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Heating, Air Conditioning, and Ventilation in a Smart Building

Using Model Predictive Control with excess thermal power from server room for temperature regulation

Master's thesis in Systems, Control, and Mechatronics

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Abstract

With increasing awareness of climate change, energy consumption and carbon emission have become a priority for many countries and companies. In commercial buildings the Heat Ventilation and Air Condition (HVAC) system is one of the largest energy consumers. This thesis proposes a controller which uses Model Predictive Control (MPC), which minimizes the energy usage from an HVAC system, while ensuring thermal comfort when the room is occupied. The controller can control the temperature in a room by using excess thermal power generated from servers in another room. The controller is compared to another one which regulates the temperature to a set value. To implement the MPC a physical representation of a room is required. This is achieved by modeling a room as an RC-circuit. The physical representation is then furthered into a state space model, where the temperature, inputs from the controller, and the disturbances are realized. With the state-space model, the MPC is implemented. The results are gathered from simulations in Matlab using data from a one week period. Our findings suggest that using the proposed method, big energy reduction can be achieved. The results show that when simulated using the same data, the proposed method used only 7.82% of the energy when compared to the other controller. Thereof, most of it came from excess thermal power came from the server room.

Keywords: Heating Air Conditioning and Ventilation (HVAC), Model Predictive Control (MPC), Physical Modeling, Optimization, Smart Building

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Abbreviations

HVAC Heat Ventilation and Air Condition. v, 1, 3, 5, 6, 8, 10, 11, 21, 31

MPC Model Predictive Control. v, 2–5, 8, 13, 17, 19–21, 31–33

PIR Passive Infrared Sensor. 2, 20

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1 Introduction

1.1 Introduction

With increasing awareness of climate change, focus on energy consumption and carbon emissions have become a priority for many countries and companies. A sector where small positive changes can have a big impact is within the building sector. Buildings are responsible for around 40% of total energy consumption in the world and about 30% of greenhouse gas emissions [1]. Even though buildings are such large consumers of energy, a 2007 study predicts an upward trend in commercial building energy usage [2]. Considering that the average lifetime of a building is 50-100 years, adaptions that improves a buildings carbon footprint can have an accumulative effect during the building's lifespan. In a commercial building the most power hungry element is its Heat Ventilation and Air Condition system, which is responsible for roughly 50% of a buildings energy usage [2]. In countries with a colder climate, e.g. Sweden, the energy usage from a HVAC system is closer to 57% [3]. Despite the HVAC system being the largest energy consumer it is still often controlled using conventional methods like set-point, on/off, P, PI, and PID controllers. These methods have been used for their simplicity, but because of their simplicity they are often inconsistent, not optimal, and end up using much more energy than needed. There are however different methods within HVAC control that show promising results but have not gained traction. One of these methods is Model Predictive Control (MPC). MPC is a promising technique because of its ability to include disturbance rejection, constraint handling, and energy conservation into the controller formulation. Despite its promising performance, MPC has not been a feasible option because it is computationally heavy compared to a more conventional control strategy. However, that has changed in recent years as computational power and sensors have become cheaper. As a result of cheaper hardware, more and higher resolution data is now available which has yielded better prediction models and opened up new possibilities such as the Internet of Things (IoT), and Smart Buildings.

Ericsson is one of the leading companies in the rapidly changing environment of communication technology. They provide Information and Communication Technology (ICT) to service providers, with about 40% of the world‘s mobile traffic carried through their networks. Ericsson was founded 140 years ago by Lars Magnus Ericsson in Sweden, on the premise that access to communications is a basic human need. The company‘s portfolio ranges across Networks, Digital Services, Managed Services and Emerging Business; powered by 5G and IoT platforms. One of Ericsson‘s newest ventures is the concept of *Smart Buildings*. With the knowledge the company holds, they are in a great position and to prepare the infrastructure, insight and platform needed for companies to build end to end solutions and tools for the future Smarter Building. In a step to further their knowledge Ericsson have started to equip their office buildings with wireless sensors and a plethora of data has been gathered so far with new sensors still being added. Each sensor unit consists of environmental sensors that measure temperature, humidity and light, along with a Passive Infrared Sensor (PIR) which detects movement in the room. Currently, Ericsson is using the PIR sensor to determine if a room is occupied or available. If a room has been booked but no one uses it, the room is made available for booking again. An overview of the rooms is then accessible on both a smart device application and displayed on a large table in the Ericsson office. Another feature in the *Smart Building* is that through the application, the user can be assisted to book a room and find it based on the user's location. However, these features only include information from the PIR sensor and the user's position, which means that the other sensors are not used in such a way that the building acts upon their values. As a result Ericsson wanted to explore how the sensors and data could be used. Considering that the unused sensors measure environmental factors, one possible way to use them is for climate control.

The authors of this thesis chose this topic due to the fact that it sounded interesting and it offered a number of possible solutions. It offered a range of flexibility for finding a solution for using the sensors and it was up to the authors to shape the work. The thesis combines the author's experience and interest in working with data, sensors, and the environment. The reason why Ericsson was chosen as the focal company for this thesis work was because it is one of the leading companies within its field, and has a good reputation.

1.2 Aim & Contribution

The aim of this thesis work is divided into 3 parts. Firstly, how the environmental sensors can be utilized in a way that fits the *Smart Building*. Secondly, how the existing data that has been collected can be used. Thirdly, make sure that the first two parts align with Ericsson's environmental policy [4], which aims to reduce energy usage and carbon emission, as well as using circular economy using waste as a resource.

The proposed solution uses a Model Predictive Control (MPC) for climate control. The controller has different temperature constraints based on if the room is occupied or not. The MPC also uses external thermal power generated in server rooms. That thermal power is currently released from the building as waste. The MPC is implemented using a physical model of two meeting rooms in Ericsson's office in Gothenburg. The results acquired by simulation in Matlab [5] using data from occupancy, number of occupants, and weather. The results are compared to another MPC which uses reference tracking to a set-point value, which is similar to the current climate controller for the building.

1.3 Literature Study

The industrial use of MPC dates back to 1980 when it was used in chemical applications such as oil refinery, which is a system with multiple inputs and outputs, as well as constraints. When compared to a Linear Quadratic Controller(LQR), which is an optimal controller that minimizes an unconstrained quadratic objective function over an infinite horizon, the MPC outperformed the LQR in process industries. The reason lies with the fact that no processes are without constraints [6]. The constrainted control and finite window is the main difference between a LQR and MPC. If a MPC would have an infinite horizon and no constraints it would result in a LQR [7]. In recent years MPC has been a popular topic in HVAC research.

In a 2013 review paper [8], Afram and Janabi-Sharif compare the performance of MPC to a variety of HVAC control systems. They found that even a simple MPC outperforms conventional control approaches that do not include predictive algorithms. Another finding in the paper is that buildings with a large thermal mass, e.g. office buildings, could use thermal storage by pre-heating or pre-cooling the building during times when a zone is unoccupied. This relates closely to the work done in this thesis, where the excess power from a server room is used to heat other zones.

The author of a 2016 Master Thesis [9] explores different methods of MPC using both a two zone model and a three zone model. The objective of each MPC method is reference tracking to a set temperature. The only disturbance that is considered in the models is a constant outside temperature. The method of modelling the zones as RC-circuits is the same as is done in this thesis.

In a 2012 research Oldewurtel et al. [10] investigate how MPC which incorporates weather prediction increase energy efficiency while keeping thermal comfort for occupants. Different controllers are tested, but when weather predictions are taken into account the highest energy saving is achieved. However the authors mention that the results are very dependent on accurate weather predictions and reliable building data. One way of ensuring good data is by deploying a sensor network like is done within a *Smart Building.*

In research conducted by Cho and Zaheer-uddin [11] it is shown that using weather prediction with a MPC in a cold climate that energy cost can be reduced by 10-12% compared to conventional methods. Those results were acquired when winter months were considered. The energy savings went up to 35.4% for warmer months. The energy savings during the winter times could be increased by using thermal storage.

1.4 Thesis Outline

This thesis is divided into six chapters. The first and current chapter introduces the problem at hand and gives motivation why this work should be done. Chapter 2 outlines the theory behind the room modelling and the MPC algorithm. In Chapter 3 the theory is applied and a control algorithm for the two zone model in Ericsson is given. Chapter 4 includes the results. Chapter 5 discuss the results, limitations and direction towards further research. Chapter 6 provides the final conclusion.

2

Theory

This chapter describes the theoretical background of three different concepts. It starts with a general overview the physical modelling of a room. Room modelling consists of inputs, disturbances and state space models. Furthermore, a general idea of a Heat Ventilation and Air Condition (HVAC) system is presented. The HVAC system is what regulates the temperature and ensures air quality in a building. The chapter then finishes with explaining how MPC works by explaining receding horizon, objective function, and optimization. The purpose of these sections is to give the reader an introduction to the concepts and its scientific status in relation to this thesis in order to be able to interpret and understand the results.

2.1 Room modelling

Room modelling is about representing and describing a physical room as a mathematical model. Equations and formulas can predict how various devices will behave in response to the inputs to these devices [12]. There are many reasons why one would want to represent a physical room as a mathematical model, e.g. to predict temperature in a room. When predicting a temperature in a room, one way to make such a prediction is to describe the room as an RC-circuit. Figure 2.1 shows a simplified circuit of the system. The resistance in the circuit is the materials which thermal energy flows through, e.g. walls and windows. The resistance for each material is described as

$$R_i = \frac{w_i}{A_i k_i} \tag{2.1}$$

where R is the resistance, i is the i^{th} material, w the width of the material, A the area, and k a thermal conductivity coefficient. The storage of thermal energy is modeled with a capacitor. Examples of energy storage materials are air, walls, and windows. The capacitance is described as

$$C_i = m_i c_{pi} \tag{2.2}$$

where C is the capacitance, m is the mass of the material, and c_p is the specific heat capacity of the material.

Without external inputs and disturbances the first order differential equation for the change in thermal energy is

$$C\frac{dT}{dt} = \sum_{i=1}^{N} \frac{\Delta T_i}{R_i} \tag{2.3}$$

where T is the temperature. Equation 2.3 is later introduced in the state space model with inputs and disturbances, explained in further details below.

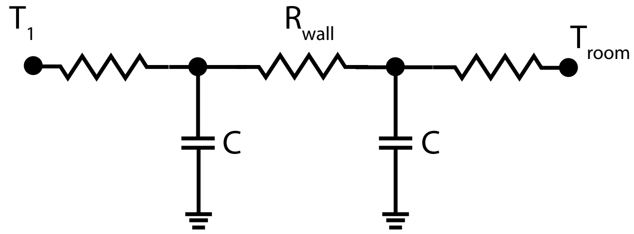

Figure 2.1: The room is modelled as an RC circuit. The resistance of the model is describing the thermal resistance of the different materials. The capacitance is describing how the materials store thermal energy, like a capacitor stores charge.

2.1.1 Inputs

A system model usually consists of signals and variables that can influence other variables in the system. These type of signals are commonly explained as external signals or inputs. Inputs can be of two types. Firstly, a control signal is an external signal that influences the system's behavior and it's time variations can be chosen [13]. The control inputs to a system are the thermal power which heats the room. The thermal power is measured in Watts [W]. If the power from the server room is used there are two thermal power inputs, one from the server room, and one from the HVAC system. If it can not be used the only controllable input is from the HVAC system. These inputs are constraint by an upper and lower threshold, based on how powerful the radiators are, how much thermal power is available from the server room, and the velocity of air coming from the HVAC system.

Secondly, the external signal or input that cannot be influenced is called uncontrollable or disturbance signal. These are the outside temperature, corridor temperature, heat generated by occupants, and electric appliances. Some of these disturbances, outside and corridor temperature, are detectable and measured. Others, like heat generated from occupants and electric appliances, are not detectable. But if the number of occupants is known then their thermal energy can be estimated since an average person generates 100 W of thermal energy when doing office tasks [14].

2.1.2 State Space Model

A state space model is a linear representation of a physical system and consists of a set of input, output, and state variables related by first order differential equations. The system is made on a matrix form and variables are made into a set of vectors;

state, input, and output. The general state space model expression of a linear system is written in the following form:

$$\dot{x}(t) = Ax(t) + Bu(t) + B_d u_d(t)$$

$$y(t) = Cx(t) + Du(t)$$

where $x(t)$ is the state vector, $\dot{x}$ is the derivative of the state vector, $u(t)$ is the input vector, $u_d(t)$ the disturbances, and $y(t)$ is the output vector. The matrices A, B, C, D relate the state and input vectors to the state derivative and output [13]. In this thesis work the A matrix relates to how energy flows through the rooms. The B matrix describes how the input effects the temperature in the rooms. The C matrix tells how the measurements relates to the states. D relates to how the input effects the measured output.

2.2 HVAC system

A heating, ventilation, and air conditioning system is used to provide comfortable temperature and decent air quality indoors [15]. It consists of an inlet fan and an exhaust fan which provide the air circulation in the system. It also includes dampers which open and close depending on how much air should go through the dampers, and the velocity of the air. Also, there are heating and cooling coils that heat or cool the air in the duct and lastly, the system includes filters that filter the air.

A typical HVAC system pumps air from the outside and into the system, where it is filtered and mixed with air already in circulation. Next the air passes through coils that heat and/or cool the air to the desired temperature for the air duct. The air is then pumped by a fan into the air duct where it travels to the zones in the building that must be supplied with air. At each zone is a reheating coil which ensures that the air entering the zone is within the thermal comfort level. To keep the air circulating, another fan pumps the air out of the room. The majority of air pumped out of the rooms is mixed with the incoming air, but the same amount of incoming air is released out into the atmosphere. Figure 2.2 shows how a simple HVAC system looks like where zone 1 and 2 represent two rooms.

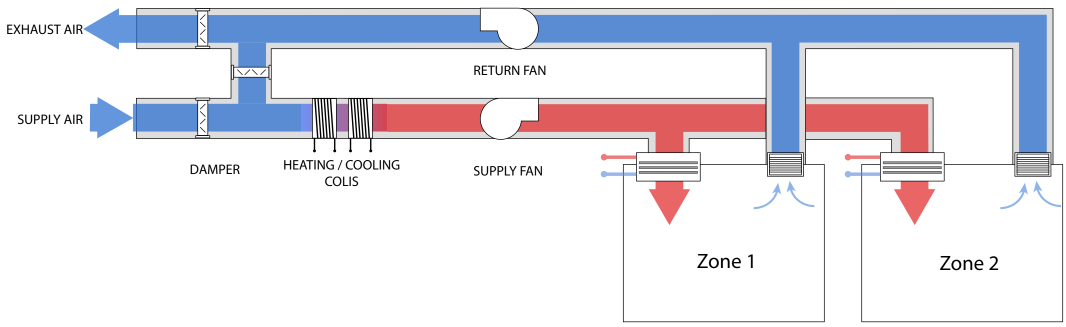

Figure 2.2: The main components of an HVAC system

The part of the HVAC system this thesis work focuses on is the thermal energy that is added to a room and is done by using a MPC.

2.3 Model Predictive Control

Model Predictive Control (MPC) is a control method where an objective function is optimized based on a set of constraints, within a finite prediction window [7]. The predicted future outputs are based on the current input, outputs, and the future control inputs. As was discussed earlier, the difference between a LQR controller and a MPC is that LQR has an infinite control horizon but the MPC has a finite horizon. This is where the concept of a receding horizon is considered.

The idea with the *receding horizon* is to choose the best control signal based on future trajectory and constraints. It is described in three steps:

1. At time instant k calculate the process response over the prediction horizon using a future control sequence.
2. Pick the control sequence which minimizes the objective function and operates within the constraints.
3. Apply the first element of the chosen control sequence, discard the rest, and move to time instant $k+1$.

Because of the receding horizon, the current information about the plant is needed for the prediction. Thus, the input can have no direct effect on the output, making the D matrix in the state space model zero [7].

Based on the state space model, the future values of each state can be estimated to span the duration of the prediction window

$$
\begin{aligned}
x(k+1|k) &= Ax(k) + Bu(k) + B_d u_d(k) \\
x(k+2|k) &= Ax(k+1|k) + Bu(k+1) + B_d u_d(k+1) \\
&= A^2 x(k) + ABu(k) + AB_d u_d(k) + Bu(k+1) + B_d u_d(k+1) \\
&\vdots \\
x(k+Np|k) &= A^{Np} x(k) + A^{Np-1} Bu(k) + A^{Np-1} B_d u_d(k) + A^{Np-2} Bu(k+1) \\
&+ \ldots + A^{Np-Nc} Bu(k+Nc-1) + A^{Np-Nc} B_d u_d(k+Nc-1).
\end{aligned}
$$

These equations are represented in matrix form in Equation (2.4)

$$X = \Psi x(k) + \Phi U + \Phi_d U_d \tag{2.4}$$

where

$$
\mathrm{X} = \begin{bmatrix} x(k+1|k) \\ x(k+2|k) \\ \vdots \\ x(k+Np|k) \end{bmatrix}
\mathrm{U} = \begin{bmatrix} u(k|k) \\ u(k+1|k) \\ \vdots \\ u(k+Nc-1|k) \end{bmatrix}
\mathrm{U}_d = \begin{bmatrix} u_d(k|k) \\ u_d(k+1|k) \\ \vdots \\ u_d(k+Nc-1|k) \end{bmatrix}
\Psi = \begin{bmatrix} A \\ A^2 \\ A^3 \\ \vdots \\ A^{Np} \end{bmatrix}
$$

$$
\Phi = \begin{bmatrix}
B & 0 & 0 & \cdots & 0 \\
AB & B & 0 & \cdots & 0 \\
A^2 B & AB & B & \ddots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
A^{Np-1} B & A^{Np-2} B & \cdots & A^{Np-Nc-1} B & A^{Np-Nc} B
\end{bmatrix}
$$

$$
\Phi_d = \begin{bmatrix}
B_d & 0 & 0 & \cdots & 0 \\
AB_d & B_d & 0 & \cdots & 0 \\
A^2 B_d & AB_d & B_d & \ddots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
A^{Np-1} B_d & A^{Np-2} B_d & \cdots & A^{Np-Nc-1} B_d & A^{Np-Nc} B_d
\end{bmatrix}
$$

2.3.1 Objective function

The objective function is the equation that is minimized given some constraints. In Equation 2.5 the objective function is represented as J and constraints are expressed on the following form, see Equations 2.6 and 2.7:

$$J(x,u) = \frac{1}{2}x^TQx + x^TF + \frac{1}{2}u^TRu + u^TE \tag{2.5}$$

$$Mx \leq b \tag{2.6}$$

$$Nu \leq \gamma \tag{2.7}$$

Where Q and R are design matrices relating to the quadratic part of the objective function. Q includes the weights put on the states, and R includes the weights for the inputs. F and E are also weight matrices for the states and inputs, but are relating to the linear terms of the objective function. M is a matrix that relates to the constraints of the states and b is the constraint vector. N is a matrix that relates to the constraints of the inputs, and γ is the input constraint vector.

Two different objective functions are considered, one quadratic and one linear. The quadratic function is considered for the reference tracking and the linear when the energy usage from the HVAC system is minimized. When the quadratic case is considered, the objective function is related to the state and how close it is to a reference value. That means that when the state is far from the reference value the result from the objective function will be high. The reference value acts as a steady state. Thus, the input value that minimizes that difference is $\Delta u(k) = u(k) - u_{ss}$, which is the deviation from the input which gives the steady state. Let $r(k)$ denote the reference value at time k, S the weight matrix on the output, and C the output matrix from the state space.

$$\begin{aligned} J(x,u) &= \frac{1}{2}(r(k+N_p) - Cx(k+N_p))^T S(r(k+N_p) - Cx(t+N_p)) \\ &+ \frac{1}{2}\sum_{i=0}^{N_p-1} \left[(r(k+i) - Cx(k+i))^T S(r(k+i) - Cx(t+i)) + \Delta u^T(k+i)R\Delta u(k+i)\right] \end{aligned} \tag{2.8}$$

Rewriting in terms of the full horizon and ignoring the constant terms, Equation (2.8) becomes

$$J(x,u) = \frac{1}{2}U^T(\Phi^T\bar{Q}\Phi + \bar{R})U + \begin{bmatrix} x(k)^T & r(k)^T \end{bmatrix} \begin{bmatrix} \Psi^T\bar{Q}\Phi \\ -\bar{T}\Phi \end{bmatrix} U \tag{2.9}$$

where $\bar{Q}, \bar{R}$ and $\bar{T}$ are

$$\bar{Q} = \begin{bmatrix} Q & & & \\ & \ddots & & \\ & & Q & \\ & & & S \end{bmatrix} \bar{R} = \begin{bmatrix} R & & & \\ & \ddots & & \\ & & R & \\ & & & R \end{bmatrix} \bar{T} = \begin{bmatrix} QC & & & \\ & \ddots & & \\ & & QC & \\ & & & SC \end{bmatrix}$$

and $\bar{Q}$ is a positive semi-definite matrix and $\bar{R}$ is a positive definite matrix.
The disturbance is not taken into account because the reference value r is the steady state value x_{ss}, which means that the disturbance cancels out

$$x(k+1) - r(k+1) = Ax(k) + Bu(k) + B_d u_d(k) - (Ax_{ss} + Bu_{ss} + B_d u_d(k)).$$

For the linear case, when the energy from the HVAC system is minimized, the objective function is seen in Equation (2.10)

$$J(x,u) = f^T[x,u]^T \tag{2.10}$$

where f is a vector which corresponds to the variables that should be optimized.

2.3.2 Optimization

The optimization used in this thesis work is called convex optimization. It minimizes convex functions over a convex set. A convex set (C) is one where a line can be drawn between any two points a, b within the set and the line is also within the set. A mathematical representation of this can be seen below:

$$a, b \,\epsilon\, C, \quad \theta \,\epsilon\, [0,1] \implies \theta a + (1-\theta)b \,\epsilon\, C, \ \forall a, b \epsilon C.$$

The convex set is bounded by the constraints on the system. If the set is not convex, there might not exist a minimum for the objective function. A convex function is a function that curves upwards, e.g. $f(x) = x^2$. Due to the upward curve, the minimum found in the optimization is a global minimum. A function that curves downward, e.g. $f(x) = -x^2$, is called a concave function. A function is convex if its Hessian matrix is positive semi-definite.

The linear objective function previously discussed in section 2.3.1 is a special case of a convex function where the Hessian matrix is zero. An example of both cases is shown in Figure 2.3.

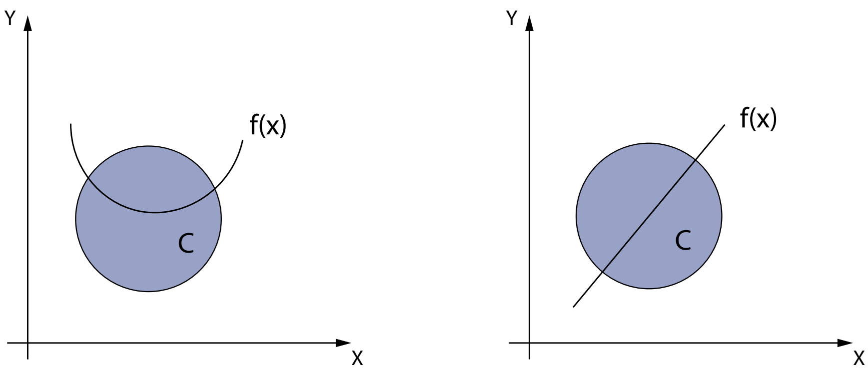

Figure 2.3: The figure shows both a linear function and a quadratic function within a convex set.

3
Methods

The initial step in the thesis work was to find use for the data and sensors, and explore in which areas the data could be used. After reviewing the sensor data, it became clear that the temperature in all meeting rooms in Ericsson's offices in Gothenburg were being controlled to a set-point value. The temperature fluctuated around 21.5°C regardless of the time of day, or if a room was occupied. This is where the premise of the problem formulation was formed. By making the temperature in the room dependent on occupation, rather than on a fixed set-point value, energy consumption could be reduced. Therefore, a controller which was capable of limiting energy usage, while keeping the temperature within a set of constraints had to be implemented. The controller chosen was a MPC. To implement the MPC, a state space model had to be constructed. It accounted for the thermal dynamics of the rooms, and incorporated the disturbances to the rooms. To further the energy savings the thermal power generated by Ericsson's server rooms was considered as an alternative heat source to the meeting rooms. The idea was to reduce the waste of pumping out the warm air in the server rooms, while heating air from the outside to warm the meeting rooms. To limit the scope of the problem, two identical rooms were chosen to share one MPC. The two rooms are subjected to disturbances from the outside, the adjacent room and corridor, and people.

The following sections derive the state space model and the MPC implementation in detail.

3.1 State Space Modelling

The thesis work focuses on two rooms that lie next to one another and share one wall. An overview is seen in Figure 3.1. The figure shows the direction of heat flow, indicated by the black arrows, which is needed to derive the state space model. The red arrows indicate the input to the system, and the blue arrows are the thermal power which is subtracted from the room.

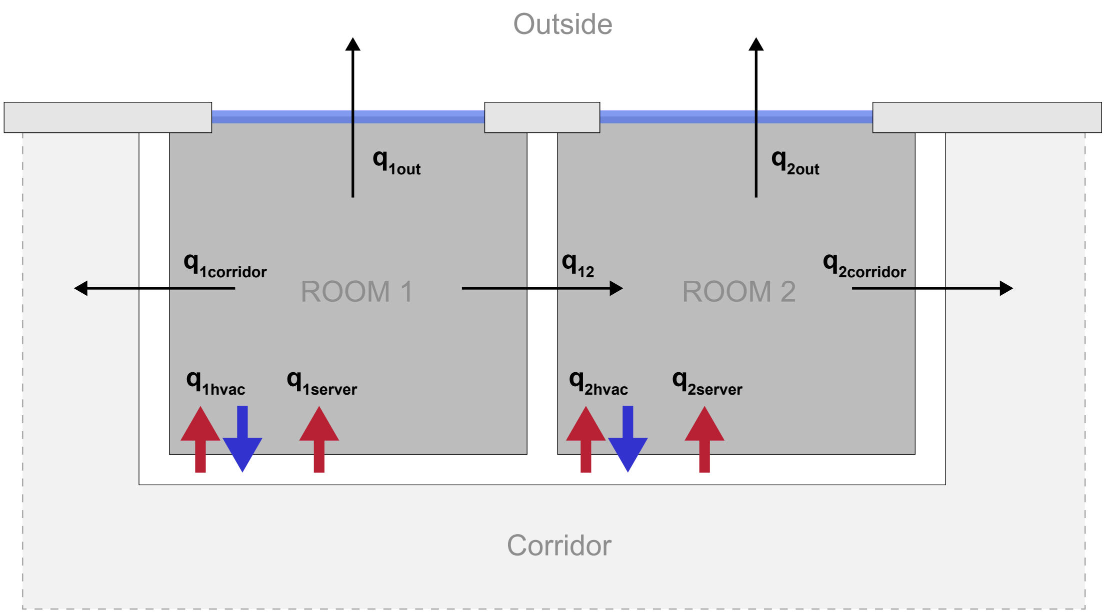

Figure 3.1: Two dimensional view of the room layout. The black arrows indicate the direction of heat flow. The colored arrow indicate the thermal power being added to or removed from the rooms.

The state space matrix is set up by deriving the mathematical equations based on Figure 3.1. Using the following steps the system in Equation (3.1) is acquired.

$$
\begin{aligned}
C_1 \frac{dT_1}{dt} &= \underbrace{q_{1server} + q_{1hvac}}_{inputs} - \underbrace{q_{12} - q_{out} - q_{corridor} + q_{people_1}}_{disturbances} \\
&= q_{1server} + q_{1hvac} + q_{people} - \frac{T_1 - T_2}{R_{12}} - \frac{T_1 - T_C}{R_{C_1}} - \frac{T_1 - T_{O1}}{R_{O1}} \\
&= q_{1server} + q_{1hvac} + q_{people} - \frac{1}{R_1} T_1 + \frac{1}{R_{12}} T_2 + \frac{1}{R_C} T_C + \frac{1}{R_{O1}} T_O
\end{aligned}
$$

$$
\frac{dT_1}{dt} = \frac{1}{C_1}(q_{1server} + q_{1hvac} + q_{people}) - \frac{1}{C_1 R_1} T_1 + \frac{1}{C_1 R_{12}} T_2 + \frac{1}{C_1 R_C} T_C + \frac{1}{C_1 R_{O1}} T_O \tag{3.1}
$$

The state equation for the right room is derived the same way, but there q_{12} has a positive sign. When the thermal power from the server room is not applied, q_{server} is disregarded.
Setting the state equations for both rooms on a state space form yields the following system

$$
\underbrace{\begin{bmatrix} \dot{T}_1 \\ \dot{T}_2 \end{bmatrix}}_{\dot{x}(t)} = \underbrace{\begin{bmatrix} -\frac{1}{C_1 R_1} & \frac{1}{C_1 R_{12}} \\ \frac{1}{C_2 R_{12}} & -\frac{1}{C_2 R_2} \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} T_1 \\ T_2 \end{bmatrix}}_{x(t)} + \underbrace{\begin{bmatrix} \frac{1}{C_1} & 0 & \frac{1}{C_1} & 0 \\ 0 & \frac{1}{C_2} & 0 & \frac{1}{C_2} \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} q_{1hvac} \\ q_{2hvac} \\ q_{1server} \\ q_{2server} \end{bmatrix}}_{u(t)} + \underbrace{\begin{bmatrix} \frac{1}{C_1 R_{C1}} & \frac{1}{C_1 R_{O1}} & \frac{1}{C_1} & 0 \\ \frac{1}{C_2 R_{C2}} & \frac{1}{C_2 R_{O2}} & 0 & \frac{1}{C_2} \end{bmatrix}}_{B_d} \underbrace{\begin{bmatrix} T_C \\ T_O \\ q_{people_1} \\ q_{people_2} \end{bmatrix}}_{u_d(t)}
$$

$$\underbrace{\begin{bmatrix} T_1 \\ T_2 \end{bmatrix}}_{y(t)} = \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}}_{C} \underbrace{\begin{bmatrix} T_1 \\ T_2 \end{bmatrix}}_{x(t)}$$

3.1.1 Numerical values

To calculate the numerical coefficients in the state space model the physical parameters of the room and its objects is considered. These parameters are related to the size of the room, the thermal capacitance, and the thermal resistance. Tables 3.1 and 3.2 show the dimension of the rooms and parametric values of the materials.

Table 3.1: Room and window dimensions in meters

	Width [B_{wi}]	Height [B_{hi}]	Length [B_{li}]
Room 1	2.7	2.7	2.3
Room 2	2.7	2.7	2.3
	Window Width [W_{wi}]	Window Height [W_{hi}]	Window Length [W_{li}]
Room 1	0.02	1.5	2.3
Room 2	0.02	1.5	2.3

Table 3.2: Different heat capacity, thermal conductivity, density and width of the different materials.

	Window glass	Sand Plaster	Cement	Air
c_p [J/kg·m^3]	840 [16]	900 [16]	1550 [16]	1005 [17]
k [W/m·K]	0.96 [18]	0.71 [18]	0.29 [18]	0.026 [18]
ρ [kg/m^3]	2500 [19]	801 [20]	1522 [20]	1.225 [20]
w [m]	0.02	0.05	0.2	

The dimensions of the room, presented in Table 3.1, make it possible to calculate the areas of the heat flow. The heat flow to the rooms depends on the area of contact and temperature at the other side of the material. Figure 3.1 shows the layout of the rooms and their surroundings. Table 3.3 shows the areas of the different heat flows.

Table 3.3: Contact areas for the different heat flows in both rooms.

Zone	Area [m^2]
Room 1 to Outside [A_{1O}]	$B_{w1}B_{h1} - W_{l1}W_{h1}$
Room 2 to Outside [A_{2O}]	$B_{w2}B_{h2} - W_{l2}W_{h2}$
Room 1 to Room 2 [A_{12}]	$B_{l1}B_{h1}$
Room1 to Corridor [A_{1C}]	$B_{w1}B_{h1} + B_{l1}B_{h1}$
Room2 to Corridor [A_{2C}]	$B_{w2}B_{h2} + B_{l2}B_{h2}$
Window 1 [A_{W1}]	$W_{l1}W_{h1}$
Window 2 [A_{W2}]	$W_{l2}W_{h2}$

The thermal resistance is what hinders the thermal flow from a room the another side of it. The resistances differ based on the material, and its area. When an area consists of two or more different materials, like a wall with window, its resistance is calculated by the parallel connection of the materials. Table 3.4 shows how the resistances for all the areas are calculated, as well as how R_1 and R_2 from the state space model are derived.

Table 3.4: The table shows how the each of the thermal resistances is calculated.

Outside resistance [R_{Oi}]	$\left(\frac{k_{concrete}A_{iO}}{w_{concrete}} + \frac{k_{window}A_{Wi}}{w_{window}}\right)^{-1}$
Corridor resistance [R_{Ci}]	$\frac{w_{plaster}}{A_{iC}k_{plaster}}$
Room 1 to Room 2 [R_{12}]	$\frac{w_{plaster}}{A_{12}k_{plaster}}$
R_1	$(\frac{1}{R_{O1}} + \frac{1}{R_{C1}} + \frac{1}{R_{12}})^{-1}$
R_2	$(\frac{1}{R_{O2}} + \frac{1}{R_{C2}} + \frac{1}{R_{12}})^{-1}$

The thermal capacitance is a materials ability to hold on to thermal energy, like a capacitor in an electric circuit can hold on to charge. The capacitance is calculated by multiplying the specific heat capacity of a material (c_p) with the material's mass. Each material is subjected to a single thermal flow. Hence the materials act like a parallel circuit of capacitors. Therefore the total heat capacity of a room is the sum of the capacitance of each material. Table 3.5 shows how the mass for each material is calculated, as well as the capacitance.

Table 3.5: The mass and capacitance for the different materials and rooms.

m_{airi}	$\rho_{air}B_{wi}B_{hi}B_{li}$
$m_{concretei}$	$\rho_{concrete}A_{iO}w_{concrete}$
m_{glassi}	$\rho_{glass}A_{iO}w_{glass}$
$m_{plasteri}$	$\rho_{plaster}A_{iO}w_{plaster}$
C_1	$c_{pair}m_{air1} + c_{pconcrete}m_{concrete1} + c_{pglass}m_{glass1} + c_{pplaster}m_{plaster1}$
C_2	$c_{pair}m_{air2} + c_{pconcrete}m_{concrete2} + c_{pglass}m_{glass2} + c_{pplaster}m_{plaster2}$

3.1.2 Discretization

When the model had been numerically derived the next step was to make the model discrete, since the MPC is a digital algorithm. The sampling time was chosen as 10 minutes. It was chosen due to the dynamics of an office building, and at which intervals meeting rooms could be booked. When a system is made discrete the following calculations are made

$$A_d = e^{A_c T_s}, \quad B_d = \int_0^{T_s} e^{A_c \tau} d\tau B_c = A_c^{-1}(A_d - I)B_c, \quad C_d = C_c$$

where the subscript d stands for discrete, the subscript c stands for continuous, and T_s is the sampling time. These calculations can be simplified by using a first order Taylor expansion. The matrices then become

$$A_d \approx I + A_c T_s$$

$$B_d \approx A_c^{-1}(I + A_c T_s - I)B_c = T_s B_c.$$

which makes them easy to implement in Matlab. The reason why a first order Taylor expansion is used to make the model discrete instead of other methods, is to keep the B matrix so that the inputs in one room does not effect the other [9], and the dynamics of the system are very slow.

3.1.3 Server Room

The server room is modeled after a general sized server room in a large office building located in colder climate. A general layout of the server room describing the heat flow can be seen in Figure 3.2 and the dimensions and specifications of the room can be seen in Table 3.6.

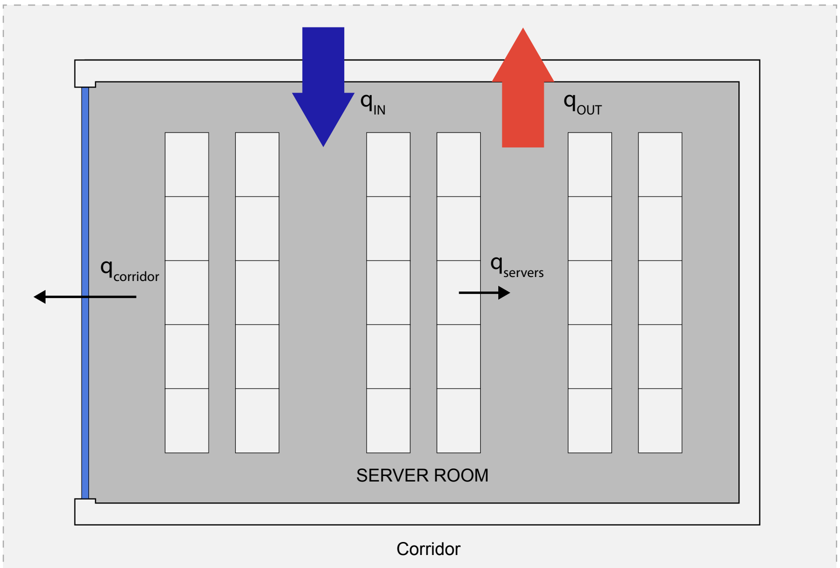

Figure 3.2: Two dimensional layout of larger server room with theoretical energy flows.

Table 3.6: Specification of room dimensions, quantity and type of servers.

Server Room Specifications			
Room Dimensions	Height [R_{hi}]	2.3	[m]
	Width [R_{wi}]	10.0	[m]
	Length [R_{le}]	10.0	[m]
	Wall Thickness [R_{th}]	0.2	[m]
Room Windows	Height [W_{hi}]	1.2	[m]
	Width [W_{wi}]	10.0	[m]
	Window Thickness [W_{th}]	0.02	[m]
Servers	Number of servers [$n_{servers}$]	600	
	Number of racks [n_{racks}]	30	
	Mass of rack with servers [$m_{servers}$]	400	[kg]
	System Heat/Power	121	[W]
	Operational Temperature [T_{Smin}, T_{Smax}]	20 - 38	[C°]
	Server Type	Dell PE860	
	Processor Type	Xeron 3070	

In reality the server room consist of multiple server types but for simulation purposes a single type commonly used server was selected to represent the the heat generation. The heat admittance is mainly dependent on on server workload and is scalable due to its linear characteristics. The room have been modeled using the same RC-circuit description as the meeting room with the resistance and capacitance variables presented in Table 3.7.

Table 3.7: Server room surface area, mass, capacitance and resistance.

$$
\begin{array}{r|l}
A_{window} & W_{wi}W_{hi} \\
A_{walls} & 4R_{wi}R_{hi} - A_{window} \\
m_{air,room} & \rho_{air}R_{wi}R_{hi}R_{le} \\
m_{walls} & \rho_{cement}A_{walls}R_{th} \\
m_{windows} & \rho_{glass}A_{window}W_{th} \\
 & \\
C_S & c_{pair}m_{air} + c_{pconcrete}m_{concrete} + c_{pglass}m_{windows} + c_{psteel}m_{rack}n_{racks} \\
 & \\
R_S & \left(\dfrac{k_{concrete}A_{walls}}{R_{th}} + \dfrac{k_{window}A_{window}}{W_{th}}\right)^{-1}
\end{array}
$$

The server room is located within the Ericsson building with no wall facing the outside. All walls connect to an inner corridor regulated at around 22°C, with one of the walls consisting mainly of a large window according to Figure 3.2. The material of the walls are concrete and the servers are mostly steel. The temperature in the room is regulated by the energy flow q_{in} and q_{out} which is controlled by a separate dedicated server room HVAC system, different from the one governing the meeting rooms. The disturbance of the system is attributed to surrounding corridor temperature $T_{corridor}$ and the energy being generated by the servers $q_{servers}$. The server room state space model below is constructed in a simular way as for the meeting rooms with $\dot{T}_S$ being the change in temperature of the server room:

$$\begin{bmatrix}\dot{T}_S\end{bmatrix} = \begin{bmatrix}-\frac{1}{C_S R_S}\end{bmatrix}\begin{bmatrix}T_S\end{bmatrix} + \begin{bmatrix}\frac{1}{C_S} & -\frac{1}{C_S}\end{bmatrix}\begin{bmatrix}q_{in}\\ q_{out}\end{bmatrix} + \begin{bmatrix}\frac{1}{R_S C_S} & \frac{1}{C_S}\end{bmatrix}\begin{bmatrix}T_{corridor}\\ q_{servers}\end{bmatrix}$$

Using Dell's own tool called Datacenter Capacity Planner [21] the maximum combined estimated heat output from the servers was calculated to $q_{s,max} = 72,6$ KJ/s for this particular server setup. The server processor utilization is represented using a sine wave function see Equation 3.2 with the energy output being the product of utilization percentage and maximum capacity. The variation is set to fluctuate between $20 - 100\%$ utilization of maximum capacity to represent average normal usage, assuming a greater server load during office hours and a lower demand the rest of the day and during weekends.

$$q_{server}(k) = q_{s,max}\frac{sin(0.044k + 0.1) + 0.6}{2.5} \tag{3.2}$$

The server room state space representation derived from the RC-circuit description is used to simulate how much energy the server room generates in an active state while maintaining a acceptable operational temperature specified by the servers. The HVAC control of the server room is regulated using linear programming optimization. Minimizing the input energy being used while keeping the room within acceptable temperature limits and generating maximum energy output. Server room control is realized using the Matlab function `linprog()` in a similar way as described in Section 3.2.3. The lower bound for the input energy is set to 100W with no upper bound for energy output:

$$\underbrace{\begin{bmatrix}-\Phi\\ \Phi\end{bmatrix}}_{A_{in}} U \leq \underbrace{\begin{bmatrix}-T_{Smin} + \Psi T(k) + \Phi_d U_d\\ T_{Smax} - \Psi T(k) - \Phi_d U_d\end{bmatrix}}_{B_{in}}$$

The resulting input control signal Q_{out} is considered to be the available energy output from the room since it is the minimum energy export needed to maintain an operational temperature of below $38°C$. In Figure 3.3 the available energy from the server room, later to be used by the MPC is presented.

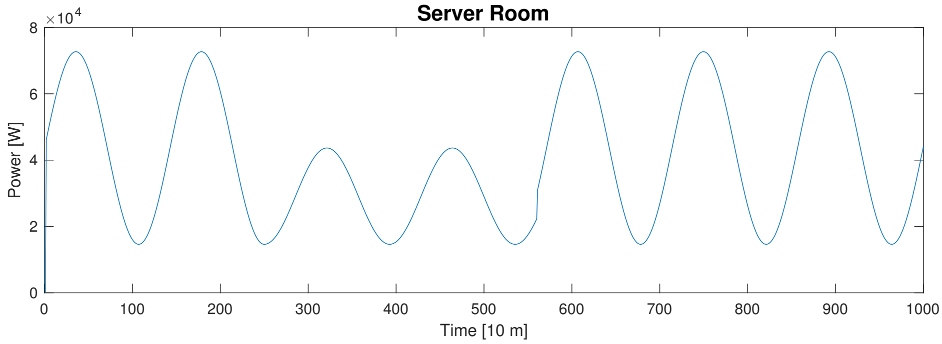

Figure 3.3: Output energy of server room being regulated at a constant temperature of $38°C$ over a 7 day period.

3.1.4 Disturbance data

The disturbance on the two rooms comes from the occupants, corridor, the other room, and the outside. The occupancy data was gathered from the PIR sensors, and the number of occupants for each meeting were obtained with a survey device which logged the number. The data from the PIR would sometimes turn a value of 1, indicating that there was somebody in the room, when nobody was using the room. Thus, the data had to be filtered and padded with the correct values. The corridor temperature was set to a constant 22°C, since it is regulated to a set point value, and no data for the actual temperature existed.
The weather data was obtained from a weather station installed on the building. It takes a sample once every hour, so to match it with the data with the sampling time of the MPC, the weather data is interpolated. It is assumed that the temperature changes linearly between samples. The outside temperature trajectory is presented in Figure 3.4.

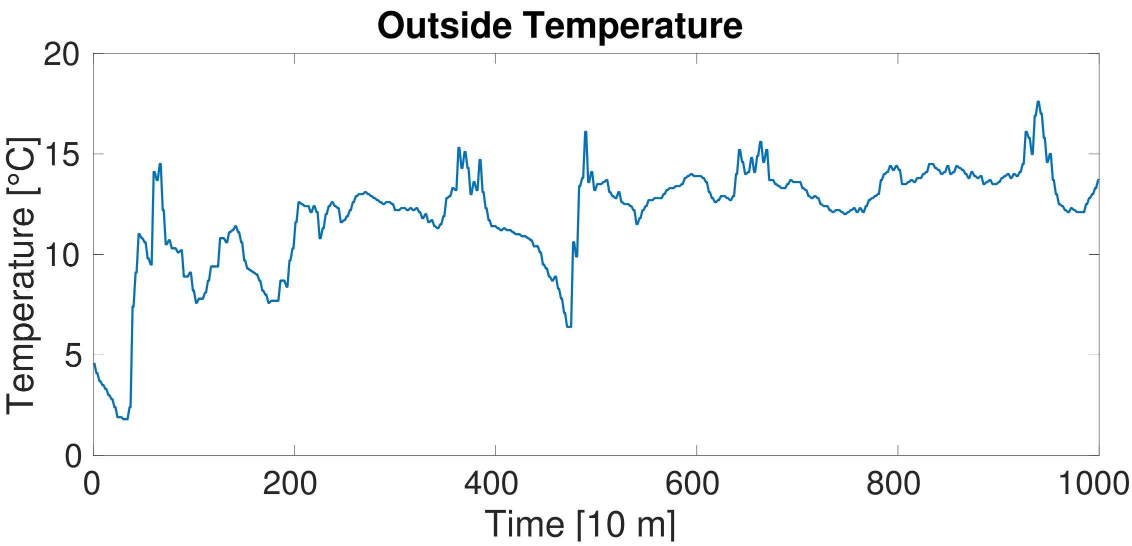

Figure 3.4: The outside temperature during the time of the simulation.

3.2 MPC

3.2.1 Objective function

There are two objective functions for the two different cases. For the reference tracking the objective function for a single time step is

$$\begin{aligned} \text{minimize} \quad & (T - T_{ref})^2 + RQ_{hvac} \\ \text{subject to} \quad & T_{min} \leq T \leq T_{max} \\ & u_{min} \leq u \leq u_{max} \end{aligned} \tag{3.3}$$

and to include the entire prediction horizon the objective function includes the Hessian and linear matrix which were derived in Equation (2.9).

For the linear case the objective is to minimize the energy used by the HVAC system. Thus the function for a single time step is

$$\begin{aligned} \text{minimize} \quad & q_{hvac_1} + q_{hvac_2} \\ \text{subject to} \quad & T_{min} \leq T \leq T_{max} \\ & u_{min} \leq u \leq u_{max} \end{aligned} \tag{3.4}$$

and to include the entire horizon, f^T from equation (2.10) becomes

$$f^T = \begin{bmatrix} 1 & 1 & 0 & 0 & \dots & 1 & 1 & 0 & 0 \end{bmatrix}.$$

When the objective functions had been implemented for the entire prediction horizon, the same had to be done for the constraints.

3.2.2 Constraints

The constraints that the MPC must operate within relate to the temperature in the room, and the thermal power used to control the temperature. The constraints on the temperature are dependent on the occupancy status on the room. If nobody is in the room the temperature range is between 15°C and 29°C, and when the room is occupied the temperature must be within 21°C and 24°C. The constraints values when a room is occupied is chosen because temperature outside of that range accounts for 96.5% of temperature complaints in commercial buildings [14]. This is incorporated in the MPC algorithm by adding a slack variable $s(k)$. The slack variable is added to form a soft constraint. This is due to the fact that output constraints can cause large changes in the control, which can yield the input variables to violate their constraints [7]. The slack variable is activated 4 time samples before a meeting starts. For each time step the change in the constraints is 1°C, until the lower bound is 21°C, and the upper bound is 24°C.

The constraints on the power used from the server room is constrained by the allowed temperature of the air that comes in to the room by the HVAC system. The other constraints on the inputs are for the radiators. The power from them can range between 0 W and 6000 W. However, due to the continuous circulation of the HVAC system, the minimum thermal power going in must be at least equal to the flow of air going in to the room at duct temperature. The duct temperature is considered constant at 10°C. Since the air does not need to be heated to 10°C, this minimum input is deducted from the total energy consumption. The MPC can choose not to use any power from the server room, which means that the lower limit is 0 W. The upper limit depends on the thermal load that the servers produce, which varies.

When the objective function includes reference tracking the power from the server room is not considered. This changes the constraints. Table 3.8 shows the constraints for both objective functions.

Table 3.8: The constraints on the MPC for both objective functions

Both objective functions	
T_{max}	$24°C + s(k)$
T_{min}	$21°C + s(k)$
Linear objective function	
$q_{servermax}$	$G_a \cdot c_{pair}(29°C)$
$q_{servermin}$	0
$q_{hvacmax}$	6000 W
$q_{hvacmin}$	0 W
$q_{server_i} + q_{hvac_i}$	$G_a \cdot c_{pair} 10°C$
$(q_{server1} + q_{server_2})_{max}$	Available power from server
Quadratic objective functions	
$q_{hvacmax}$	6000 W
$q_{hvacmin}$	$G_a \cdot c_{pair} \cdot 10°C$

These constraints must be met for the entire control and prediction horizon. Using the matrix form from Equation (2.4), the inequality constraint matrices for the linear cost function are formed as such

$$\underbrace{\begin{bmatrix} -\Phi \\ \Phi \\ -M1 \\ M2 \end{bmatrix}}_{A_{in}} U \leq \underbrace{\begin{bmatrix} -T_{min} + \Psi T(k) + \Phi_d U_d \\ T_{max} - \Psi T(k) - \Phi_d U_d \\ -U_{min} \\ U_{max} \end{bmatrix}}_{B_{in}}$$

where $M1$ and $M2$ correspond to the lower and upper bounds on the inputs respectively. To apply the constraints during the entire prediction horizon, the matrices M_{min} and M_{max} are multiplied by a triangular matrix Λ, using a block matrix multiplication.

$$M_{min} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix} M_{max} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 \end{bmatrix} \Lambda = \begin{bmatrix} I & 0 & 0 & \dots & 0 \\ I & I & 0 & \dots & 0 \\ I & I & \ddots & & \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ I & I & I & \dots & I \end{bmatrix}$$

The inequality matrices for the quadratic objective function differ from the linear, because the optimized values are the deviation Δu from the steady state u_{ss}. Thus, the inequality matrices are

$$\begin{bmatrix} -\Phi \\ \Phi \\ -N1 \\ N1 \end{bmatrix} \Delta U \leq \begin{bmatrix} -T_{min} + \Psi T(k) \\ T_{min} - \Psi T(k) \\ -U_{min} + u(k) \\ U_{max} - u(k) \end{bmatrix}$$

where $N1$ is the matrix which corresponds to the constrained states. It is calculated the same way as $M2$, because the matrix that corresponds to M_{max}, is also an identity matrix but with two states.

3.2.3 Matlab Implementation

For the linear objective function the Matlab function `linprog()` is used with the dual-simplex algorithm. It takes in the f vector which corresponds to the inputs that are minimized, and the inequality matrices A_{in} and b_{in}. The Dual Simplex is a linear programming algorithm which performs a simplex algorithm. A simplex algorithm looks for the optimum value by evaluating the objective function at the vertices of a set, which are made by the constraints. It iteratively updates the vertex set until the solution does not improve in any direction, which means that the optimum is found [22].

For the quadratic objective function the Matlab function `quadprog()` is used with the interior point convex algorithm. It takes in the Hessian matrix H and F^T from Equation (2.9), along with the inequality matrices A_{in} and b_{in} The interior point convex algorithm performs five steps [23].

1. Presolve/Postsolve. The problem is simplified, redundancies removed, and the constraints simplified.
2. Generate Initial Point
3. Predictor-Corrector. The inequalities are put on a different form, and a point where the KKT conditions are met is found.
4. Stopping Conditions
5. Infeasibility Detection

For the quadratic case the steady state value of the input must be calculated. The disturbance changes this value, so it must be calculated for every time step. It is done the following way

$$\begin{bmatrix} x_{ss} \\ u_{ss} \end{bmatrix} = \begin{bmatrix} I - A & -B \\ C & 0 \end{bmatrix}^{-1} \begin{bmatrix} B_d u_d(k) \\ r \end{bmatrix}$$

and to get the next control input the first values from `quadprog()` are added to u_{ss}.

4

Results

This chapter shows the results from the simulations. The results from the two rooms are presented in a separate sections, where each section includes results from both the quadratic and linear objective functions. Lastly, the total usage in kWh is presented. The results are acquired by simulating one week of data. During that course Room 1 is occupied for 280 minutes, and Room 2 is occupied for 730 minutes. The controllers have a prediction and control horizon that checks 6 time steps ahead, or 1 hour. The initial conditions are set to 22°C in both rooms. The reference value in the rooms was set to 21.5°C.

4.1 Room 1

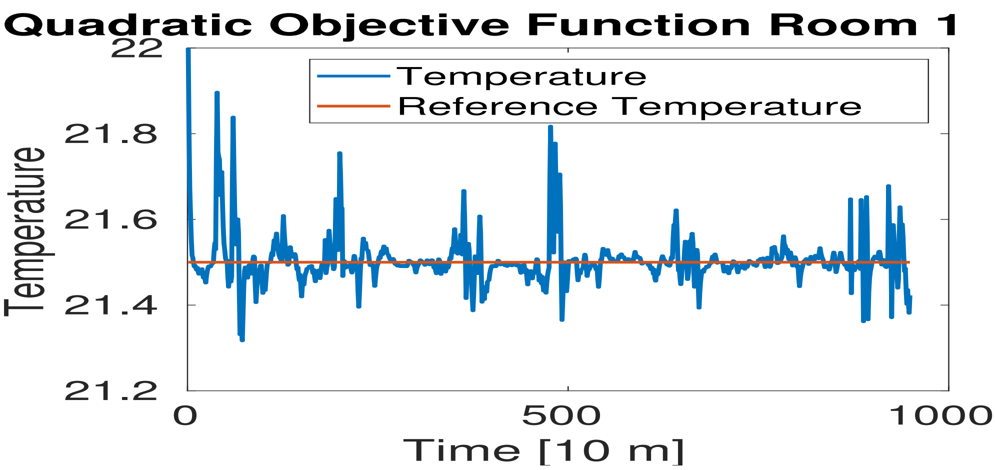

Figure 4.1: The temperature in room 1 for the quadratic objective function

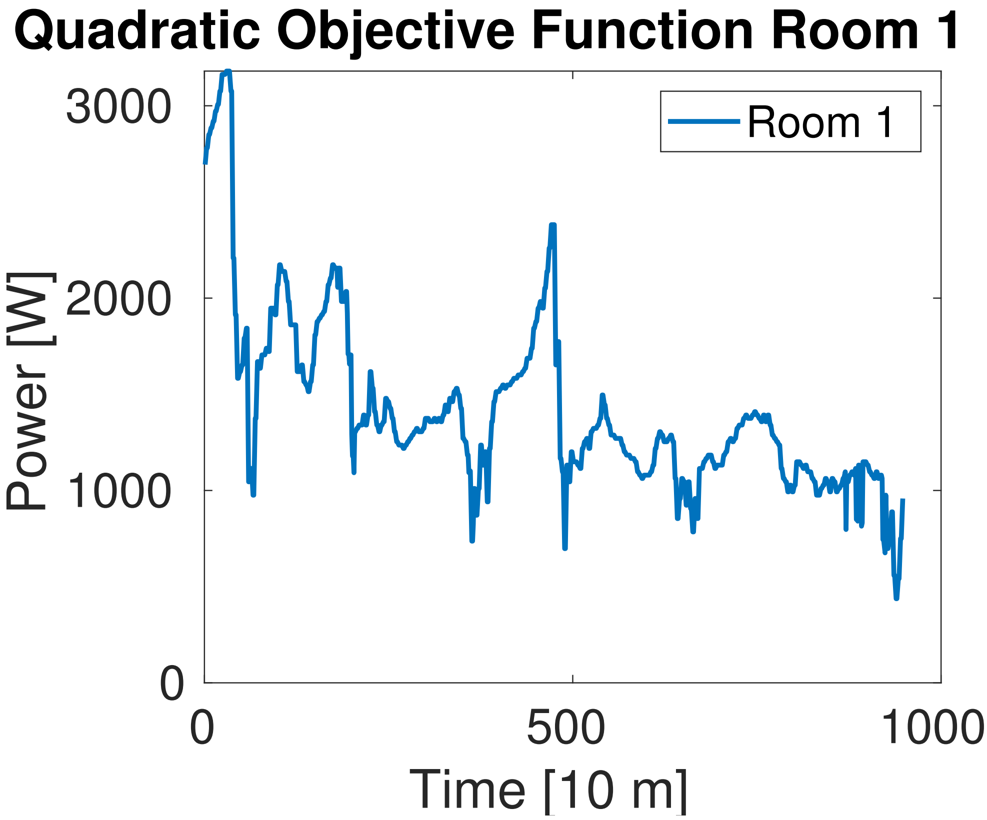

Figure 4.2: The thermal power usage for room 1

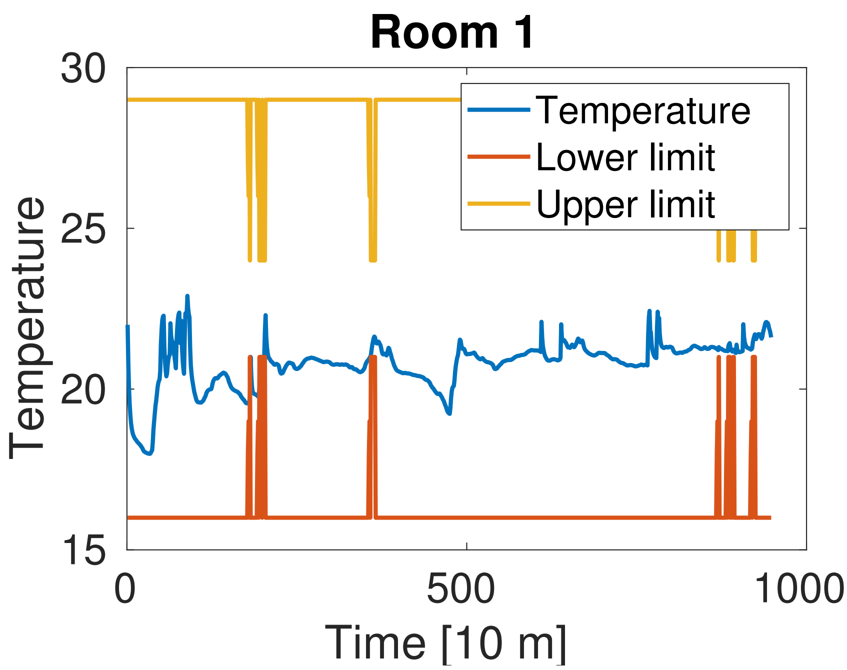

Figure 4.3: The temperature in room 1 for the occupancy based constraints

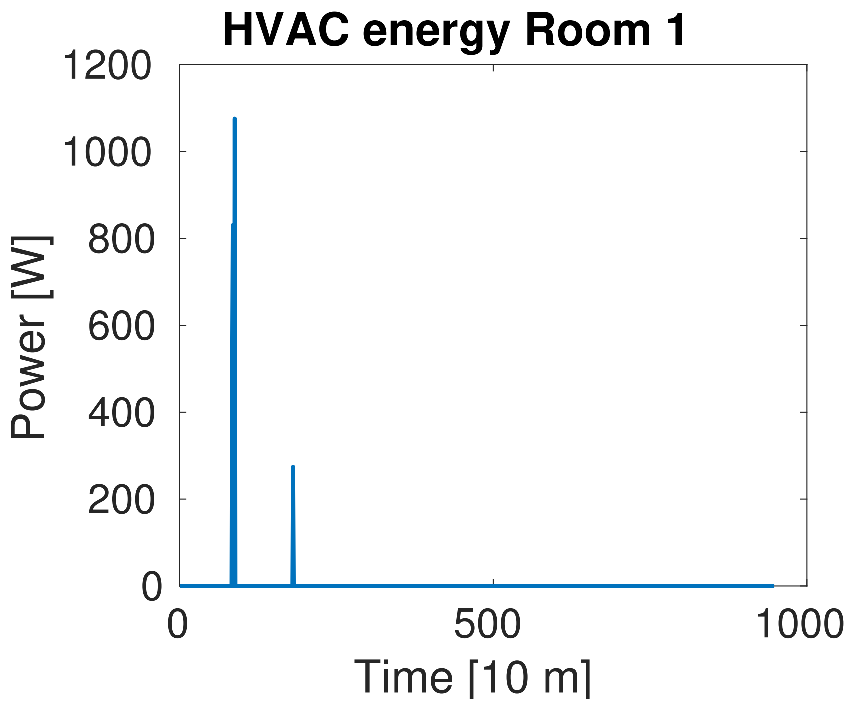

Figure 4.4: The HVAC energy usage in room 1 for the occupancy based constraints

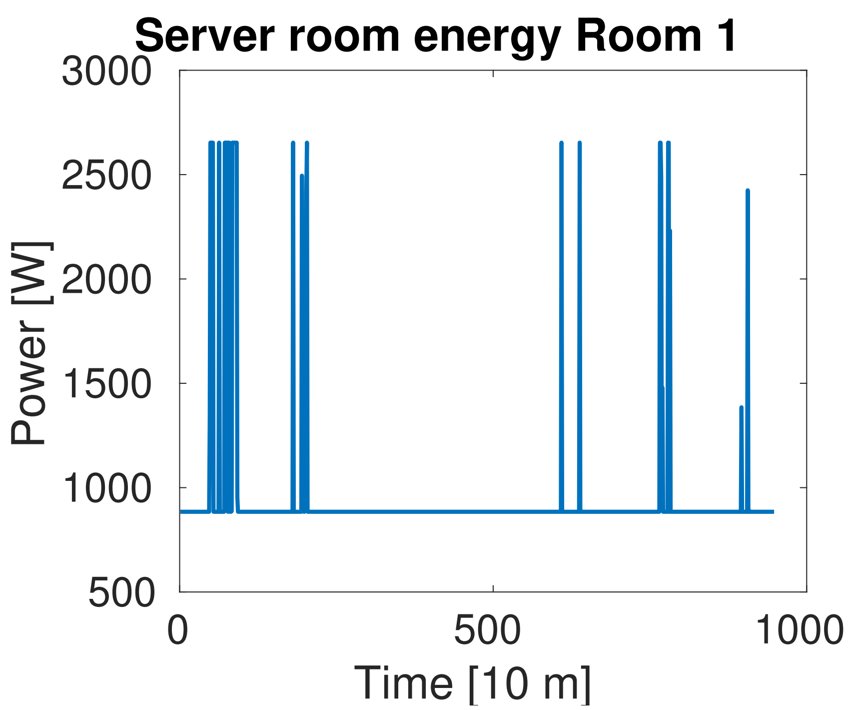

Figure 4.5: The thermal power from the server room provided to room 1 for the occupancy based constraints

4.2 Room 2

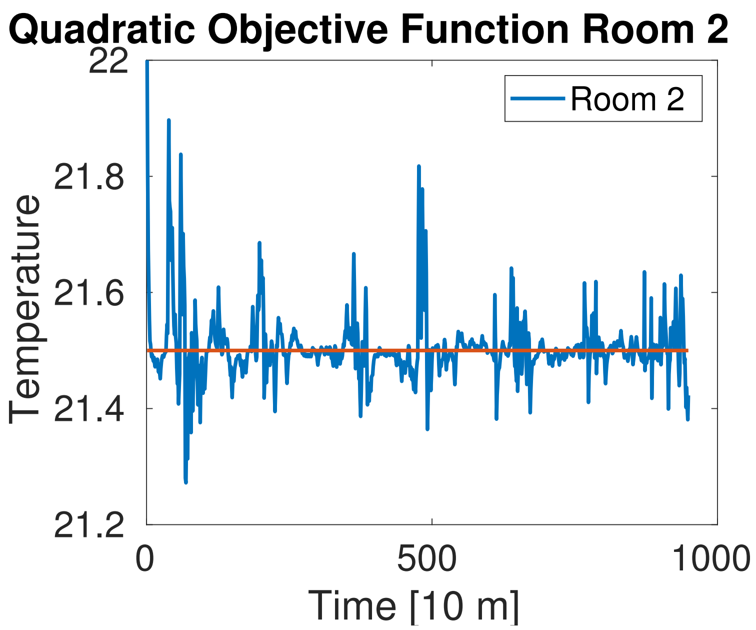

Figure 4.6: The temperature in room 2 for the quadratic objective function

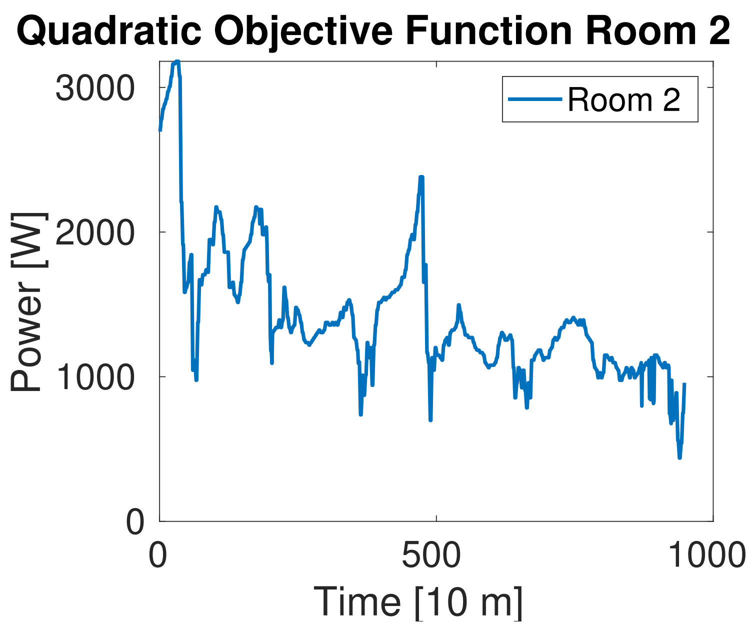

Figure 4.7: The thermal power usage for room 2

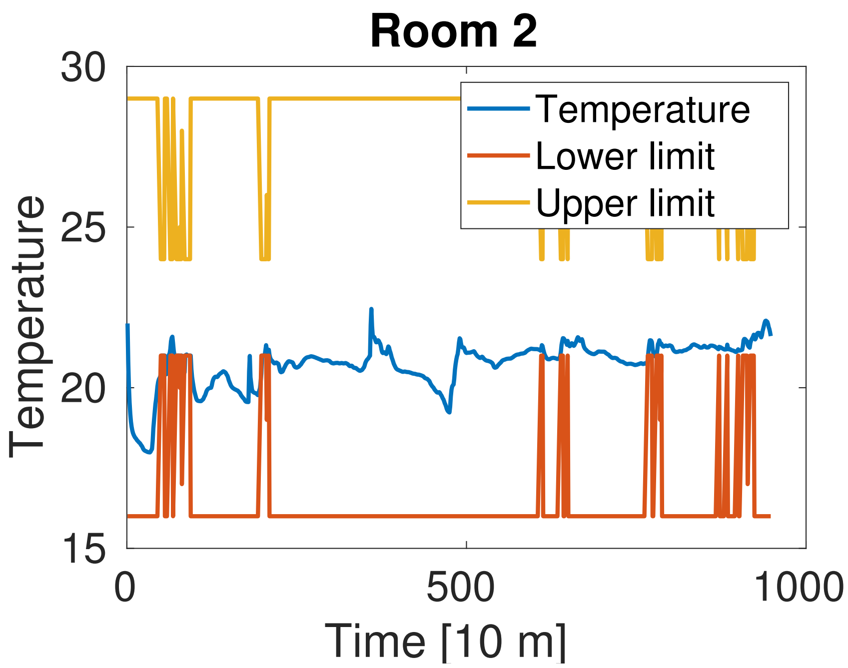

Figure 4.8: The thermal power from the server room provided to room 2 for the occupancy based constraints

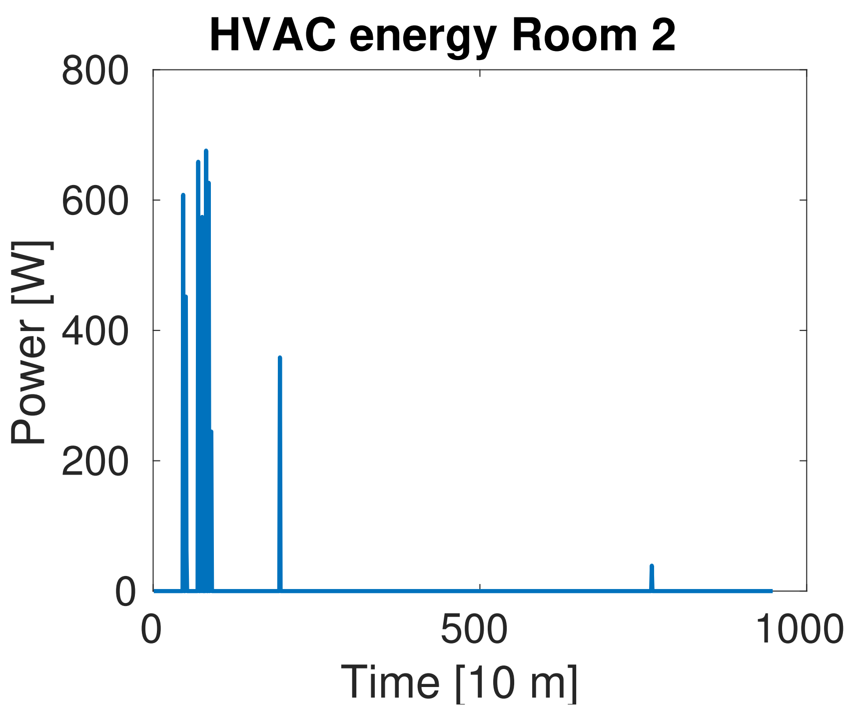

Figure 4.9: The HVAC energy usage in room 2 for the occupancy based constraints

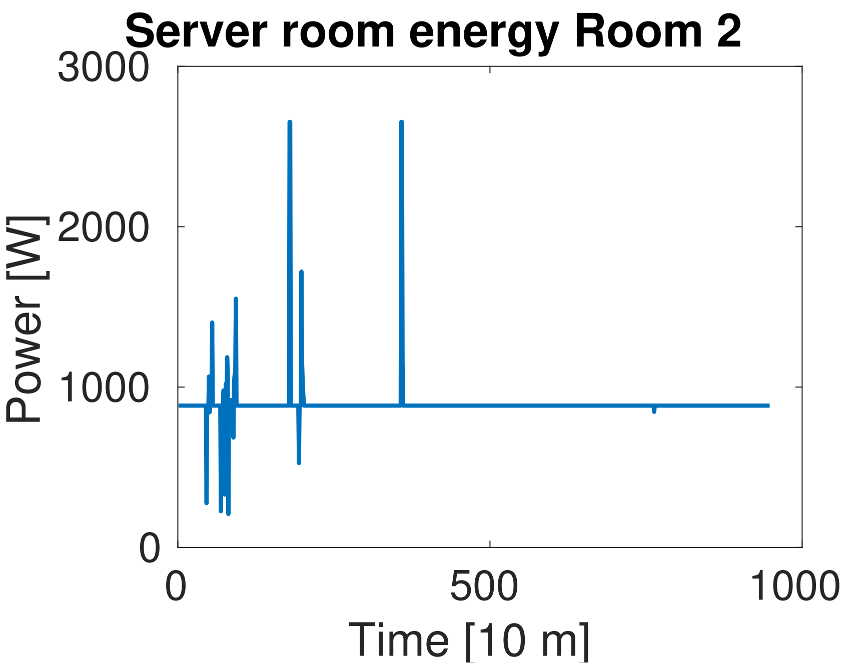

Figure 4.10: The server energy usage in room 2 for the occupancy based constraints

4.3 Numerical results

After accounting for the duct temperature, the total kWh for both cases are calculated and presented in Table 4.1.

Table 4.1: Results for one week of use

	kWh from HVAC	kWh from server room	Total
Quadratic objective function			
Room 1	83.9		83.9
Room 2	81.6		81.6
Total both rooms			**167.5**
Linear objective function			
Room 1	1.0	10.3	11.3
Room 2	0.8	1.0	1.8
Total both rooms			**13.1**

5
Discussion

This chapter discusses and interprets the results, addresses the limitations, and recommendations for future research.

5.1 Comparison between the quadratic and linear MPC

The results show that the total energy usage of the MPC which uses the linear objective function is only 7.8% of the energy usage by the MPC which uses the quadratic objective function. The energy where the HVAC system is activated is only 1.8 kWh. Analyzing the plots, it can be seen that the heating from the HVAC system is only activated before a meeting occurs. The reason for this big difference is due to the fact that the quadratic MPC has to use energy to stay near the reference value. The linear MPC can input the minimum required temperature when the room is unoccupied.

Considering that the rooms are occupied 3% and 7% for Room1 and Room2 respectively during a week, it is hard to justify having a controller with a fixed reference value, when the objective is reducing energy consumption.

The results show that the controller has a good potential to lower the energy use from a building. By implementing such a controller a win-win situation is generated where carbon emission, and the operating cost of a building are both reduced. Even if a building does not have a server room which generates so much excess thermal power, the total energy usage is still far lower than for the set-point controller.

5.2 Limitations

Certain assumptions and simplifications were made in this thesis work. Instead than focusing on the entire Ericsson office, 2 rooms were chosen to model and control. The reason was to be able to get results during the duration of the thesis project. The theory for the room modelling, and MPC is fundamentally the same when applied on a big scale. However, it was assumed that the two rooms had could utilize all the thermal power generated by the servers. In reality, each server room could provide thermal power to multiple rooms.

Another assumption was that it was known when people would be in the rooms. In reality, people do not always book a room beforehand, which could result in the temperature in a room to be outside of the thermal comfort zone.

It was assumed that all occupants created the same amount of thermal power. That is not true, and how much each person produces is dependent on height, weight, and metabolic rate.

5.3 Future Work

When the MPC is implemented on a larger scale, e.g. an office building, having a central MPC is not feasible because of the computational complexity. A solution to that is to do a distributed controller that would control a few rooms or even a single room. Then every room would have control over itself, and the computational complexity is reduced immensely.

Using the thermal capacitance properties of the room could be utilized so that a it can be "charged" with thermal power when there is excess of it, or when energy prices are low.

There are more disturbances that effect the temperature in the room than are mentioned in this thesis work, e.g. solar radiation. These disturbances are observable, like the thermal power from the occupants. These disturbances can be estimated with an observer.

Storing the thermal energy in a water tank would be a good idea, energy can be kept there and the heat fluctuations in the server room would be limited.

6
Conclusion

The objective of this thesis was to make a MPC that uses thermal power generated by servers in another part of the same building, while satisfying a number of constraints. The MPC that is implemented is compared to a controller which has a reference value at 21.5°C. The energy usage of the two controllers is then compared. Another difference between the two controllers is that the one which uses thermal power from the servers also has different constraints. When nobody is scheduled to use the room the temperature range is wider than when the room is occupied. The results from both controllers were acquired from simulation, and the same data was used in both cases. The data spans a week, and includes weather and occupation data. The controller proposed in this thesis work only used 7.8% of the energy compared to the controller using the reference value. Thereof, the majority of energy was provided by the excess thermal energy from the server room. The thesis work shows that commercial buildings have the potential of reducing their energy usage greatly by using the proposed controller.

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