is consumed. Battery also contributes in additional savings of electricity cost and increases energy consumption.
Table 5.1: Comparison between RBC and MPC for case A: time-varying tariff with a prediction horizon of 4 hours.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Electricity cost</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Chf] [%]</td>
<td>kWh</td>
</tr>
<tr>
<td>RBC: I-A, II-A</td>
<td>1316 -8608</td>
<td>-</td>
</tr>
<tr>
<td>RBC: III-A, IV-A</td>
<td>1062 -7013</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Performance bound</th>
<th>Electricity cost</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Chf] [%]</td>
<td>kWh</td>
</tr>
<tr>
<td>I-A</td>
<td>1280 -2.73</td>
<td>8947</td>
</tr>
<tr>
<td>II-A</td>
<td>1269 -3.57</td>
<td>9001</td>
</tr>
<tr>
<td>III-A</td>
<td>937 -11.7</td>
<td>6632</td>
</tr>
<tr>
<td>IV-A</td>
<td>926 -12.8</td>
<td>6616</td>
</tr>
</tbody>
</table>

Table 5.2: Comparison between RBC and MPC for case A: time-varying tariff with a prediction horizon of 8 hours.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Electricity cost</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Chf] [%]</td>
<td>kWh</td>
</tr>
<tr>
<td>RBC: I-A, II-A</td>
<td>1316 -8608</td>
<td>-</td>
</tr>
<tr>
<td>RBC: III-A, IV-A</td>
<td>1062 -7013</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Performance bound</th>
<th>Electricity cost</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Chf] [%]</td>
<td>kWh</td>
</tr>
<tr>
<td>I-A</td>
<td>1184 -10.0</td>
<td>8618</td>
</tr>
<tr>
<td>II-A</td>
<td>1148 -12.8</td>
<td>8851</td>
</tr>
<tr>
<td>III-A</td>
<td>877 -17.42</td>
<td>6470</td>
</tr>
<tr>
<td>IV-A</td>
<td>856 -19.4</td>
<td>6571</td>
</tr>
</tbody>
</table>
CHAPTER 5. SIMULATION RESULTS

Table 5.3: Comparison between RBC and MPC for case A: time-varying tariff with a prediction horizon of 12 hours.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Electricity cost</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Chf]</td>
<td>[%]</td>
</tr>
<tr>
<td>RBC: I-A, II-A</td>
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</tr>
<tr>
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<td>1062</td>
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Performance bound

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<td>I-A</td>
<td>1183</td>
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</tr>
<tr>
<td>IV-A</td>
<td>837</td>
<td>-21.2</td>
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Table 5.4: Comparison between RBC and MPC for case A: time-varying tariff with a prediction horizon of 16 hours.

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<td>-10.3</td>
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<td>II-A</td>
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<td>-13.9</td>
</tr>
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<td>III-A</td>
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<td>-18.3</td>
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<td>IV-A</td>
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Table 5.5: Comparison between RBC and MPC for case A: time-varying tariff with a prediction horizon of 20 hours.

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<td>[Chf]</td>
<td>[%]</td>
</tr>
<tr>
<td>RBC: I-A, II-A</td>
<td>1316</td>
<td>-</td>
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<tr>
<td>RBC: III-A, IV-A</td>
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Performance bound

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<td>[Chf]</td>
<td>[%]</td>
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<td>1183</td>
<td>-10.1</td>
</tr>
<tr>
<td>II-A</td>
<td>1135</td>
<td>-13.8</td>
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<tr>
<td>III-A</td>
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<td>-18.3</td>
</tr>
<tr>
<td>IV-A</td>
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<td>-21.8</td>
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Table 5.6: Comparison between RBC and MPC for case A: time-varying tariff with a prediction horizon of 24 hours.

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<td>[Chf]</td>
<td>[%]</td>
</tr>
<tr>
<td>RBC: I-A, II-A</td>
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<td>-</td>
</tr>
<tr>
<td>RBC: III-A, IV-A</td>
<td>1062</td>
<td>-</td>
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Performance bound

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<td>[%]</td>
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<tr>
<td>I-A</td>
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<td>II-A</td>
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<td>-13.3</td>
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<tr>
<td>III-A</td>
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<td>-17.8</td>
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<tr>
<td>IV-A</td>
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<td>-21.7</td>
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Table 5.7: Comparison between RBC and MPC for case B: high/low tariff with a prediction horizon of 4 hours.

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</thead>
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<td>[Chf]</td>
<td>[%]</td>
</tr>
<tr>
<td>RBC: I-B, II-B</td>
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<td>8608</td>
</tr>
<tr>
<td>RBC: III-B, IV-B</td>
<td>986</td>
<td>7013</td>
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</table>

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<th>Energy consumption</th>
</tr>
</thead>
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<tr>
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<td>[%]</td>
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<tr>
<td>I-B</td>
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<tr>
<td>II-B</td>
<td>1358</td>
<td>9452</td>
</tr>
<tr>
<td>III-B</td>
<td>936</td>
<td>6781</td>
</tr>
<tr>
<td>IV-B</td>
<td>921</td>
<td>6777</td>
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Table 5.8: Comparison between RBC and MPC for case B: high/low tariff with a prediction horizon of 8 hours.

<table>
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<th>Energy consumption</th>
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</thead>
<tbody>
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<td>[%]</td>
</tr>
<tr>
<td>RBC: I-B, II-B</td>
<td>1257</td>
<td>8608</td>
</tr>
<tr>
<td>RBC: III-B, IV-B</td>
<td>986</td>
<td>7013</td>
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</tbody>
</table>

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<th>Performance bound</th>
<th>Electricity cost</th>
<th>Energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[Chf]</td>
<td>[%]</td>
</tr>
<tr>
<td>I-B</td>
<td>1170</td>
<td>8386</td>
</tr>
<tr>
<td>II-B</td>
<td>1142</td>
<td>8567</td>
</tr>
<tr>
<td>III-B</td>
<td>832</td>
<td>6306</td>
</tr>
<tr>
<td>IV-B</td>
<td>816</td>
<td>6394</td>
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Table 5.9: Comparison between RBC and MPC for case B: high/low tariff with a prediction horizon of 12 hours.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Electricity cost [Chf]</th>
<th>Energy consumption [%]</th>
<th>kWh</th>
<th>[%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBC: I-B, II-B</td>
<td>1257</td>
<td>-</td>
<td>8608</td>
<td>-</td>
</tr>
<tr>
<td>RBC: III-B, IV-B</td>
<td>986</td>
<td>-</td>
<td>7013</td>
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</tbody>
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Performance bound

<table>
<thead>
<tr>
<th>Benchmark</th>
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<th>Energy consumption [%]</th>
<th>kWh</th>
<th>[%]</th>
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<tbody>
<tr>
<td>I-B</td>
<td>1167</td>
<td>-7.15</td>
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<tr>
<td>II-B</td>
<td>1127</td>
<td>-10.3</td>
<td>8648</td>
<td>0.46</td>
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<tr>
<td>III-B</td>
<td>825</td>
<td>-16.3</td>
<td>6281</td>
<td>-10.43</td>
</tr>
<tr>
<td>IV-B</td>
<td>801</td>
<td>-18.8</td>
<td>6395</td>
<td>-8.81</td>
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Table 5.10: Comparison between RBC and MPC for case B: high/low tariff with a prediction horizon of 16 hours.

<table>
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<th>Electricity cost [Chf]</th>
<th>Energy consumption [%]</th>
<th>kWh</th>
<th>[%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBC: I-B, II-B</td>
<td>1257</td>
<td>-</td>
<td>8608</td>
<td>-</td>
</tr>
<tr>
<td>RBC: III-B, IV-B</td>
<td>986</td>
<td>-</td>
<td>7013</td>
<td>-</td>
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</tbody>
</table>

Performance bound

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Electricity cost [Chf]</th>
<th>Energy consumption [%]</th>
<th>kWh</th>
<th>[%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>I-B</td>
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<td>-6.92</td>
<td>8123</td>
<td>-5.63</td>
</tr>
<tr>
<td>II-B</td>
<td>1129</td>
<td>-10.2</td>
<td>8413</td>
<td>-2.26</td>
</tr>
<tr>
<td>III-B</td>
<td>826</td>
<td>-16.2</td>
<td>6084</td>
<td>-13.2</td>
</tr>
<tr>
<td>IV-B</td>
<td>788</td>
<td>-20.1</td>
<td>6310</td>
<td>-10.0</td>
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</table>
### Table 5.11: Comparison between RBC and MPC for case B: high/low tariff with a prediction horizon of 20 hours.

<table>
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<tr>
<td></td>
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<td>[%]</td>
</tr>
<tr>
<td>RBC: I-B, II-B</td>
<td>1257</td>
<td>-</td>
</tr>
<tr>
<td>RBC: III-B, IV-B</td>
<td>986</td>
<td>-</td>
</tr>
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</table>

### Table 5.12: Comparison between RBC and MPC for case B: high/low tariff with a prediction horizon of 24 hours.

<table>
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<td>[%]</td>
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<td>-7.16</td>
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<tr>
<td>RBC: III-B, IV-B</td>
<td>1117</td>
<td>-11.1</td>
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</table>

<table>
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<th>Energy consumption</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>[Chf]</td>
<td>[%]</td>
</tr>
<tr>
<td>I-B</td>
<td>1167</td>
<td>-7.16</td>
</tr>
<tr>
<td>II-B</td>
<td>1123</td>
<td>-10.6</td>
</tr>
<tr>
<td>III-B</td>
<td>827</td>
<td>-16.1</td>
</tr>
<tr>
<td>IV-B</td>
<td>782</td>
<td>-20.7</td>
</tr>
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Chapter 6

Sensitivity analysis

In this chapter, sensitivity analysis will be presented, including prediction horizon, internal gains and day-ahead price. Different parameters values will be examined in order to investigate their effect on the system.

6.1 Prediction horizon

Here, the sensitivity analysis with respect to prediction horizon is presented. In order to investigate the analysis, the results of annual electricity cost, energy consumption, heat pump consumption, cooling energy, EWH energy and battery charging power from grid with different prediction horizons (3, 4, 5, 6, 7, 8, 10, 12, 16, 20, 24 hours) are shown In order to focus on the influence of prediction horizon, Case IV-A is selected as the case study.

6.1.1 Electricity cost

Figure 6.1 illustrates the electricity costs with different prediction horizons. It is clear that the electricity cost decreases as prediction horizon increases. The decrease in electricity cost saturates around 16 hours of prediction horizon as shown in Figure 6.1. This implies that prediction horizons greater than 16 hours do not improve system performance in terms of electricity cost. In addition, it is interesting to note that the electricity costs for cases of 20 hours and 24 hours are slightly higher than the case of 16 hours. This unexpected increase can be explained as follow: Since there are another two terms, heat pump penalty and room temperature reference, in addition to electricity cost in the objective function (See Section 4.4), the total cost in the objective function might be reduced even with an ascent in the electricity cost. Another possibility might be the nonlinearity caused by EWH. Further discussion can be found in Section 6.1.2.
CHAPTER 6. SENSITIVITY ANALYSIS

Figure 6.1: Plot of annual electricity cost with different prediction horizons [Case IV-A].

Figure 6.2: Plot of annual system energy consumption with different prediction horizons [Case IV-A].
6.1.2 Energy consumption

Figure 6.2 depicts the annual energy consumption with different prediction horizons. Similar behavior of the energy consumption is observed in Figure 6.2 compared to Figure 6.1 until 16 hours of prediction horizon. As prediction horizon increases, the total energy consumption decreases. However, for prediction horizons of 20 hours and 24 hours, the energy consumption is surprisingly higher than that of prediction horizon of 16 hours causing higher electricity cost for 20 hours and 24 hours. In order to understand the behavior of the system, the energy consumption of all components with different prediction horizons is calculated and shown in Figures 6.3 - 6.6. However, analysis of uncontrollable load is not included since it is fixed and the energy can not be shifted.

In Figure 6.4, it can be seen that the heat pump energy increases with the prediction horizon until 12 hours. Therefore, it can be concluded the slow dynamics between room temperature and floor heating system needs more than 12 hours of prediction horizon such that MPC is able to control the room temperature while optimizing the heat pump energy. As Figure 6.3 demonstrates, the heat pump energy decreases after prediction horizon of 16 hours. Therefore, there is still potential for improvement of controlling heat pump by increasing the prediction horizon.

![Annual heat pump energy (kWh) vs Prediction horizon (hr)](image)

Figure 6.3: Plot of annual heat pump energy consumption with different prediction horizons [Case IV-A].
For cooling, beyond 3 hours of prediction horizon, the annual cooling energy is between 148 kWh and 150 kWh. Hence, it is evident that the optimization of cooling requires prediction horizon of 4 hours such that the system is able to forecast the dynamics between cooling slab and room and control the room temperature while using the least amount of energy.

![Figure 6.4: Plot of annual cooling energy with different prediction horizons [Case IV-A].](image)

The dependence of EWH energy consumption on prediction horizon, as shown in Figure 6.5, demonstrates a very similar behavior compared to the plot of total energy (Figure 6.2). In both figures, there is a decrease up to prediction horizon of 16 hours and then increase is observed for prediction horizons of 20 hours and 24 hours. In addition, the energy consumption of EWH is relatively high compared to other components and is about 80% of total consumption. This particular evidence indicates the reason of similarity in two figures.

For battery energy, it can be found that the energy has a linear increasing trend until prediction horizon of 16 hours and then the energy saturates after 16 hours. This phenomenon can be explained as follows: For prediction horizons more than 16 hours, the MPC is able to forecast the peak prices from the low-price time intervals and hence the battery is to be utilized with its maximum potential by saving energy at low prices and using at high prices.

The dependence of EWH energy consumption on prediction horizon, as
shown in Figure 6.5, demonstrates a very similar behavior compared to the plot of total energy (Figure 6.2).

![Figure 6.5: Plot of annual EWH energy with different prediction horizons [Case IV-A].](image-url)
After the break-down analysis for each component, a clear evidence indicates that the performance of EWH leads to the rises of total energy in prediction horizons of 20 hours and 24 hours. In addition, this activity of increasing energy consumption signifies the ascent in the electricity cost, which is mentioned in Section 6.1.1. Further discussion for EWH can be found in Appendix D.

### 6.2 Internal gains

Figure 6.7 illustrates the profiles of room temperatures with different values of internal gains shown in Table 6.1. As the figure illustrates, higher internal gains result in a more fluctuating behavior of room temperature. The fluctuation is caused by the different settings of internal gains for occupants being inside or outside (See Section 3.2.2 for settings of internal gains). For standard value (red line in Figure 6.7), it is revealed that internal gains have an immediate effect on room temperature. On the other hand, the influences of heat pump power and ambient temperature to the room temperature are relatively small and slow in comparison to internal gains. Thereby, it can be concluded that internal gains dominate the evolution of room temperature.
Figure 6.7: Temperature profiles of room for 1st week with different values of internal gains: standard, low and zero [Case IV-A].

Table 6.1: Values for internal gains levels

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Standard</th>
<th>Low</th>
<th>Zero</th>
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<tr>
<td>Internal gains by occupants (away)</td>
<td>W/m²</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Internal gains by occupants (home)</td>
<td>W/m²</td>
<td>4.5</td>
<td>2.5</td>
<td>0</td>
</tr>
<tr>
<td>Internal gains by equipment (away)</td>
<td>W/m²</td>
<td>3</td>
<td>2.1</td>
<td>0</td>
</tr>
<tr>
<td>Internal gains by equipment (home)</td>
<td>W/m²</td>
<td>10.5</td>
<td>4.9</td>
<td>0</td>
</tr>
</tbody>
</table>
6.3 Day-ahead price

In order to investigate the influence of day-ahead price on the system, the duration of changing price and the level of price steps are chosen as parameters for the sensitivity analysis. One thing should be noted here: the price signal is originally constant as a fixed price at 14 Rp./kWh, and the level of changing price is the percentage of difference compared to the original constant price. For example, a scenario with step level of −50% and duration of 2 hours results in a price drop to 7 Rp./kWh for two hours. A diagram in Figure 6.8 clearly illustrates these two parameters. In addition, two different types of systems, a full system (Case IV) and a building-only system (Case I), are assessed in this analysis. Both systems are computed with different price steps and price-changing durations, and the energy consumption for all the scenarios with different price level and price changing duration is generated. By comparing with 0% change, the difference for each scenario is plotted in two forms: one in energy unit (kWh) and the other on in percentage (%).

Figure 6.8: Schematic representation of day-ahead price signal. Duration and step level are the sensitivity analysis parameters in Section 6.3.

The results of Case IV, scenarios with PV and battery, are shown in Figure 6.9 and Figure 6.10. As both figures illustrate, the system tends to increase its energy consumption if price has a decrease of more than 40% and the system is likely to reduce its energy consumption if prices increase more than 40%. For up-regulation (negative change in price), according to Figure 6.9, the energy difference in percentage decreases exponentially with price-changing duration, meaning the system is less likely to respond to the price signal for a longer duration of changing-price. This phenomena can
be associated to the trend exhibited in Figure 6.10, where the difference of energy rises less with increase in price-changing duration. Furthermore, Figure 6.10 indicates that the amount of up-regulation energy is similar for different durations and 90% of the energy shifting potential can be reached within a duration of 2 hours.

For down-regulation (positive change in price), it can be noticed that a linear trend for energy difference as price-changing duration increases as shown in Figure 6.10. Therefore, it can be concluded that similar amount of down-regulation energy is available for each hour and hence, as price-changing duration increases, the total amount of down-regulation energy increases linearly. Conversely, as price-changing duration become longer, the deviation of price step becomes smaller with respect to time. Thereby, the system response becomes smaller for a longer duration of changing-price and therefore the plot in Figure 6.9 seems to be more flat for longer price-changing duration.

Regarding to Case I (system without PV and battery), its analysis is focused on the potential of shifting energy by utilizing thermal inertia. The results of Case I can be found in Figure 6.11 and Figure 6.12. It can be observed that both systems have similar behavior except one aspect: The magnitude of energy difference is smaller in Case I due to the additional contribution of the battery to shifting energy.
Figure 6.9: Sensitivity analysis of day-ahead price: system energy difference with different steps and durations in percentage [Case IV].

Figure 6.10: Sensitivity analysis of day-ahead price: system energy difference with different steps and durations in kWh [Case IV].
Figure 6.11: Sensitivity analysis of day-ahead price: system energy difference with different steps and durations in percentage [Case I].

Figure 6.12: Sensitivity analysis of day-ahead price: system energy difference with different steps and durations in kWh [Case I].
Chapter 7

Real-time price control

In this chapter, the analysis of real-time price control is presented. Different from day-ahead price signal, the real-time price control is an instant price signal at the moment when the price is changed. Therefore, the system with MPC controller can NOT forecast the changing price till it is changed. Here, the analysis will focus on three aspects: the response of thermal inertia, the real-time price control for next 24 hours and the real-time price control for next 6 hours. Firstly, in order to analyze the response of thermal inertia, the evolution of EWH temperature and room temperature will be examined. The result will be shown by two selective examples, one with positive price step and another one with negative price step. Subsequently, the responses of system power for next 24 hours after real-time price control will be presented. Finally, the real-time price control for next 6 hours will be investigated for systems with/without battery in a detailed manner.

7.1 Response of thermal inertia (EWH and room)

In order to investigate the response of components and associated thermal inertia after applying a real-time price signal, the temperature evolution of the EWH and the room, as well as the power profiles of the heating elements, are examined. In this section, the response will be illustrated with examples with a +50\% price signal and a −50\% price signal in the following figures. The response of price signal at different time of a day is also considered. The tests for +50\% and −50\% price signals at 0 am, 4 am, 8 am, 12 pm, 4 pm and 8 pm are shown in Figures 7.1 - 7.12.

For down regulation induced by the +50\% price signal, it can observed that there is no potential for EWH to decrease its power in all cases. This is because the least amount of EWH energy is already scheduled as the system is optimized via deterministic MPC. For heat pump, Figure 7.3 and Figure 7.5 show that it is still possible to decrease the heat pump power via the positive price step. Different from the case where the EWH power used as a
direct input, the heat pump power injects thermal power to the floor heating water system first and slowly influences the whole building, including the room. Because of this process, the water heating system and the floor with their thermal inertia act as a capacity bank so that the room temperature is less influenced by the instant change of power as long as the aggregated heat pump energy remains the same. Such behavior, where the room temperature is still considerably close to the original evolution, can be found in Figures 7.1 - 7.12.

For up regulation induced by the $-50\%$ price signal, both components (heat pump and EWH) instantly increase the power such that the energy can be saved for next few hours. As the figures (Figures 7.2, 7.4, 7.6, 7.8, 7.10 and 7.12) show, the amount of increasing power differs from time to time. This difference of increasing power can be explained as follow: The solution obtained from MPC via objective function is based on system state and input and the system state and scheduled input are different at different time. Hence, the amount of increasing power depends not only on the price but also on the system state.
CHAPTER 7. REAL-TIME PRICE CONTROL

Figure 7.1: Response of thermal inertia including room and EWH for a real-time +50% price signal at 0 am.

Figure 7.2: Response of thermal inertia including room and EWH for a real-time -50% price signal at 0 am.
Figure 7.3: Response of thermal inertia including room and EWH for a real-time +50% price signal at 4 am.

Figure 7.4: Response of thermal inertia including room and EWH for a real-time -50% price signal at 4 am.
CHAPTER 7. REAL-TIME PRICE CONTROL

Figure 7.5: Response of thermal inertia including room and EWH for a real-time +50% price signal at 8 am.

Figure 7.6: Response of thermal inertia including room and EWH for a real-time -50% price signal at 8 am.
Figure 7.7: Response of thermal inertia including room and EWH for a real-time +50% price signal at 12 pm.

Figure 7.8: Response of thermal inertia including room and EWH for a real-time -50% price signal at 12 pm.
Figure 7.9: Response of thermal inertia including room and EWH for a real-time +50% price signal at 4 pm.

Figure 7.10: Response of thermal inertia including room and EWH for a real-time -50% price signal at 4 pm.
CHAPTER 7. REAL-TIME PRICE CONTROL

Figure 7.11: Response of thermal inertia including room and EWH for a real-time +50% price signal at 8 pm.

Figure 7.12: Response of thermal inertia including room and EWH for a real-time -50% price signal at 8 pm.
7.2 System response for next 24 hours

In previous section, only the two different price signals, −50% and +50%, are explored. Here, price signals from −100% to 100% are introduced to investigate the system response. As shown in the previous section, different time of real-time control would lead to different responses to the system. However, only the results of price change at 8 am are presented here, and the rest are provided in Appendix E.

Figure 7.13 shows the power profiles of different price signals (−100% to 100%) for 24 hours starting from price changing time. As illustrated, the power of the first hour (price signal time) increases dramatically when there is a negative change in price. Same plot is shown in Figure 7.14 from a different angle in order to see how the system varies to the positive changes in price. It is clear that the amount of changing power corresponding to the positive price changes is relatively small compared to the negative price changes. From the figure, the system is able to respond to the negative price change, meaning the system has the ability to shift the energy from future to present. However, the potential to shift the energy from present to future is limited.
In addition, it is noteworthy that the difference of the power profiles is negligible 6 hours after real-time price control, meaning the real-time price signals have considerable impacts on system for only 6 hours. This phenomena can be clearly observed in Figure 7.13 as the deviation of system response is only noticeable for the first 6 hours. Hence, a detailed analysis of these 6 hours is provided in next section.

7.3 System response for next 6 hours

As mentioned in Section 7.1, different starting time of changing price would change the potential of shifting energy in the system. Also, it has been shown that the deviation of system response is only considerable in the first six hours and the system response to the positive price changes is limited. Thus, the following analysis focuses on the first 6 hours and the positive price changes for different starting time of a day. Moreover, the results of the comprehensive system (Case IV) and the building-only system (Case I) are presented separately in order to investigate the effect of battery.

Comparing two systems (Case IV and Case I), it can clearly be seen that Case IV is more capable of shifting energy than Case I. However, the additional shifting energy by Case IV is only observed for the cases that the price step decreases more than 30%. This can be interpreted as: The
battery has an efficiency of 73% and therefore it is willing to respond to real-time signals only if the absolute value of the negative price step in % is greater than battery efficiency.

Moreover, it can be revealed that the load induced by real-time price control is shifted mainly from the period of 2nd and 3rd hours to the 1st hour. From the 4th hour to the 6th hour, the shifted load starts to reduce as time elapses and the system slowly surges back to the original state. In addition, it can be seen again that different time of a day results in different potential of shifting energy. Furthermore, Figure 7.15 and Figure 7.21 shows that the system tends to shift more energy to first hour as the real-time price decreases more, and the system is more sensitive when the changing price ranges from 0% to -40%. For system without battery (Case I), the level of price signal has a linear influence on system after the first hour when the price signal is given from 0 am to 10 am as illustrated in Figure 7.22 - 7.26. This is because the heat pump power is only activated from 0 am to 10 am and therefore it is an evidence that the heat pump is more sensitive to price signal than the EWH. On the other hand, the difference of power is the same after the first hour when the price signal is given from 11 am to 11 pm as the EWH is less sensitive to price signal and would shift the same amount of energy as long as there is a decreasing change in price.
Figure 7.16: System power for different real-time price signals (-100% to 0%) and different starting time for the 2nd hour [Case IV].

Figure 7.17: System power for different real-time price signals (-100% to 0%) and different starting time for the 3rd hour [Case IV].
CHAPTER 7. REAL-TIME PRICE CONTROL

Figure 7.18: System power for different real-time price signals (-100% to 0%) and different starting time for the 4th hour [Case IV].

Figure 7.19: System power for different real-time price signals (-100% to 0%) and different starting time for the 5th hour [Case IV].
Figure 7.20: System power for different real-time price signals (-100% to 0%) and different starting time for the 6th hour [Case IV].

Figure 7.21: System power for different real-time price signals (-100% to 0%) and different starting time for the 1st hour [Case I].
Figure 7.22: System power for different real-time price signals (-100% to 0%) and different starting time for the 2nd hour [Case I].

Figure 7.23: System power for different real-time price signals (-100% to 0%) and different starting time for the 3rd hour [Case I].
Figure 7.24: System power for different real-time price signals (-100% to 0%) and different starting time for the 4th hour [Case I].

Figure 7.25: System power for different real-time price signals (-100% to 0%) and different starting time for the 5th hour [Case I].
Figure 7.26: System power for different real-time price signals (-100% to 0%) and different starting time for the 6th hour [Case I].
Chapter 8

Conclusions and outlook

This chapter summarizes the most important findings and achievements of this thesis and concludes with an outlook for further research.

8.1 Conclusions

In this thesis, model predictive control strategies that can investigate performance bound in terms of electricity cost reduction for smart buildings in a dynamic price environment are presented. Local generation, building and storage units are modeled together as a smart building system. Based on two control strategies, the behavior of the building system has been examined. The first control strategy is the rule based control which is the current control practice for building automation and is therefore used in the presented investigation as a benchmark. The second control strategy is deterministic model predictive control with perfect knowledge. The result of this control strategy gives the performance bound. Thereby, the maximum potential of improvement in terms of controlling can be found by comparing the results of the RBC and the MPC. The most important conclusions are briefly listed below.

Value of using MPC: Based on the results of annual simulations, it is revealed that the MPC is able to reduce the electricity cost up to 10% and utilize PV energy 20% more without compromising on user comfort. In these simulations, battery storage contributes in additional 3-4% savings, but it increases energy consumption by 2-3%. Furthermore, it has been found that the duration of prediction horizon has a significant influence on the performance of the system, and different components have different saturating points regarding the prediction horizon. In this study, the improvement of system performance is limited for prediction horizons of greater than 16 hours.

Utilization of thermal inertia: The credit of electricity cost savings is induced by the system flexibility, which is the thermal inertia of system.
CHAPTER 8. CONCLUSIONS AND OUTLOOK

Based on different scenarios, the flexibility of the system has been verified and the results have shown that the building and EWH have considerably high thermal inertia. Furthermore, it has been proven that the building and EWH are able to respond to day-ahead price signals and shift demand of thermal loads to low price time intervals. Also, they are able to respond to real-time price signals and shift demand from future to present up to 6 hours ahead. However, only the building has the potential to shift demand from present to future and the amount of shifting energy is relatively small.

**Influence of internal gains:** It has been revealed that internal gains due to occupants and equipment dominate the evolution of room temperature. Due to deterministic MPC, the room temperature can be controlled within a desired range while the electricity cost is reduced as well. However, such a case where perfect knowledge is available to MPC is never realistic. Therefore, it is interesting to see how prediction errors in internal gains would influence the system.

**Value of battery:** The function of battery for smart buildings makes the system more flexible by shifting energy and reducing electricity costs. Based on the simulation results, the battery saves 40 - 50 Chf annually and leads to a payback period of 20 years (with a capital cost of 200 Chf/kWh). Due to the life time of battery, which usually lasts 8 - 10 years, the battery has a negative Net Present Value (NPV) in this study. Nevertheless, the NPV depends on base-peak price spread. For example, if a base-peak price spread of 40 Rp./kWh is induced everyday, the battery might have a positive NPV.

### 8.2 Outlook

Since this thesis focuses considerably on the theoretical potential of the improvement for smart buildings, the goal is to establish a framework for future research. Therefore, the thesis initiates many interesting research opportunities for future projects. Based on the presented results and findings, possible future research topics are provided below:

**Increase room complexity:** Due to the simplicity of the room, the investigation of many possible impacts to the room is limited. Thereby, increasing room complexity, such as implementing window openings and ventilation to the model, is important to study a more realistic model and examine other effects in reality.

**Stochastic MPC and prediction error:** A remarkable research topic is to extend the optimization problem by considering uncertainty and formulating a stochastic MPC problem. This extension would have impacts on user’s comfort and electricity savings. Therefore, it is interesting to analyze how much electricity can be saved and what level of user’s comfort is compromised by introducing uncertainties.
Building aggregations: A research topic for further extension that is interesting from a power system perspective. As aggregation of buildings should have impacts on demand functions, it is worth to study the extended controllability of building aggregations. However, different buildings should have their own stochastic settings such that the impacts of aggregation can be examined.

Types of buildings: It is suggested to inspect the system responses of different types of buildings. For example, a well-insulated building should have different thermal inertia compared to a poor-undulated one. Since the flexibility of buildings in terms of shifting energy depends on the thermal inertia, the response also varies with the type of building.

Sensitivity analysis for gains in the objective function: Another topic offers a further analysis of the presented system by different gains defined in the objective function. This analysis should explore the influence of the gains to the potential for up-regulation and down-regulation.
### Appendix A

## Model parameters

### A.1 Heatpump

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
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</thead>
<tbody>
<tr>
<td>(c_1)</td>
<td>Coefficient for COP source temperature dependency</td>
<td>0.0569</td>
<td>1/K</td>
</tr>
<tr>
<td>(c_2)</td>
<td>Coefficient for COP supply temperature dependency</td>
<td>-0.0661</td>
<td>1/K</td>
</tr>
<tr>
<td>(COP_0)</td>
<td>Constant term in linear fit for COP</td>
<td>5.593</td>
<td>-</td>
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### A.2 Battery

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
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<tbody>
<tr>
<td>$c$</td>
<td>Battery capacity ratio</td>
<td>0.315</td>
<td>-</td>
</tr>
<tr>
<td>$k$</td>
<td>Battery rate constant</td>
<td>1.24</td>
<td>1/h</td>
</tr>
<tr>
<td>$Q_{Ba,max}$</td>
<td>Battery maximum capacity</td>
<td>5</td>
<td>kWh</td>
</tr>
<tr>
<td>$Q_{Ba,min}$</td>
<td>Battery minimum capacity</td>
<td>2</td>
<td>kWh</td>
</tr>
<tr>
<td>$\eta_{ch}$</td>
<td>Battery charging efficiency</td>
<td>86.24%</td>
<td>-</td>
</tr>
<tr>
<td>$\eta_{dis}$</td>
<td>Battery discharging efficiency</td>
<td>85.32%</td>
<td>-</td>
</tr>
<tr>
<td>$\eta_{rt}$</td>
<td>Battery overall efficiency</td>
<td>73%</td>
<td>-</td>
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### A.3 PV

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<th>Symbol</th>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V_{mps}$</td>
<td>Peak power voltage</td>
<td>34.478</td>
<td>V</td>
</tr>
<tr>
<td>$I_{mps}$</td>
<td>Peak power current</td>
<td>4.65</td>
<td>A</td>
</tr>
<tr>
<td>$\Delta V_{mps}$</td>
<td>Temperature effect on peak power voltage</td>
<td>-4.58e-3</td>
<td>-</td>
</tr>
<tr>
<td>$\Delta I_{mps}$</td>
<td>Temperature effect on peak power current</td>
<td>2.42e-3</td>
<td>-</td>
</tr>
<tr>
<td>$G_s$</td>
<td>Standard direct radiation</td>
<td>1000</td>
<td>W/m²</td>
</tr>
<tr>
<td>$K_1$</td>
<td>Constant coefficient for MPPT voltage</td>
<td>-10.01</td>
<td>-</td>
</tr>
<tr>
<td>$K_2$</td>
<td>Constant coefficient for MPPT voltage</td>
<td>-1850.80</td>
<td>-</td>
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<tr>
<td>$A$</td>
<td>Diode ideality factor</td>
<td>1</td>
<td>-</td>
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<td>$k$</td>
<td>Boltzmann constant</td>
<td>1.38e-23</td>
<td>J/K</td>
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<td>$q$</td>
<td>Charge of an electron</td>
<td>1.60e-19</td>
<td>C</td>
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<tr>
<td>$T_{NOCT}$</td>
<td>Normal operating cell temperature</td>
<td>47</td>
<td>°C</td>
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<tr>
<td>$G_s$</td>
<td>Standard direct radiation</td>
<td>1000</td>
<td>W/m²</td>
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<tr>
<td>$T_s$</td>
<td>Standard temperature</td>
<td>298.15</td>
<td>K</td>
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### A.4 Electric Water Heater

<table>
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<th>Symbol</th>
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<th>Value</th>
<th>Unit</th>
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</thead>
<tbody>
<tr>
<td>$A_{tank}$</td>
<td>Surface of EWH</td>
<td>2.0049</td>
<td>m²</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Water thermal diffusivity</td>
<td>0.1434e-6</td>
<td>m²/s</td>
</tr>
<tr>
<td></td>
<td>Height</td>
<td>1.19</td>
<td>m</td>
</tr>
<tr>
<td>$c_p$</td>
<td>Specific heat of water</td>
<td>4185.5</td>
<td>J/(kg·K)</td>
</tr>
<tr>
<td>$R$</td>
<td>Thermal resistance of EWH</td>
<td>2</td>
<td>m²·K/W</td>
</tr>
<tr>
<td></td>
<td>Volume of EWH</td>
<td>0.19</td>
<td>m³</td>
</tr>
<tr>
<td>$T_{amb}$</td>
<td>Ambient temperature</td>
<td>19.7</td>
<td>°C</td>
</tr>
<tr>
<td></td>
<td>Inlet water temperature</td>
<td>14.4</td>
<td>°C</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Water density</td>
<td>1000</td>
<td>kg/m³</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Efficiency</td>
<td>95%</td>
<td>-</td>
</tr>
</tbody>
</table>
Appendix B

System state, input and disturbance

The system has the following state:

\[ x_{k,1} = \text{Temperature of incoming water } [^\circ \text{C}] \]
\[ x_{k,2} = \text{Temperature of first layer in EWH (Bottom layer)}[^\circ \text{C}] \]
\[ \vdots \]
\[ x_{k,11} = \text{Temperature of 10th layer in EWH (Top layer)}[^\circ \text{C}] \]
\[ x_{k,12} = \text{Ambient temperature of EWH } [^\circ \text{C}] \]
\[ x_{k,13} = \text{Available charge of battery } (Q_{Ba1} \text{ in Section 3.1.4})[\text{kWh}] \]
\[ x_{k,14} = \text{Bound charge of battery } (Q_{Ba2} \text{ in Section 3.1.4})[\text{kWh}] \]
\[ x_{k,15} = \text{Room temperature } (X_1 \text{ in Section 3.1.1})[^\circ \text{C}] \]
\[ x_{k,16} = \text{Temperature in building } (X_2 \text{ in Section 3.1.1})[^\circ \text{C}] \]
\[ \vdots \]
\[ u_{k,26} = \text{Temperature in building } (X_{12} \text{ in Section 3.1.1})[^\circ \text{C}] \]
\[ u_{k,27} = \text{Water supply temperature } (X_{13} \text{ in Section 3.1.1})[^\circ \text{C}] \]
\[ u_{k,28} = \text{Water return temperature } (X_{14} \text{ in Section 3.1.1})[^\circ \text{C}] \]
The system has the following actuators $u_k := [u_{k,1}, \cdots , u_{k,20}]^T$:

$u_{k,1} =$ tank power from grid [kW]  
$u_{k,2} =$ tank power from PV [kW]  
$u_{k,3} =$ tank power from battery [kW]  
$u_{k,4} =$ battery discharge power to grid [kW]  
$u_{k,5} =$ battery charge power from grid [kW]  
$u_{k,6} =$ battery charge power from PV [kW]  
$u_{k,7} =$ uncontrollable power from battery [kW]  
$u_{k,8} =$ heat pump power from battery [kW]  
$u_{k,9} =$ uncontrollable power from PV [kW]  
$u_{k,10} =$ heat pump power from PV [kW]  
$u_{k,11} =$ heat pump power from grid [kW]  
$u_{k,12} =$ slab cooling thermal power [kW]  
$u_{k,13} =$ slab heating thermal power [kW]  
$u_{k,14} =$ room radiator thermal power [kW]  
$u_{k,15} =$ heat pump thermal power [kW]  
$u_{k,16} =$ building electric power from battery [kW]  
$u_{k,17} =$ building electric power from PV [kW]  
$u_{k,18} =$ building electric power from grid [kW]  
$u_{k,19} =$ PV power sold to grid [kW]  
$u_{k,20} =$ uncontrollable power from grid [kW]  

The weather and internal gains $v_k$ are formed as:

$v_{k,1} =$ solar radiation [W/m$^2$]  
$v_{k,2} =$ outside air temperature [$^\circ$C]  
$v_{k,4} =$ internal gains due to persons [W/m$^2$]  
$v_{k,5} =$ internal gains due to equipment [W/m$^2$]
Appendix C

Comparison between radiator and heat pump

An example of the analysis comparing the controllability of radiator and heat pump is provided here. Figure C.1 indicates that the heat pump is capable to respond to the price signals as the power is activated during the low-price time intervals. In contrary, the radiator is not capable to respond to the price signals as no matching trend between the power and the price is found in Figure C.2.
APPENDIX C. COMPARISON BETWEEN RADIATOR AND HEAT PUMP

Figure C.1: Profiles of the 1st week, including price signal (top), room temperature along with ambient temperature (middle) and heat pump power (bottom) [Case IV-A].

Figure C.2: Profiles of the 1st week, including price signal (top), room temperature along with ambient temperature (middle) and radiator power (bottom) [Case IV-A].
Appendix D

EWH analysis

In order to understand how prediction horizon influences the behavior of the EWH, a further analysis for EWH is presented. Both price scenarios of time-varying and high/low tariff are investigated here. For time-varying tariff, evolution of EWH temperature for prediction horizons of 16 hours, 20 hours and 24 hours with their associated power shown in Figure D.1, Figure D.2 and Figure D.3. For high-low tariff, evolution of EWH temperature are shown in Figure D.4, Figure D.5 and Figure D.6.

Comparing these figures, it is clear that the system tends to increase the EWH temperature by increasing power during low price time intervals as prediction horizon increases. Since a longer prediction horizon makes the system forecast further in the future, more energy is required to maintain the system within constraints for a longer time horizon, while the MPC controller optimizes the system by minimizing electricity cost. Therefore, more energy consumption during the low-price time intervals is scheduled for longer prediction horizon in order to reduce more in electricity cost.

However, it can be observed that the electricity cost for 24 hours of prediction horizon is surprisingly higher than 16 hours of prediction horizon by a small amount (See Section 6.1). The reason is suspected to be the nonlinearity of the EWH. Since there is a correction procedure for EWH after MPC optimization, a deviation caused by the correction might incur the increase in energy consumption of EWH and therefore in electricity cost.
Figure D.1: Profiles of the 1st week, including price signal (top), average EWH temperature (middle) and EWH power (bottom) [Case:IV-A] at 16 hours of prediction horizon.

Figure D.2: Profiles of the 1st week, including price signal (top), average EWH temperature (middle) and EWH power (bottom) [Case:IV-A] at 20 hours of prediction horizon.
Figure D.3: Profiles of the 1st week, including price signal (top), average EWH temperature (middle) and EWH power (bottom) [Case:IV-A] at 24 hours of prediction horizon.

Figure D.4: Profiles of the 1st week, including price signal (top), average EWH temperature (middle) and EWH power (bottom) [Case:IV-B] at 16 hours of prediction horizon.
APPENDIX D. EWH ANALYSIS

Figure D.5: Profiles of the 1st week, including price signal (top), average EWH temperature (middle) and EWH power (bottom) [Case:IV-B] at 20 hours of prediction horizon.

Figure D.6: Profiles of the 1st week, including price signal (top), average EWH temperature (middle) and EWH power (bottom) [Case:IV-B] at 24 hours of prediction horizon.
Appendix E

Results of real-time price control

<table>
<thead>
<tr>
<th>Power Profiles with different Price Step</th>
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</thead>
<tbody>
<tr>
<td>Power [kW]</td>
</tr>
<tr>
<td>−100%</td>
</tr>
<tr>
<td>−90%</td>
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<tr>
<td>−80%</td>
</tr>
<tr>
<td>−70%</td>
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<td>−60%</td>
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<td>−50%</td>
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<td>−40%</td>
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<td>0%</td>
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<td>80%</td>
</tr>
<tr>
<td>90%</td>
</tr>
<tr>
<td>100%</td>
</tr>
</tbody>
</table>

Figure E.1: Power profiles of different real-time price signals (-100% to 100%) at 0 am [Case IV-A].
Figure E.2: Power profiles of different real-time price signals (-100% to 100%) at 4 am [Case IV-A].

Figure E.3: Power profiles of different real-time price signals (-100% to 100%) at 12 pm [Case IV-A].
Figure E.4: Power profiles of different real-time price signals (-100% to 100%) at 4 pm [Case IV-A].

Figure E.5: Power profiles of different real-time price signals (-100% to 100%) at 8 pm [Case IV-A].
Bibliography


