OPTIMAL CONTROL OF BUILDING ENERGY WITH SMART-GRID INTERACTION

By

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A THESIS

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To My Family, Mentors, Friends and Michigan Tech

Table of Contents

List of Figures

List of Tables

List of Abbreviation

AMI	Advanced Metering Infrastructure
WSN	Wireless Sensor Network
WAN	Wide Area Network
CO_2	Carbon Dioxide
i	Index for electrical devices
J	Generalised cost function to minimize cost of energy by all electrical devices *i*
J_1	Cost of energy consumed by all electrical devices *i*
J_2	Consumption of energy by all electrical devices *i*
J_3	Cost of carbon dioxide emissions
J_4	Peak demand charges
w_1	Weight on cost of energy consumed by all electrical devices *i*
w_2	Weight on consumption of energy by all electrical devices *i*
w_3	Weight on cost of carbon dioxide
w_4	Weight on peak load of smart home due to all electrical devices *i*
P_i	Rated power of device *I (W)*
A	Set of all electrical devices *i*
t	A time instant
$s_i(t)$	State of device i at time t, binary; ON/OFF
$P^{max}(t)$	Allowed peak load of the energy hub at time t
T	Time interval duration
MILP	Mixed Integer Linear Programming
DR	Demand response
DAE	Differential algebraic equations
ISO	Independent system operator
LMP	Locational marginal prices
HVAC	Heating, Ventilation and Air Conditioning
MPC	Model Predictive Control/Controller
$\dot{Q}_{cond}$	Rate of heat transfer by conduction (J/s)

k	Conductive coefficient of heat transfer $(W/m.K)$
A	Surface area available for transfer of heat (m^2)
x_{th}	Thickness of layer available for conduction of heat (m)
$\frac{dT}{dx}$	Temperature change with respect to change in thickness of layer (x)
$\dot{Q}_{conv}$	Rate of heat transfer by convection (J/s)
h	Convective coefficient of heat transfer
$\dot{Q}_{emit}$	Rate of heat transfer by radiation (J/s)
ε	Emissivity of radiating surface
σ	Stefan-Boltzmann constant $(5.67 \times 10^{-8} \frac{W}{m^2.K^4})$
T_{emit}	Temperature of a radiation emitting surface (K)
$\dot{E}_{in}$	Rate of heat energy into a control volume (J/s)
$\dot{E}_{out}$	Rate of heat energy out of a control volume (J/s)
$\frac{dE}{dt}$	Rate of change of heat energy in a control volume
RC	Resistance-capacitance
I	Current in electrical circuit (Amp)
V_1, V_2	Voltages (V) at points 1 and 2 respectively in an electrical circuit
R	Resistance of an electrical circuit (Ω)
T_1, T_2	Temperatures at points 1 and 2 respectively (K)
C	Heat storage capacity $(J/kg.K)$
j	Wall of room $(where\ j = 1,2,3,4)$
C_p	Specific heat capacity of air $(J/kg.K)$
T_s	Temperature of air supplied by HVAC to a room (K)
T_r	Temperature of room air (K)
T_{wj}	Temperature (K) of nodes at the centre of wall j
T_{dj}	Temperature (K) outside wall j
T_{d4}	Temperature of environment outside window (K)
$R_{wj_{in}}$	Thermal resistance of inner part of wall j (K/W)
$R_{wj_{out}}$	Thermal resistance of outer part of wall j (K/W)
R_{win}	Thermal resistance of window (K/W)

R_j	Density ($\frac{kg}{m^3}$) of wall *j*
R_i	Density of inner three walls $\frac{kg}{m^3}$
R_o	Density of outer wall $\frac{kg}{m^3}$
ρ_a	Density of air ($\frac{kg}{m^3}$)
Vol_r	Volume of room (m^3)
COP	Coefficient of performance of heat pump
A_{win}	Area of window (m^2)
Th_w	Thickness of window glass (*m*)
K_w	Conductivity of window glass ($W/m.K$)
R_i	Density of inner three walls of a room ($\frac{kg}{m^3}$)
R_o	Density of outer wall of a room ($\frac{kg}{m^3}$)
k_j	Conductivity ($W/m.K$) of wall *j*
K_i	Conductivity of inner three walls of a room ($W/m.K$)
K_o	Conductivity of outer wall of a room ($W/m.K$)
h_{in}	Convection coefficient of inner three walls of a room ($W/m^2.K$)
h_o	Convection coefficient of outer wall of a room ($W/m^2.K$)
L_j	Thickness (*m*) of wall *j*
L_i	Thickness (*m*) of inner three walls
L_o	Thickness (*m*) of outer wall
C_w	Wall specific heat capacity ($J/kg.K$)
C_{wj}	Heat storage capacity (J/K) of wall *j*
C_r	Heat storage capacity of room (J/K)
A_{wj}	Surface area (m^2) of wall *j*
$\dot{m}$	Mass flow rate of air into a room from the heat pump fan ($\frac{kg}{sec}$)
$\%S_f$	Percent sensitivity function
$T_{r,base}$	Base room air temperature value
ΔT_r	Change in base room temperature value
X_{base}	Base parameter value
ΔX_{base}	Change in base parameter value
$\dot{W}$	Electricity used by heat pump (*W*)

$\dot{W}_k$	Power (W) at k^{th} hour
N	Control horizon
k	Prediction horizon
$T_{r_{lb}}^{k}$	Lower bound temperature (K) for room air temperature for k^{th} hour
$T_{r_{ub}}^{k}$	Upper bound temperature (K) for room air temperature for k^{th} hour
ε_{lb}	Slack variable for lower bound of room air temperature
ε_{ub}	Slack variable for upper bound of room air temperature
ρ	Penalty on room air temperature bounds
$Cost_k$	Cost of electricity as per power usage in k^{th} hour
P_r	Predicted cost of electricity for kth hour per MWh ($/MWh)
α	Weight on dynamic pricing term
BMS	Building energy management system
T_{sample}	Sampling time with value of 1 for continuous model and 60 minutes for discrete model
SDP	Semidefinite programming
LMI	Linear matrix inequalities

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Abstract

Nowadays, buildings with smart grid interaction are a new platform that allows implementation of innovative control technology in order to save energy and reduce cost of energy. It connects technology to the building environment making it beneficial to the residents of the building as well as the environment outside the building. The feature *dynamic pricing* of the smart grid leads to smart use of electricity in a building allowing shutdown and start-up of appliances based on high and low peak periods of dynamic pricing, respectively. Due to large HVAC energy consumption particularly heating cost during winters in the office buildings at Michigan Technological University, the thesis focuses on optimizing the energy use for HVAC system. A mathematical energy model pertaining to HVAC system of the building is developed in this thesis. Model Predictive Control (MPC) is implemented on the building energy model to develop two controllers having different cost functions, namely minimize power consumption and minimize price of power consumption. The data used for the building energy model is collected from one of the office buildings in Michigan Technological University. Both MPC controllers are compared to the existing On/Off controller in the building to determine the better controller. Further, the model is extended to six buildings connected to the same node in a smart grid. Algorithm of the better MPC controller is modified in order to ensure that the total power consumption (HVAC and Non-HVAC) of six buildings lies within the maximum allowable load at the node. Results demonstrate that MPC benefits the consumer as well as keeps the peak loads on the grid under limit.

Chapter 1

1 Introduction

With the growing energy consumption, the need for planned energy consumption has gained a focus in past few decades. Wastage of electricity (through human negligence, line losses, or damages to the grid by natural calamities), rising fuel costs and greenhouse gas emissions, needs to be controlled using advanced technology. This technology enables planned energy consumption, prevents any wastage of energy and controls emission of CO_2. In short, technology which plans and implements energy management smartly and makes the power grid robust and reliable is the need of the hour. Thus 'Smart Grid' and 'Smart Buildings' are a need of the 21^{st} century.

The following sub-sections deal with getting familiar with the concept of smart buildings and smart grid, the building-grid dynamics and mathematical modelling for the grid as well as that for energy consumption by the building in smart grid.

1.1 Background

1.1.1 Smart Buildings

Institute for Building Efficiency [1] provides an overview to 'Smart Building' concept. A smart building connects many aspects together for energy optimization. It connects all the systems of the building so that they share information and can turn down their operation when it is not needed. For example, an air-conditioner is connected to (1) sensor which detects temperature outside the building, (2) a sensor which detects presence of people in the room, and (3) a sensor which detects the frequency of opening of door of the room. Using the information from all these sensors, the air-conditioner determines what temperature it should maintain and it can reduce the cooling if there is nobody in the room. This concept is applied to lighting system, heating system, security, etc. Due to such an advanced control system, electricity is saved as well as people get a comfortable environment for working.

As described by Institute for Building Efficiency [1], the use of sensors is important in a smart building advanced energy control. Järvinen and Vuorimaa [2] explain the importance of position of sensors. They conducted experiments to determine optimum position for sensors and validated the results. The optimum position for sensors allows lights in a room to remain OFF if a person is only passing along the hallway outside the room.

A smart building not only cuts down on power consumption but when paired with smart grid helps in reducing the cost of electricity for the consumers. This interaction of a building with smart grid is discussed in subsequent sections.

Certain systems in the smart building are used for detecting the amount of greenhouse gas emissions and tracking the source of the emissions so that it can filter and process the gases before they are released into the atmosphere. As the fuel for the vehicles is depleting, the use of hybrid electrical vehicles will increase in near future. A smart building will provide charging ports for the hybrid electrical vehicles. Thus smart buildings connect technology to the environment. Hledik [3] describes how CO_2 emissions can be reduced to a great extent (reduction by 16% by the year 2030) by the rigorous use of smart meters, dynamic pricing, smart grid infrastructure and use of renewables and hybrid vehicles. in a smart building.

1.1.2 Smart Building-Smart Grid Dynamics

Reference [4] gives an insight into smart grids. Smart grids were first established in 20th century [4] by turning the traditional grids into many interconnected local grids. A grid is vulnerable to natural disasters, leading to damage in the distribution grid. A smart grid uses improved technology to prevent or detect faults thus making the grid a more reliable source of energy. Additionally, a smart grid is used most effectively, if the building that it is connected to is a 'Smart Building'.

In the traditional electrical grids, the energy flow was unidirectional, i.e. from the grid to the building. But nowadays even buildings produce energy to some extent through the use of solar panels, electrical vehicle batteries, etc. which is supplied to the grid. Traditional grids become unstable if there are many feed-in points for input of energy and even if some amount of energy is added at the distribution level, the transmission level cannot sustain it. Smart grids can accommodate large amount of energy supplied by buildings. Thus the smart grid enables bidirectional flow of energy and also manages the safety issues arising out of the reverse flow. For example, sometimes there is a rapid rise in load on the grid, e.g. rapid rise in HVAC system usage during extreme environmental conditions. Traditional grids use a couple of standby generators along with a large generator, to deal with the rapid load rise. In smart grids, instead of using standby generators, a few clients are warned about the overload and requested to reduce the load temporarily.

Dynamic pricing is a variable pricing to prevent overload on the grid. The cost of electricity is high during peak loads and the cost is low during low load periods. The smart grid informs the building about the high and low peak periods, so that the building can take appropriate actions. It is possible for the consumer to adjust the power consumption by scheduling the low priority devices during the low peak periods. This not only reduces the total cost of electricity for the consumer but also helps in flattening the peaks in the load profile of the smart grid.

A smart grid allows communication between supplier and consumers. As the cost of energy is higher at peak load periods and low at low load periods, the suppliers can strategically plan the sale of energy. Suppliers can use flexible generators, to sell energy according to low/peak periods for maximum profit. Smart grids enable the use of advanced sensors in the buildings e.g. security systems against fire that shut off the power and make urgent calls to safety services.

Setting up smart grid with non-compatible technology is pointless. Smart grid must be supported with technology capable of materializing the ideas and advantages of smart grids. Brown [5] gives an overview of the advanced technology used for smart grid implementation and the impact of automation and advanced metering on the distribution system design. Hart [6] mentions the use of Advanced Metering Infrastructure (AMI) to realize the efficient working of a smart grid. AMI carries out most of the functions of smart grid like 2-way communication, detecting technical and non-technical losses, self-healing, utility billing and integration of renewable sources into the grid.

Similar to AMI, wireless sensor network (WSN) can also be used in a smart grid. WSN carries out functions just like AMI in addition to being a low-cost solution for smart grid. Gungor, et. al. [7] investigated the challenges for setting WSN but in spite of the challenges mentioned, it has a very bright future. To get an overall idea about the working of smart grid, one can refer to [8] 'Semantic Information Modelling for Emerging Applications in Smart Grid' (2012) which has a derived semantic model for smart grid based on the detailed information about functioning of smart grid including the type of electric appliances used in the building and the application of smart grid.

1.2 Case studies: Benefits of Smart Building in Smart Grid

Tejani, et. al. [9] carried out an experiment to prove that more energy is saved with the use of smart technology in a smart home. A smart home consists of -

o Wireless internet connection

o Smart gateway – it connects the different systems of the home to each other and to external services through the internet connection.

o Sensors – few sensors gather information from the devices and send it to controller; few sensors send the processed signals from the controllers back to the devices.

o Standard appliances/devices

While experiments were conducted to calculate the amount of energy saved with the smart gateway control 'ON', data was collected for each of the appliances in each room of the house with and without smart gateway control over a period of one year (so that variation is recorded for all seasons). From the data it was observed that the duration for which the devices are ON, either decreases or remains the same except for fan. The duration for which fan is ON increases because as the duration of air-conditioner reduces, to keep the comfort level in the room at optimum level, the fan remains ON for a longer time. Power and cost of energy were calculated based on collected data. It was observed that with smart gateway control, there was significant energy and cost saving. For example, energy and cost saving for living room was 1264 kWh and $227.5 respectively; energy and cost saving for master bedroom as well as children's bedroom were 629.6 kWh and $113 respectively;

In another study, Bozchalui, et. al. [10] have presented an optimization model for residential building. They address the issue that most of the electrical appliances are designed to perform only a particular function. The design of appliances do not take under consideration multiple objectives such as user-needs, comfort level, low energy consumption, low energy cost, etc. Hence smart controllers were used for the appliances to achieve energy optimization along with low energy cost. An optimization model was developed for appliances along with smart controllers. Smart homes can be considered as energy hubs, where energy is stored, converted, consumed and also produced. This hub consists of a central controller which is connected to smaller controllers of individual appliances and the operation of the appliances can be controlled through the central controller. This can be understood better from Figure 1.1.

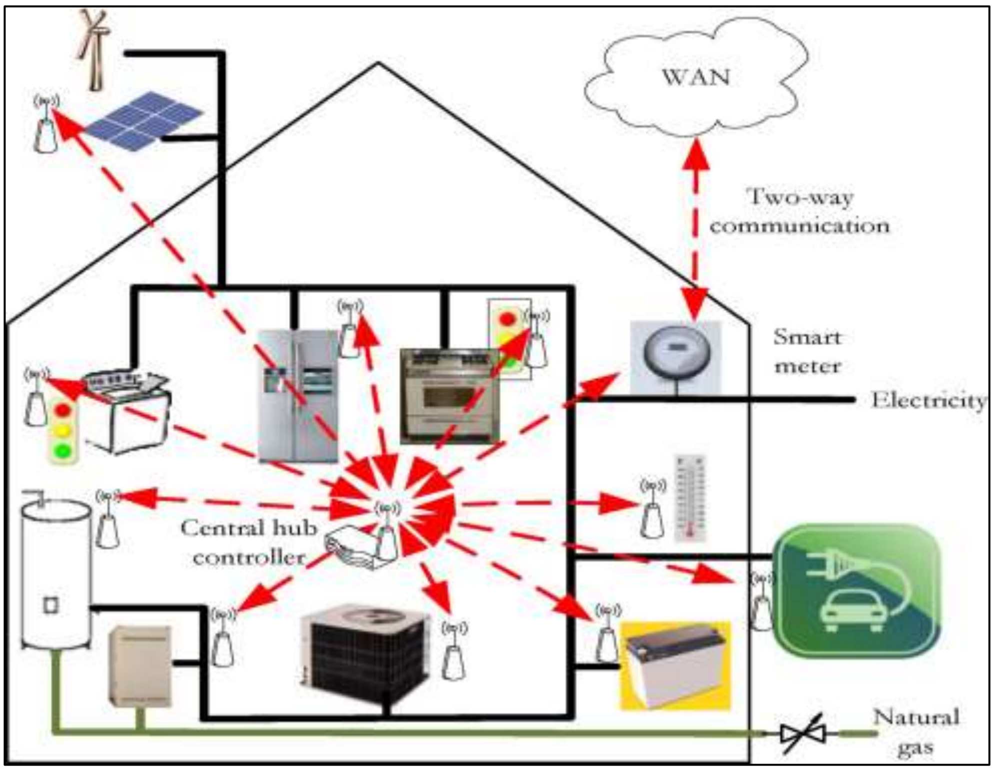

Figure 1.1: Residential energy hub structure [10] (WAN stands for Wide Area Network) © [2012] IEEE

The mathematical model of such an energy hub is affected by factors like customer behaviour patterns, time of use of the appliance, type of pricing, outside environmental conditions and carbon dioxide emissions. Based on these factors an optimization model was developed [10] as seen in equations (1.1) to (1.4).

$$min\, J = min(w_1 J_1 + w_2 J_2 + w_3 J_3 + w_4 J_4) \tag{1.1}$$

$$s.t. \sum_{i \in A} P_i s_i(t) \le P^{max}(t), \quad \forall t \in T \tag{1.2}$$

$$Device\ i\ operational\ constraints, \quad \forall i \in A \tag{1.3}$$

$$A = \{ac, esd, dry, dw, fr, ht, il, pv, pmp, stv, wr\} \tag{1.4}$$

where J_1 = cost of energy

J_2= consumption of energy

J_3= cost of CO_2 emissions

J_4= peak demand charges

w_1, w_2, w_3, w_4 = weights on cost function terms for J_1, J_2, J_3, J_4 respectively.

i = index of devices

A = set of devices

P_i = rated power of device *i*

$s_i(t)$ = state of device *i* at time *t*, binary (ON/OFF)

$P^{max}(t)$ = allowed peak load of the energy hub at time *t*

T = time interval duration

Equations (1.1) to (1.4) illustrate the optimization framework for which appropriate values of the weights are chosen in the objective function J depending on the prioritization of J_1, J_2, J_3, J_4. Operational constraints are defined for different appliances mentioned in the set *A*. These constraints include the operational time of devices, start-up and shut-down conditions, temperature limits for heat exchanger devices, minimum up time and down time, energy storage levels and illumination levels in a certain zone. The objective function along with the constraints, forms a Mixed Integer Linear Programming (MILP) optimization problem which can be solved in linear optimization software packages.

The optimization model was run for a house in Ontario, Canada. Several formulae were defined to calculate the values of the model parameters close to real life situations. On collecting data, and solving the optimization model, it was found that residential energy hub connected to a smart grid can provide upto 20% and 50% savings on energy cost and peak demand, respectively. The developed model takes into consideration the user comfort, CO_2 emissions and integration of smart grids into the daily residential life.

1.3 Modelling of Building-Smart Grid Interaction

A mathematical model of a physical system is the representation of the behaviour of the system taking into consideration the effects of various parameters and factors. It helps in better understanding of the system behaviour patterns under different situations and aids in better control of parameters. A number of models for buildings in smart grids have been developed so far. Each one has a different logic with different kinds of inputs. But all the models more or less have the same objective i.e. to minimize the energy cost and consumption. The models can be categorized as described in subsequent sub-sections.

1.3.1 Load variation and frequency of appliances' usage

All the appliances are not ON all the time. Some are switched ON/OFF very frequently, some are ON during the day/night only, some are on standby mode using lower power than the rated power, etc. Thus this variation in the frequency of use of appliances causes the load on the grid to vary.

Zhang, et. al. [11] developed an agent based model for office buildings. They categorized the appliances based on their frequency of use and then found the energy consumption by multiplying the time of use by their power rating. For simulation of the model, a case study was performed in an academic building in the School of Computer Science at University of Nottingham. The paper classified the consumers (agents) based on their behaviour as OutOfSchool, InCorridor, InOwnOffice and InOtherRooms. The agents were also divided in groups as per their time in the building like Early Birds, Timetable Compliers and Flexible Workers. In the simulation, the different agent behaviours were simulated. The appliances mainly under consideration were lighting system and computers. The power drawn by them in their different operational modes was measured using a power meter. Thus total energy consumption was calculated through simulation and using rated power values. Simulation had two parts – (1) appliances were turned ON/OFF automatically (2) appliances were switched ON/OFF by the agents. It was observed that if agents were made aware of energy conservation, the second simulation saved more power as the appliances were turned OFF immediately after use. Whereas in automation, the appliances turn OFF after approximately 20 minutes after usage. But this result ignored the fact that the agents do not bear the cost of electricity so they tend to be careless.

In another study, Shuma-Iwisi [12] took into account not only the ON-OFF modes of an appliance, but also the standby mode of that appliance. A standby mode is where the appliance is plugged into the socket, but is either waiting to be switched ON by a remote control or is performing some other functions than its normal function. Whenever an appliance is in the standby mode, it draws low power and that is called standby energy losses. In the case study conducted in 11 suburbs of greater Johannesburg, the standby energy losses were estimated using a bottom-up model. The region under case study was divided in clusters. For each cluster, saturation level was estimated for all appliances (i.e. number of houses in a specific area having that particular appliance). Appliances with high saturation were considered for further study. The load variation included the time for which appliance is in standby mode, active mode and shut off mode. Thus total energy consumption and standby power losses were calculated by multiplying the power with time for each mode of operation. The model considered average load variation instead of dynamic load variation over a large area, which might lead to inaccurate estimation of energy consumption and standby power losses.

Muthalib and Nwankpa [13] developed a circuit based model in which a relation is established between the building loads (power used) and building temperature maintained. This model is easy to incorporate into power grid as it is a circuit model. The model has three important parameters namely building nominal load, building nominal temperature and sensitivity of building nominal load with respect to building temperature. Building nominal load depends on demand response (DR). Greater the DR, larger is the nominal load. Building nominal temperature depends on the function of the building. The sensitivity of load, if negative, indicates power is required for cooling and as sensitivity increases and goes beyond zero, it indicates heating loads. Lower the sensitivity, larger is the thermal inertia, and more conducive it is for building DR technology. The circuit model was integrated into the electrical grid model using differential algebraic equations (DAE). This provided a modelling platform to capture the building-grid dynamics. If the model parameters are correctly estimated, the model is useful in finding the load variation limits and also informs the system operator to change settings of transformer in order to prevent voltage constraint being violated due to DR actions since voltage is a function of DAE (i.e. building-grid interaction).

Morvaj, et. al. [14] developed an algorithm in order to increase or decrease the demand with respect to available power supply in the grid. They have explained briefly the concepts of smart city, smart grid, smart building, smart meter (for two-way communication) and demand response programs. Demand response program is a means of interaction between the consumer and supplier of electricity. Since the price of electricity depends on whether the demand is more or less than supply (price increases or decreases respectively), it is important to manage the demand of the building in order to reduce the cost of power for the consumer. A model for a building energy direct control was developed such that when the price of electricity changes due to supply-demand imbalance, the controllable loads in the building are automatically turned on/off. The model includes human behaviour. Since human behaviour is unpredictable, it is modelled using uniform distribution i.e. probability distribution with same probability in each time interval. The simulations using this model proved that the power consumption with direct control lead to more power saving with reduced cost compared to power consumption with only price signal value and no direct control. The model behaviour for power consumption with respect to the price signal value is as expected through different scenarios for supply-demand imbalance.

1.3.2 Dynamic pricing

Dynamic pricing is an important factor that needs to be considered while developing a mathematical optimization model for the building-grid interaction in order to reduce the cost of energy.

Conejo, et. al. [15] demonstrated an optimization model with the objective of maximizing benefit to consumer provided that there is minimum energy use and also the load level should remain within maximum and minimum limits every hour. The first model developed in the paper assumed that for every hour (say t hour), the prices and energy use for the previous hour (t-1 hour) are known. This model helps to determine the energy use and load level for the 't' hour. But since price for all 24 hours is not a known quantity, they modified the model to make it more robust. The new model now receives the price for t-1 hour dynamically at the beginning of the hour. This makes the model more realistic. Simulations of the model were carried out to obtain energy use per hour. Thus knowing the load level at the beginning of the hour, the consumer can plan his energy use in order to avoid the peaks in the energy consumption graph. The implementation of the model can be realized only if there is bi-directional communication device between supplier of energy and the consumer.

Roozbehani, et. al. [16] described a model which can help stabilizing the market prices for electricity. The model has three participants namely, consumer, producer and independent system operator (ISO). According to the model, the consumer receives the market electricity prices at time, say t, generated by the ISO. Then the consumer adjusts his energy consumption according to the prices. This demand adjustment is calculated over an hour and is transmitted to the producer who adjusts his supply according to the demand. By the start of t+1 hour, new prices are generated and the process of adjusting demand, supply and prices goes on. This model was simulated using two algorithms. First was by generating prices every hour as described in the model, and second was communicating directly the Locational Marginal Prices (LMP) to the consumers. It was observed that by using the first algorithm, the variation in prices is smoother and it gives consumer some time to adjust the demand, whereas by LMP algorithm, there is a sudden change in prices giving almost no time for demand adjustment. Thus the pricing model developed gives a much more stabilized pricing than the LMP model.

Halvgaard, et. al. [17] developed a linear state space model with predictive control by heat pump. The model uses different ways to shift the load on the grid to low price period. First method was to sense the frequency of the grid (demand>supply means frequency drops and demand<supply means frequency rises). According to the frequency of the grid, the heat pump will decide whether to start the compressor early or delay the operation of heating. Another way was to feed in the controller of heat pump with the dynamic variation in prices and accordingly schedule the compressor operation. But this control is not flexible to unforeseen changes in demand and supply. Third way was to use the pricing information and have the

utilities send signals of demand variation to the heat pump. The method used in [17] is to use the current and future prices to optimize energy consumption of building. The objective of the model was to predict energy consumption by the heat pump and minimize the cost of electricity used by heat pump in order to maintain a constant thermal comfort inside the building. The assumptions while developing the model are that the price of electricity is known at all times, no outdoor factors like wind and humidity (except ambient temperature and solar radiation) or human influences building temperature and temperature throughout the building is uniform. The model includes variables of building namely, room air temperature, floor temperature, water temperature in floor heating pipes, ambient temperature, ground temperature, heat pump compressor input power and solar radiation power. Taking these variables into account, it is easier to decide when to shift the building load to lower price periods. On carrying simulation of the model, the simulation results indicated that desired control of temperature was achieved by the developed model.

A summary of modelling of building-smart grid interaction can be shown in Figure 1.2.

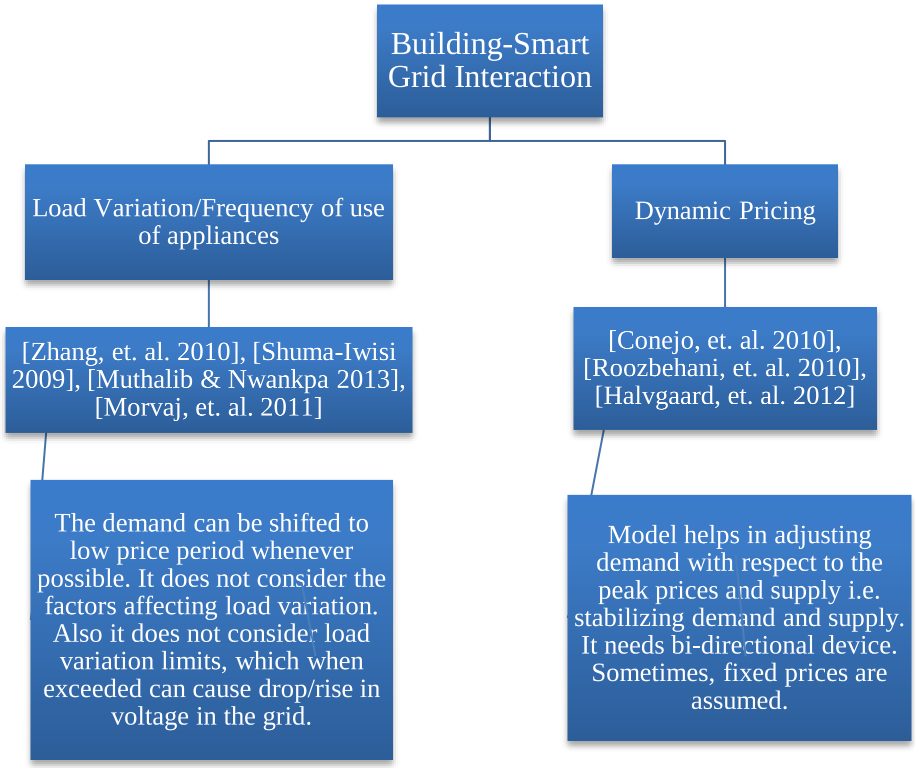

Figure 1.2: Categorization of Models for building-smart grid dynamics

1.4 Scope of Thesis

The previous sections explained the importance of modelling and controlling building-grid energy which forms the basis of this thesis. Thus the objectives of this thesis are defined as:

1) Developing a control oriented model for a campus building with focus on Heating Ventilation and Air Conditioning (HVAC) system. HVAC is the most controllable load in the building and also accounts for about 44% of energy use in buildings.
2) Designing predictive control techniques for building energy saving

3) Minimizing building energy cost in interaction with a smart grid
4) Peak load constraining for building to grid integration

1.5 Thesis Organization

Chapter 1 explained the literature study that helped in determining the objectives of the thesis as well as act as a guideline for next chapters. Chapter 2 entitled 'Building-Energy Model', deals with developing a resistance-capacitance model for the building (test bed is Lakeshore Centre, Houghton, MI), validating it and testing the sensitivity of the model with respect to various building parameters. Chapter 3 entitled 'Building Energy Optimization' explains the optimization of the building energy model and minimizing the energy using methods of Model Predictive Control (MPC). Performance of MPC is tested by comparing its results with a common On/Off controller under different environmental conditions. Chapter 4 entitled 'Energy Cost Minimization and Energy Profile Peak Constraining', uses MPC building model to minimize the cost of energy consumed. It uses dynamic pricing to optimize cost of energy. The MPC algorithm is further enhanced to constrain the peaks in the optimized energy profile so the load from the building lies within the maximum allowable load set by the power grid. Chapter 5 explains the conclusions of the thesis and provides recommendations for future work.

Chapter 2

2 Building-Energy Model

One of the objectives of this thesis is to minimize the energy consumption by the building. For that, developing the energy model for a building is one of the important steps. The energy model of a building can be one illustrating the electricity consumption by lighting or HVAC or the office equipment or all these things together. The decision as to the energy model should pertain to which energy consuming part of the building depends on what activities are dominant enough to consume maximum electricity and ease of control strategy application.

HVAC is the largest single source of energy consumption in buildings and is also the most controllable load in buildings. This thesis centres on developing an HVAC energy model for buildings. This HVAC energy model is developed based on the knowledge of basics of thermodynamics and the approach studied in previous study [10] that was explained briefly in the previous chapter.

This chapter includes basics of thermodynamics and energy transfer mechanisms in a building model, a brief introduction to resistance-capacitance model or the thermal circuit, the development of mathematical model for nodal thermal circuit of a room, experimental validation of model and finally sensitivity analysis of the model to determine key influential parameters in a building model.

2.1 Heat Transfer Mechanisms in a Building Model

To model the energy dynamics for the room, it is essential to be familiar with the mechanisms of heat transfer [27]. Heat can transfer through conduction, convection and radiation. The basic principle in all three mechanisms is that heat is always transferred from high temperature/energy area to low temperature/energy area.

Conduction constitutes exchange of particular energy whenever there is a temperature difference between two media. Heat transferred by conduction ($\dot{Q}_{cond}$) is given by Fourier's law [27] shown in equation (2.1).

$$\dot{Q}_{cond} = -kA\frac{dT}{dx} \tag{2.1}$$

where, k is the thermal conductivity. A is the surface area between the interacting media while $\frac{dT}{dx}$ is the temperature change with respect to change in thickness of layer (*x*). The negative sign indicates that heat is conducted in direction of decreasing temperature of a heat source.

Convection occurs when a fluid flows adjacent to a solid surface. It can be natural or forced convection depending on if the flow is natural or forced. Convection is a combination of conduction and fluid motion. If a solid surface is hot, heat is first transferred to the adjacent layer of fluid by conduction and then due to the fluid flow, the hotter fluid is replaced by the cold fluid. This phenomenon is modelled by Newton's law of cooling [27] shown in equation (2.2).

$$\dot{Q}_{conv} = hA(T_1 - T_2) \tag{2.2}$$

where $\dot{Q}_{conv}$ is the rate of heat transferred by convection; h is the convection coefficient; *A* is the surface area of the solid exposed to fluid flow; T_1 is temperature of solid surface and T_2 is temperature of the fluid.

Radiation constitutes heat transfer through electromagnetic waves. It does not require any medium. It can take place in vacuum. Radiation can take place between any two media irrespective of their physical state. Surfaces emit, absorb and transmit radiation through electromagnetic waves and hence it is the fastest means for heat transfer. The rate of heat transfer by radiation can be given by Stefan-Boltzmann law [27] shown in equation (2.3).

$$\dot{Q}_{emit} = \varepsilon\sigma A T_{emit}^4 \tag{2.3}$$

where ε is the emissivity of the surface; σ is the Stefan-Boltzmann constant with a value of $5.67 \times 10^{-8} \frac{W}{m^2.K^4}$; *A* is the surface area emitting radiation; T_{emit} is the temperature of the emitting surface.

Mechanisms of energy transfer consist of heat, work and mass flow. Work transfer is transfer of energy not caused by thermal gradient. Mass flow causes energy transfer due to the flow of mass in and out of a system. The generalized concept of the energy transfer is that the rate of change of energy of a system equals the difference between the rates of energy transfer in and out of the system. It is given by shown in equation (2.4).

$$\dot{E}_{in} - \dot{E}_{out} = \frac{dE}{dt} \tag{2.4}$$

The following thesis considers conduction and convection means of heat transfer for the building. Radiation is not considered in this thesis.

Heat transfer in and out of the building takes place through conduction and convection. When the temperature indoor is not uniform, heat travels from higher temperature region to lower temperature region. This transfer of heat to attain uniformity in air temperature indoors is due to convection. Convection currents are set naturally from higher temperature zone to lower temperature zone or forced convection currents in presence of an external factor like fans or blowers. Any solid surface in the building e.g. the objects in the rooms or walls, has an air film adjacent to it. Consider heat transfers through walls. If the air is hotter than the wall surface, the air film receives heat from the outer air layers via convection. The heat from the air film is transferred to the wall surface via conduction. Heat transfer through wall takes place via conduction. If the wall surface is hotter than outer layers of air, heat from the wall surface travels to the air film via conduction. Heat travels from the air film to outer layers of air through convection. Thus temperature indoors is a result of heat transfer mainly through the walls into the room or out of the room and heat input into the room by the heat pump. The heat transfer through wall is shown schematically in Figure 2.1.

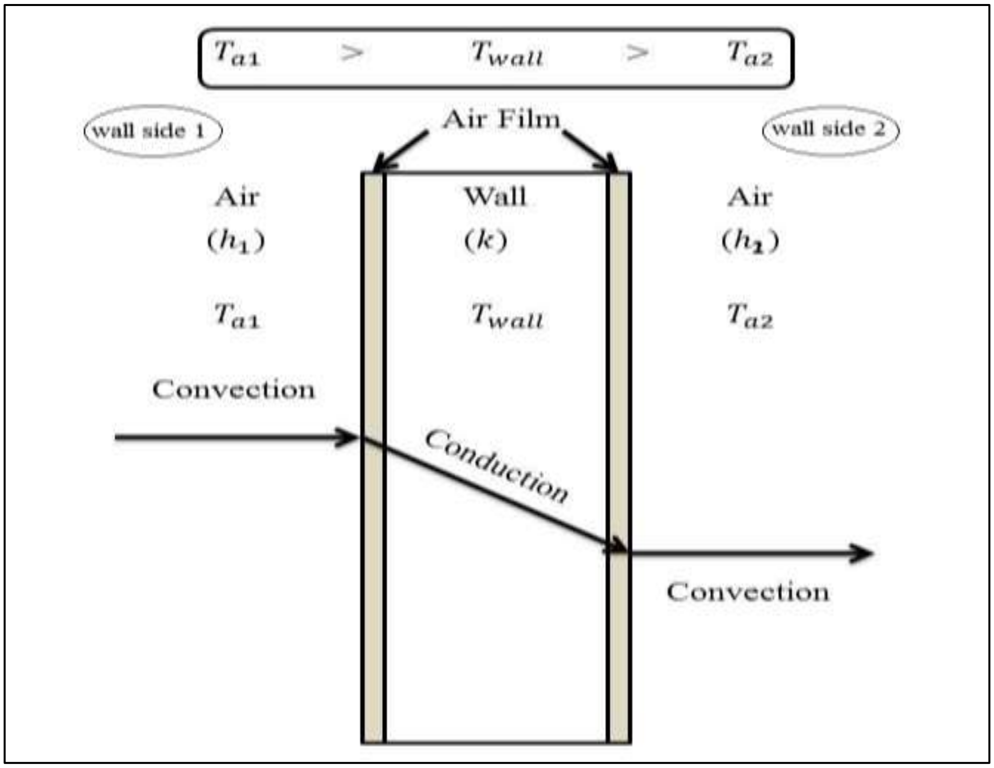

Figure 2.1: Schematic of Heat Transfer through a Wall

2.2 Model Development

The Lakeshore Centre of Michigan Technological University is selected as test bed in this thesis. This test bed has a heat pump for each of the rooms as seen in Figure 2.2. The approach in this thesis is modelling one of the rooms pointed in Figure 2.2 from Lakeshore Centre and then scaling up the model to represent a building.

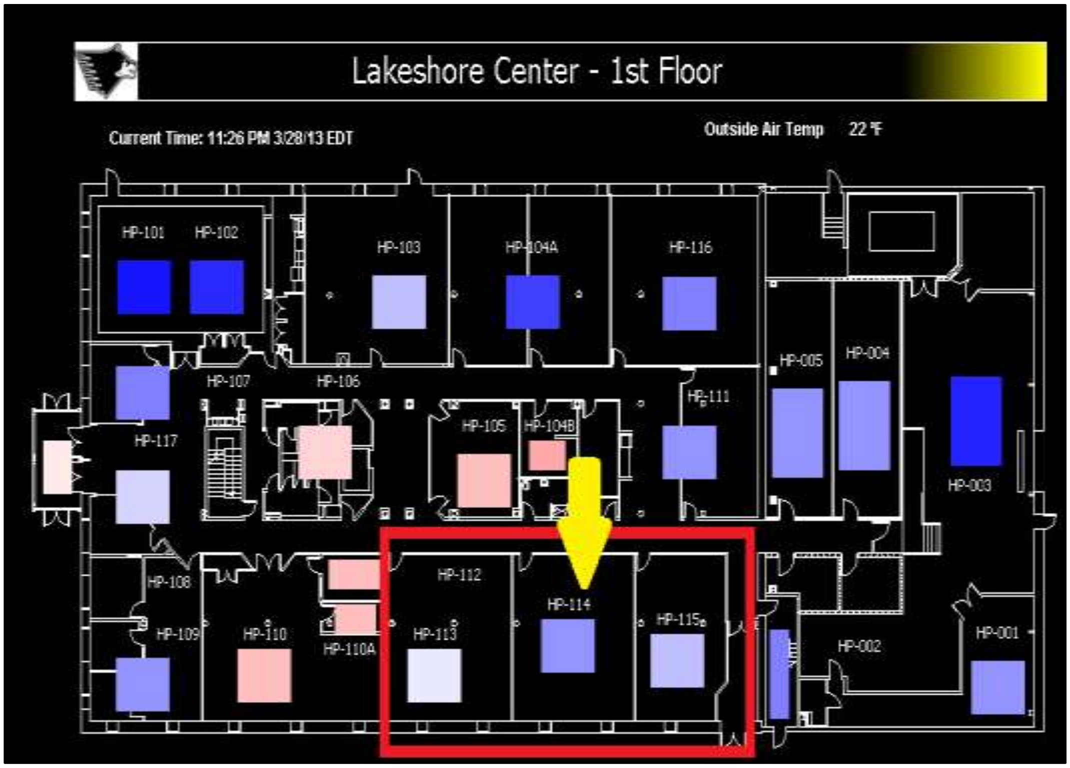

Figure 2.2: Layout of first floor of Lakeshore Centre showing all rooms and all heat pumps on that floor. [See Appendix C for documentation of permission to republish this material]

The energy model for the room is developed based on the heat transfer [27] taking place between the room and its walls and between the walls and its adjacent rooms or environment. The heat transfer mechanisms considered for the following model are conduction and convection. The model is a resistance-capacitance model (RC model) or a thermal circuit with an analogy to the resistance and capacitance of the electrical circuit [27].

The thermal resistance for the heat transfer between the room and its walls and between the walls and outside environment is conductive and convective. The thermal capacitance in the model is the heat storage capacity of the room as well as the walls.

The representation of a thermodynamic model in terms of electric circuit is called a thermal circuit. To explain thermal circuit better, refer equations (2.5), (2.6), (2.7) that give the analogy between thermal and electrical energy flow.

The voltage(V_1, V_2), current(I) and resistance (R) in an electrical circuit are related as follows:

$$I = \frac{V_1 - V_2}{R} \tag{2.5}$$

Rate of heat transferred by conduction and convection are given by,

$$\dot{Q}_{cond} = \frac{T_1 - T_2}{\frac{x_{th}}{kA}} \tag{2.6}$$

$$\dot{Q}_{conv} = \frac{T_1 - T_2}{\frac{1}{hA}} \tag{2.7}$$

The current flowing in the circuit is analogous to the heat flowing($\dot{Q}_{cond}, \dot{Q}_{conv}$); the voltage difference is analogous to the temperature difference between which the heat flows. Thus by this analogy, the conductive and convective resistances for a thermal circuit can be given by $\frac{x_{th}}{kA}$ and $\frac{1}{hA}$, respectively.

In order to calculate the resistances and the capacitances, nodes are decided. As seen in Figure 2.3, there are total nine nodes – four nodes at the centre of each wall width, one inside the room and four outside each wall of the room. Data of the nodes inside and outside the room is collected using temperature sensors which will be explained in section 2.3.

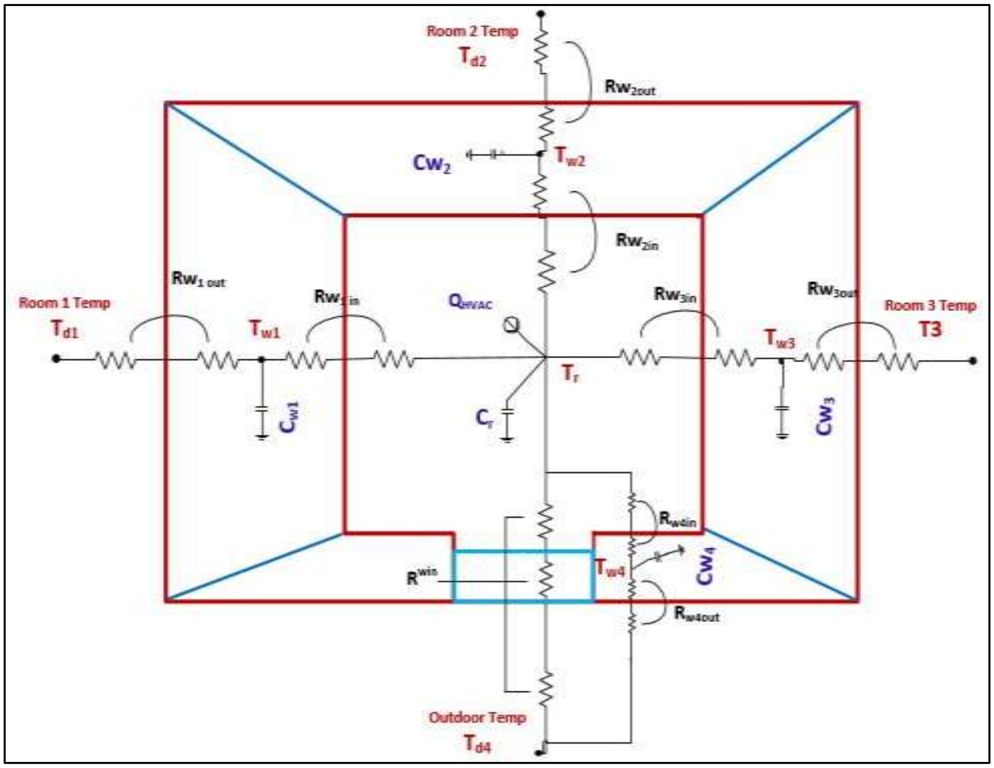

Figure 2.3: Schematic of the room model indicating the thermal nodes [19] [See Appendix C for documentation of permission to republish this material]

The energy model has two parts, first being the heat transfer in and out of the room and the second part being the heat transfer in and out of the walls. The equation governing both parts of the model is

$$\dot{E}_{in} - \dot{E}_{out} = C\frac{dT}{dt} \tag{2.8}$$

$\dot{E}_{in}$ and $\dot{E}_{out}$ is the rate of heat in and out of the room/walls; C is the heat storage capacity of the room/walls and $\frac{dT}{dt}$ is the rate of change in temperature of room/walls.

2.2.1 Heat Transfer in and out of room

Based on the equation (2.8), the first part of the model for the room is given by equations (2.9) and (2.10).

$$\dot{E}_{in} = \dot{m} \times C_p \times (T_s - T_r) \tag{2.9}$$

$$\dot{E}_{out} = \frac{T_r - T_{w1}}{R_{w1_{in}}} + \frac{T_r - T_{w2}}{R_{w2_{in}}} + \frac{T_r - T_{w3}}{R_{w3_{in}}} + \frac{T_r - T_{w4}}{R_{w4_{in}}} + \frac{T_r - T_{d4}}{R_{win}} \tag{2.10}$$

where, $\dot{m}$ = mass flow rate of air (kg/sec) supplied by the HVAC into the room

C_p = specific heat capacity of air (J/kg.K)

T_s = temperature (K) of the air supplied by HVAC to the room

T_r = temperature (K) of the room

T_{wj} = temperature (K) of nodes in centre of walls ($where\ j = 1\ to\ 4$)

T_{d4} = temperature (K) of the environment outside the window

$R_{wj_{in}}$ = thermal resistance of the inner part of walls ($where\ j = 1\ to\ 4$)

R_{win} = thermal resistance of the window

Thus giving us the first part as:

$$\left[\dot{m} \times C_p \times (T_s - T_r)\right] - \left[\frac{T_r - T_{w1}}{R_{w1_{in}}} + \frac{T_r - T_{w2}}{R_{w2_{in}}} + \frac{T_r - T_{w3}}{R_{w3_{in}}} + \frac{T_r - T_{w4}}{R_{w4_{in}}} + \frac{T_r - T_{d4}}{R_{win}}\right] = C_r \frac{dT_r}{dt} \tag{2.11}$$

where, C_r is the heat storage capacity of the room.

$$C_r = \rho_a \times Vol_r \times C_p \tag{2.12}$$

where, ρ_a = density of air ($\frac{kg}{m^3}$)

Vol_r = volume of room (m^3)

2.2.2 Heat Transfer in and out of walls

The governing energy equation for the walls yields,

$$\dot{E}_{in} = \frac{T_r - T_{wj}}{R_{wj_{in}}} \;\; ; \;\; \dot{E}_{out} = \frac{T_{wj} - T_{dj}}{R_{wj_{out}}} \; ; \;\; where\ j = 1\ to\ 4 \tag{2.13}$$

where, $R_{wj_{out}}$ is the thermal resistance of the outer part of the walls and T_{dj} is the outside temperature for each wall.

Thus the second part of the model is obtained as seen in equation (2.14).

$$\left[\frac{T_r - T_{wj}}{R_{wj_{in}}}\right] - \left[\frac{T_{wj} - T_{dj}}{R_{wj_{out}}}\right] = \; C_{wj}\frac{dT_{wj}}{dt} \; ; \;\; where\ j = 1\ to\ 4 \tag{2.14}$$

where, C_{wj} is the heat storage capacity of the walls ($where\ j = 1\ to\ 4$) and is calculated as

$$C_{wj} = C_w \times R_j \times A_{wj} \times L_j; \quad where\ j = 1\ to\ 4 \tag{2.15}$$

C_w is the specific heat ($J/kg.K$) of the walls; R_j is the density of wall j; A_{wj} is surface area (m^2) of wall j and L_j is the width (m) of wall j.

$R_{wj_{in}}$, $R_{wj_{out}}$ and R_{win} are the thermal resistances given by:

$$R_{wj_{in}} = \frac{1}{h_{in} \times A_{wj}} + \frac{L_j/2}{k_j \times A_{wj}} \tag{2.16}$$

$$R_{wj_{out}} = \frac{1}{h_{out} \times A_{wj}} + \frac{L_j/2}{k_j \times A_{wj}} \tag{2.17}$$

$$R_{win} = \frac{1}{h_{in} \times A_{wj}} + \frac{Th_w}{k \times A_{wj}} + \frac{1}{h_{out} \times A_{wj}} \tag{2.18}$$

where h_{in} = convection coefficient of the inner part of walls ($\frac{W}{m^2.K}$)

h_{out} = convection coefficient of the inner part of walls ($\frac{W}{m^2.K}$)

A_{wj} = surface area of walls (m^2)

k_j = conduction coefficient of walls ($\frac{W}{m.K}$)

L_j = width of walls (m) ($where\ j = 1\ to\ 4$).

Th_w = width of window glass (m)

Overall the energy model consists of five energy equations. The values of the parameters were either known or chosen based on the environmental conditions and/or building material properties. The values of the parameters are listed in the Table 2.1.

Table 2.1: Values of the parameters used in the Energy Model for the building

Parameter	Description	Value
C_p	Specific heat capacity of air	1005 $J/kg.K$
ρ_a	Density of air	1.205 $\frac{kg}{m^3}$
COP	Coefficient of performance of heat pump	3.2
A_{win}	Area of window	3 m^2
Th_w	Thickness of window glass	0.01 m
K_w	Conductivity of window glass	0.96 $W/m.K$
R_i	Density of inner three walls	240 $\frac{kg}{m^3}$
R_o	Density of outside wall	2000 $\frac{kg}{m^3}$
$K_i = k_j$ ($where\ j = 1,2,3$)	Conductivity of inner three walls	0.048 $W/m.K$
K_o= k_j ($where\ j = 4$)	Conductivity of outside wall	0.72 $W/m.K$
h_{in}	Convection coefficient for inner three walls	5 $W/m^2.K$
h_o	Convection coefficient for outside wall	20 $W/m^2.K$
C_w	Heat storage capacity of walls	800 $J/kg.K$

A_{wj} $(where\ j = 1{,}3)$	Surface area of inner walls	27.54 m^2
A_{wj} $(where\ j = 2)$	Surface area of inner walls	22.95 m^2
A_{wj} $(where\ j = 4)$ = $A_{w2} - A_{win}$	Surface area of outside wall	19.95 m^2
L_i = L_j $(where\ j = 1{,}2{,}3)$	Thickness of inner three walls	0.15 m
L_o = L_j $(where\ j = 4)$	Thickness of outside wall	0.70 m
$\dot{m}$	Mass flow rate of air into the room from the heat pump fan	0.52 $\frac{kg}{sec}$

2.3 Experimental Setup

The test bed under study was the Lakeshore Centre at Michigan Technological University (Figure 2.4). The energy consumption by different devices of the building [26] is shown in Figure 2.5 that was determined using carrier HAP software.

Figure 2.4: Test Bed – Lakeshore Centre, Michigan Technological University [See Appendix C for documentation of permission to republish this material]

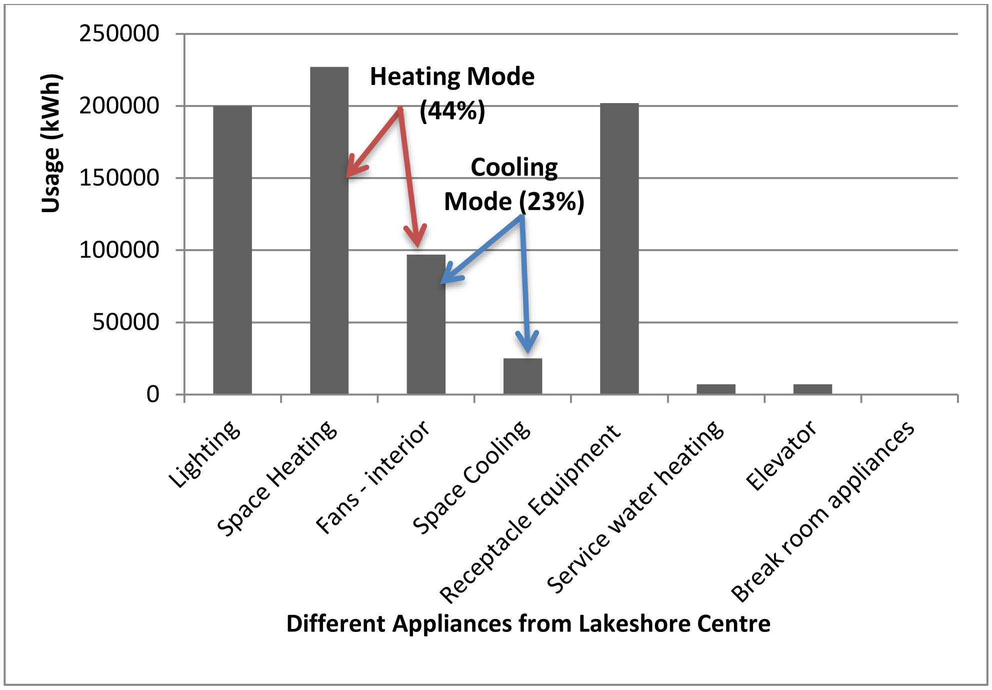

Figure 2.5: Electrical Energy usage for Lakeshore Centre [26] [See Appendix C for documentation of permission to republish this material]

As seen from Figure 2.5, the energy consumption by the HVAC is 44% in winter and 23% in summer. Hence controlling the energy usage by HVAC is important. Since HVAC consumes 44% power in winter, the objective of this thesis is to optimize the energy consumption pertaining to heat pump only. The room used for modelling and data collection is the one pointed with an arrow in Figure 2.2.

As seen in Figure 2.6, three walls of the room have two adjacent rooms and one adjacent corridor while the wall with a window faces the outside environment. The wall with a window is almost five times thicker than the rest of the three walls while the window has a double layered glass. The Building Management System (BMS) adjusts room temperature using an ON/OFF HVAC controller along with a temperature sensor (Uni-curve Type II) on one of the walls and records data using temperature data logger installed on another wall of the room. The accuracies of the sensor and the logger are ±0.2°C and ±0.8°C respectively. The measured room temperature is the average value obtained from temperature sensor and the sensor from the data logger. Thus the indoor as well as outdoor temperature data is obtained through BMS. The data which is used for validation (Section 2.4) of the model of the room is sampled every minute. The positions of the temperature sensor and data logger are as shown in Figure 2.6

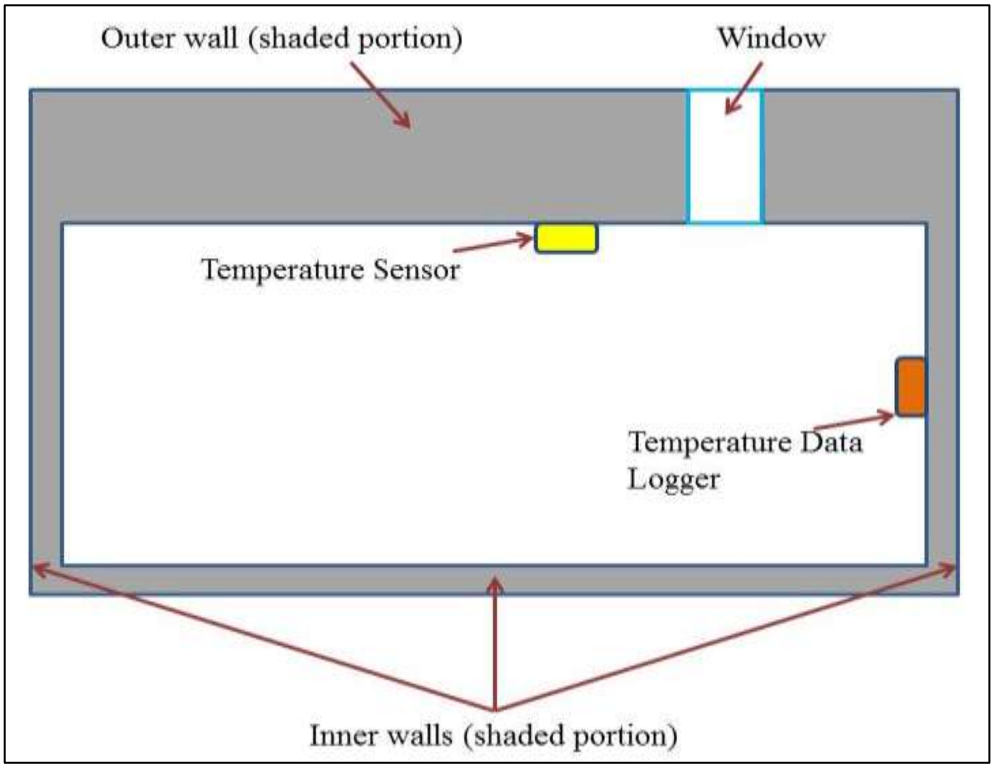

Figure 2.6: Schematic of room indicating position of temperature sensor and data logger

The room under consideration is supplied heat through a Ground Source Heat Pump. The make is ClimateMaster. It is a horizontal heat pump, with voltage 220V and flow rate 906 cfm. Lakeshore Centre has individual heat pumps for each of the rooms or zones in the building. The set point of each heat pump can be set individually based on the purpose that the room or zone serves. Thus, the room under consideration is subjected to different set points of adjacent rooms and corridor as well as extreme conditions of outside environment in winter.

2.4 Validation of the Model

The model has five differential equations and thus can be turned into a state space model. The states of the model are – room temperature and the four wall temperatures. The input for the model (matrix u in equation (2.22)) is the temperature of the air supplied by the heat pump. The disturbances to the model (matrix d in equation (2.23)) are the four temperatures outside each wall. These disturbances include the temperature variation in the two adjacent rooms, in the adjacent corridor and the outside environmental temperature. The model can be represented as:

$$\dot{x} = Ax + Bu + Fd \tag{2.19}$$

$$y = Cx \tag{2.20}$$

where,

$$x = [T_r, T_{w1}, T_{w2}, T_{w3}, T_{w4}] \tag{2.21}$$

$$u = T_s \tag{2.22}$$

$$d = [T_{d1}, T_{d2}, T_{d3}, T_{d4}] \tag{2.23}$$

$$y = T_r \tag{2.24}$$

The parameters in the model are thermal properties of the building material, dimensions of the room and air properties. The matrices A, B, F and C are shown in Appendix A. The simulation result obtained along with experimental measurements is shown in Figure 2.7.

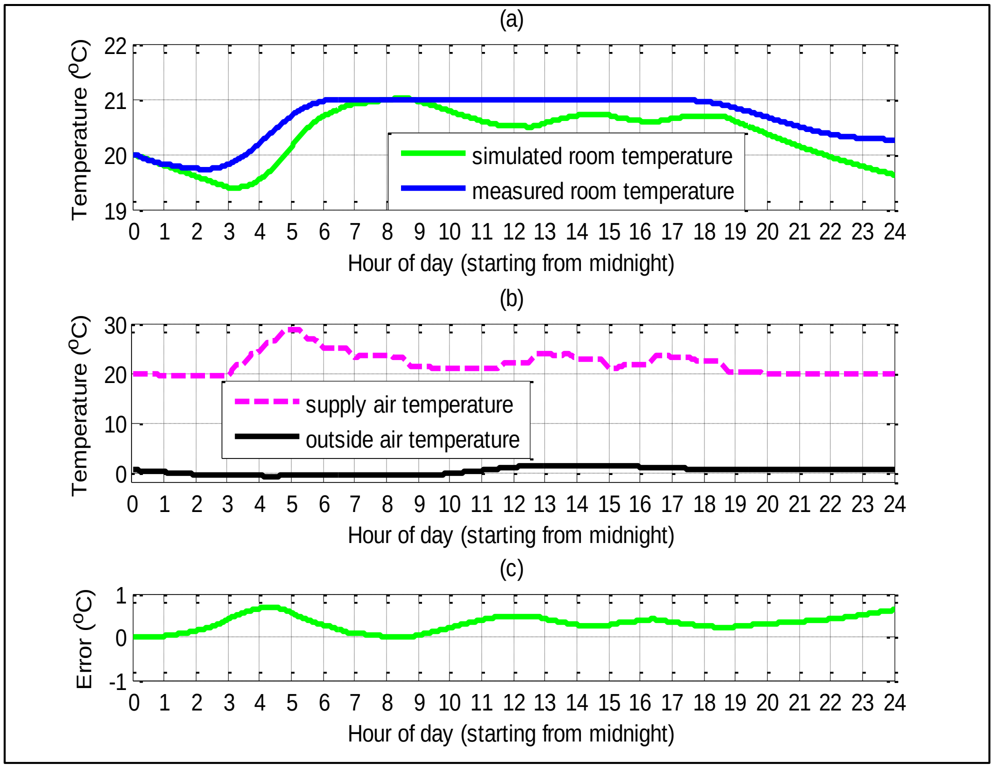

Figure 2.7: (a) Simulation Plot of Energy Model for the room showing simulated room temperature and measured room temperature both (b) Plot shows the input supply temperature and the dominant disturbance to the model which is the outside environmental temperature (c) Plot shows the error between the simulated and measured room temperatures. The error is less than 1 °C.

As can be seen from the Figure 2.7, the simulated and the measured room temperatures nearly coincide. There is a small deviation (less than 1°C) of the simulated room temperature from the measured room temperature since the radiation and internal heat generation effects are not considered into the model. Thus the energy model is validated and proves to be a very good mathematical representation of the room.

2.5 Sensitivity Analysis

Now that the model has been validated, it is important to know how variation of different parameters affects the output of the model. Such analysis is called sensitivity analysis of the model. This analysis will be useful in better selection of building materials, size of windows, size and type of heat pumps, etc. to implement better climate control strategies in buildings.

Sensitivity function for the room temperature is the ratio of unit change in room temperature to unit change in a parameter. Sensitivity has no units since its numerator and denominator are ratios of same quantities respectively. The base values of the parameters based on which the change is calculated are the values given in Table 2.1. The sensitivity function is given by equation (2.25).

$$\%S_f = \frac{\Delta T_r}{T_{r,base}} \times \frac{X_{base}}{\Delta X_{base}} \times 100 \tag{2.25}$$

where $\%S_f$ = Percent sensitivity function

$T_{r,base}$ = base room temperature value

X_{base} = base parameter value

ΔX_{base} = change in base parameter value

ΔT_r = change in base room temperature value

Sensitivity analysis is performed by changing one parameter at a time while keeping the remaining parameters constant. The range within which parameters are varied is specific to the properties of that parameter, the existing conditions of temperature, dimensions of walls, etc.

The change in base values (ΔX_{base}) of parameters is ±10% of the base value (X_{base}).

When all the parameter values are increased by 10%, their effect on the room temperature is as shown in Figure 2.8.

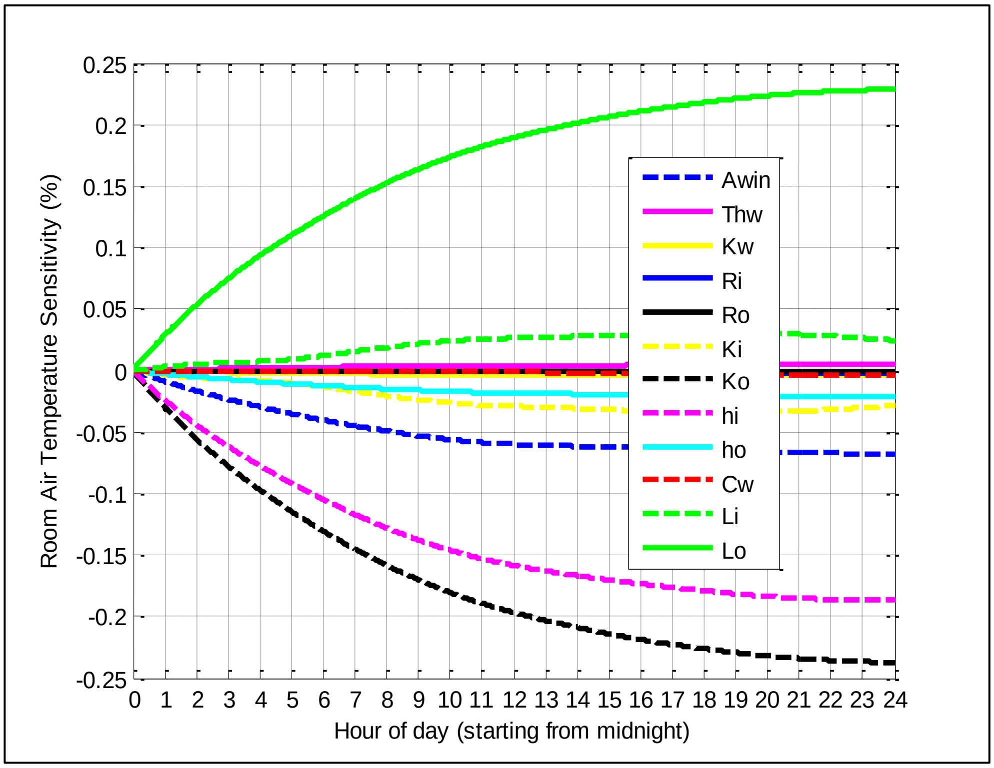

Figure 2.8: Percent sensitivity of room temperature with respect to twelve parameters

The variation of sensitivity of room temperature with respect to the parameters over 24 hours cannot be seen distinctly in Figure 2.8. In order to understand the effect of each parameter on room temperature, six time instants were chosen. For each time instant, a bar graph is plotted, each bar representing the percent sensitivity of room temperature with respect to each parameter at the same time instant with other parameters being unchanged. Figure 2.9 and Figure 2.10 show the bar graphs.

For each time instant, the bar graph has sensitivities for each parameters plotted on a same scale. Since the scale is same for all parameters, one can see the parameters which dominantly affect the room temperature in each time instant. The purpose of bar graphs is thus only to determine the dominant parameters.

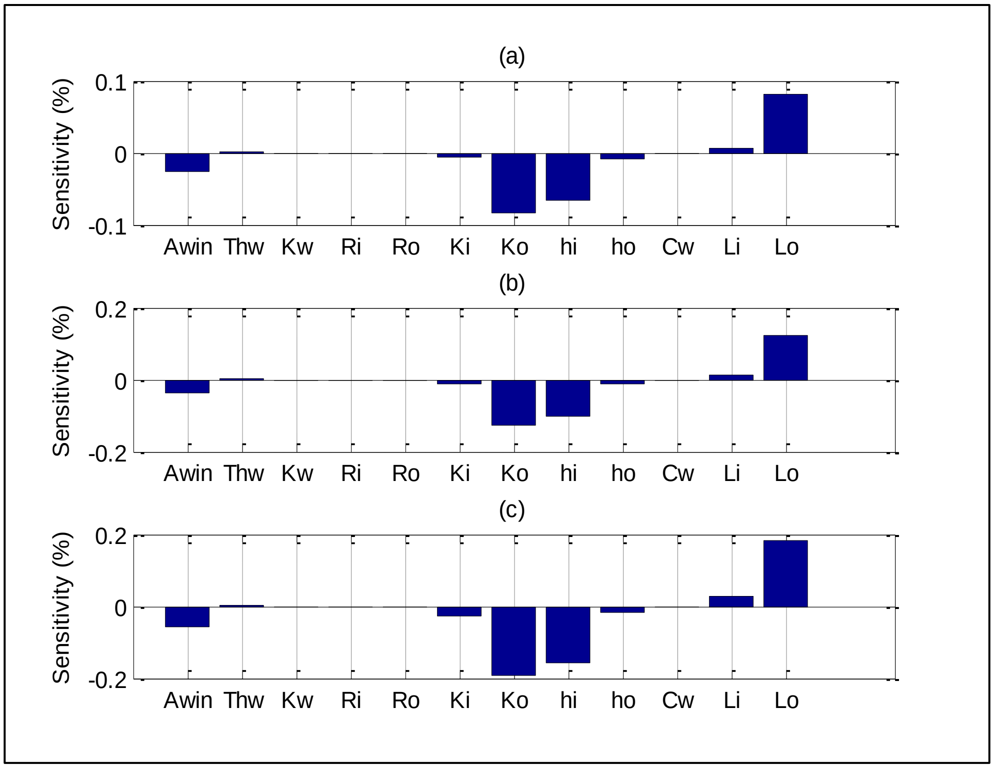

Figure 2.9: (a) Sensitivities at the 4th hour after midnight (b) Sensitivities at the 6th hour after midnight (c) Sensitivities at the 10th hour after midnight

As can be seen in the bar graphs in Figure 2.9 and Figure 2.10, sensitivities are either positive or negative. Positive sensitivity indicates that increase/decrease in the value of parameter results in increase/decrease in room temperature, respectively. Negative sensitivity indicates that the change in parameter value results in change in room temperature in opposite direction.

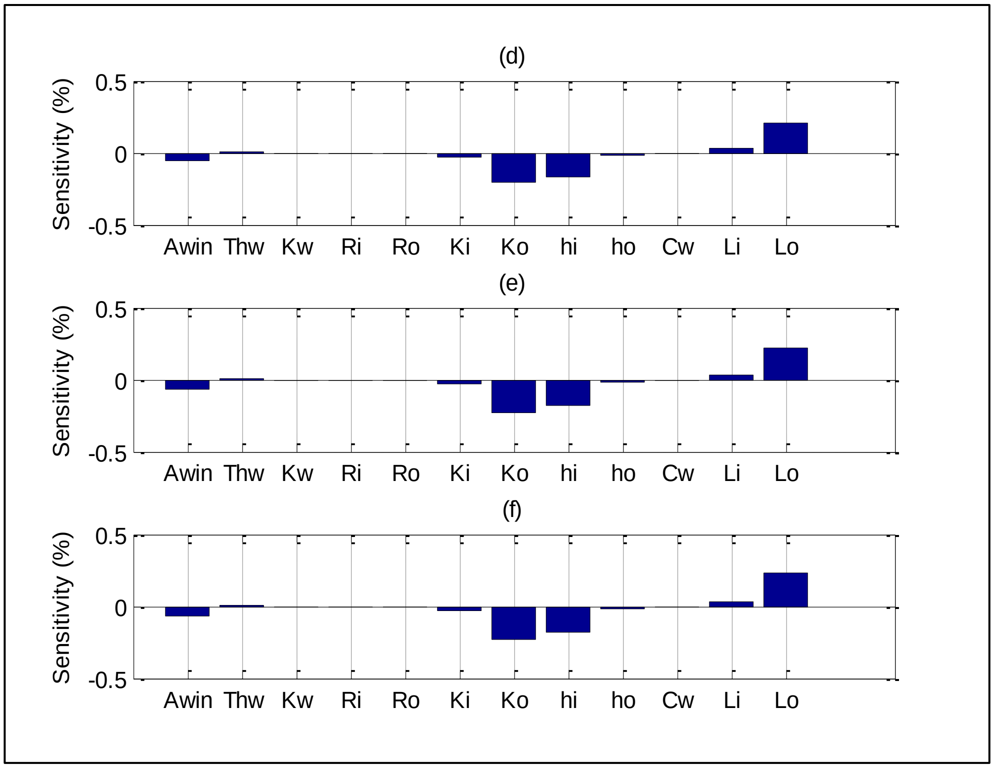

Figure 2.10: (d) Sensitivities at the 14th hour after midnight (e) Sensitivities at the 18th hour after midnight (f) Sensitivities at the 23rd hour after midnight

The effect of each parameter on room temperature is summarized in Table 2.2.

Table 2.2: Effect of different parameters and variables on the room temperature

Parameter	Description	Effect on room temperature (T_r) by increasing the parameter value by 10%
A_{win}	Area of window	T_r decreases
Th_w	Thickness of window glass	T_r increases
K_w	Conductivity of window glass	Almost zero sensitivity
R_i	Density of inner 3 walls	Almost zero sensitivity
R_o	Density of outside wall	Almost zero sensitivity
K_i	Conductivity of inner 3 walls	T_r decreases
K_o	Conductivity of outside wall	T_r decreases
h_i	Convection coefficient for inner 3 walls	T_r decreases
h_o	Convection coefficient for outside wall	T_r decreases
C_w	Heat storage capacity of walls	Almost zero sensitivity
L_i	Thickness of inner walls	T_r increases
L_o	Thickness of outside wall	T_r increases

On carefully observing the bar graphs, we can conclude that significantly dominant parameters are area of window (A_{win}), conductivity of outside wall (K_o), convection coefficient for inner walls (h_i) and thickness of the outside wall (L_o). Figure 2.11 shows comparison of sensitivity of room temperature with respect to dominant parameters 24 hours.

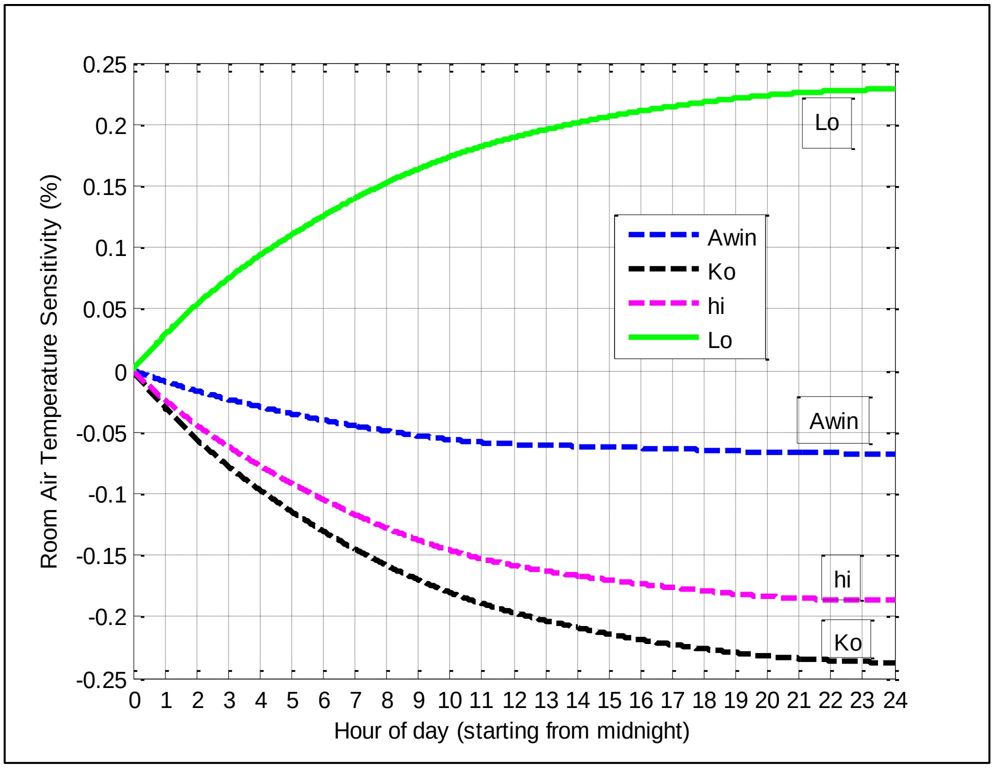

Figure 2.11: Sensitivity of room temperature with respect to dominant parameters

Effect of the dominant parameters on room temperature is such that the slope of the sensitivities is steep at the beginning and with time the slope of sensitivities tends to zero. Sensitivity of room temperature with respect to L_o is positive whereas the sensitivity of room temperature with respect to A_{win}, K_o and h_i is negative. The four parameters A_{win}, K_o, h_i, L_o are some of the parameters that define the resistance coefficient in heat transfer process. The graphs for sensitivities with respect to L_o and K_o seem to be reflection of each other about the X axis. Please note the sensitivity results can depend on the base point operating condition. The sensitivity results reported in this section are valid around the base operating point in this study.

This chapter provided an experimentally validated building energy model and analysed the effect of each parameter and variable on the room temperature thus enabling us to carry out further operations on the model. The next chapter uses this energy model for optimizing the power consumed by the heat pump by converting this continuous model into a discrete model.

Chapter 3

3 Building-Energy Optimization

3.1 Background

Optimization is a process of determining the best possible result/outcome for a problem, based on the constraints or restrictions on the flexibility of certain parameters that constitute the problem. The problem could be a situation in our day to day lives or it could be situation that can be represented as a mathematical equation. People without realizing use optimization in their day to day lives. For example, a student needs to pack his bag for school. For him the aim could be carrying minimum weight on his shoulders. So the student will take only those books which will be needed for that day's classes, he might even leave out a couple reference books. Thus the student makes optimum decision based on the restrictions on the weight and the number of classes that day.

Mathematically, optimization has made great advances and has been extremely helpful in different fields like management, manufacturing processes, engineering, research and development etc. Optimization helps in finding the best strategy/control/design which further helps in increasing efficiency, productive time, profit, etc.

Many great scientists like Newton, Leibnitz, Lagrange, Cauchy, Bernoulli, Euler etc. made contributions to the optimization field. They introduced many theoretical methods to solve different types of problems e.g. Lagrange Duality theory, Newton's method, etc. But a speedy progress was made only after the introduction of computer methods to solve optimization problems. The use of computers helps solve the most complicated and time consuming optimization problems, thus saving human time and energy. Softwares like MATLAB, GAMS, etc. have tools which already contain specific algorithms for most 'widely solved' type of problems.

The aim for this chapter is to minimize the energy consumed by the building. The algorithm used to achieve it will be the optimal control strategy which when implemented in a building, will result in minimal consumption of energy. The following chapter explains the structure of an optimization problem, the optimization problem formulation for our model, the simulation and finally the optimum results. The model and the algorithm developed for optimization is then tested for different environmental conditions. A comparison between the optimal controller and the traditional On/Off controller is studied to determine a better controller suitable as per the usage of the existing building test bed at Michigan Technological University.

3.2 Structure of Optimization Problem

Every optimization problem consists of an objective function and some constraints. An objective function is an equation which when solved using the optimum values, results in achieving the aim of the problem. The structure of a typical optimization [18] problem is represented by equations (3.1) to (3.4).

$$\min f(x) \tag{3.1}$$

$$s.t.\ g_i(x) \leq 0 \quad for\ i = 1, \ldots, m \tag{3.2}$$

$$h_j(x) = 0 \quad for\ j = 1, \ldots, n \tag{3.3}$$

$$x \leq 0\ or\ x \geq 0 \tag{3.4}$$

The problem is read as minimize the function $f(x)$ subject to the inequality constraints $g_i(x)$, the equality constraints $h_i(x)$ and the bounds for the variable x. The equality and inequality constraints and the bounds on variable x, are called design or operational constraints. The constraints come into the picture due to the practical limits on spatial and operational parameters of a design. The variable x is called as the design or decision variable. It is the value of this variable x, that is selected based on the design/operational constraints to minimize the value of the objective function $f(x)$. The objective function $f(x)$ is also called the cost function. One can maximize or minimize $f(x)$. In order to maximize, a negative of the cost function is considered. Thus {- $f(x)$} is minimized resulting in a desired maximum value. The cost function can have a constant optimum value with respect to time or the optimum value can change over time. If the optimum value of the cost function is constant with respect to time it is called a static cost function. If the optimum value of the cost function keeps changing with time, it is called a dynamic cost function.

An optimization problem can also be represented graphically. The inequality constraints and bounds define a feasible surface, called the constraint surface. Any point on the constraint surface is a feasible solution and any point outside the constraint surface is infeasible solution. The constraints are sometimes redundant constraints. For example, suppose there are two constraints $5x + 3 \leq 23$ and $x \leq 6$. Since the first constraint is effectively $x \leq 4$, the constraint $x \leq 6$ is redundant. An optimization problem does not always have to have constraints. Such problems are called unconstrained optimization problems.

Depending on the nature of a problem, the numbers in the equations can be integers or real, deterministic or random. Likewise, the equations can also be linear or non-linear, quadratic or polynomial.

The structure of the optimization problem given at the start of this section is for only one variable x. If there are multiple decision variables, the problem has the same format with more constraints for additional decision variables. A generalized format for an optimization problem with single or multiple decision variables [18] is represented by equations (3.5) to (3.14).

$$\min f(x, y, z) \tag{3.5}$$

$$s.t.\ g_{i_1}(x) \leq 0 \quad for\ i_1 = 1, \dots, m_1 \tag{3.6}$$

$$g_{i_2}(y) \leq 0 \quad for\ i_2 = 1, \dots, m_2 \tag{3.7}$$

$$g_{i_3}(z) \leq 0 \quad for\ i_3 = 1, \dots, m_3 \tag{3.8}$$

$$h_{j_1}(x) = 0 \quad for\ j_1 = 1, \dots, n_1 \tag{3.9}$$

$$h_{j_2}(y) = 0 \quad for\ j_2 = 1, \dots, n_2 \tag{3.10}$$

$$h_{j_3}(z) = 0 \quad for\ j_3 = 1, \dots, n_3 \tag{3.11}$$

$$x \leq 0\ or\ x \geq 0 \tag{3.12}$$

$$y \leq 0\ or\ y \geq 0 \tag{3.13}$$

$$z \leq 0\ or\ z \geq 0 \tag{3.14}$$

Classification of an optimization problem is based on constraints (Constrained, Unconstrained), based on type of equations (Linear/Non-linear, Quadratic, Polynomial) and based on nature of decision variables (Integer/Real, Deterministic/Stochastic). Depending on the nature of the cost function, the constraints and the decision variables, different algorithms/methods are used to obtain the optimal solution. Some of the commonly used optimization methods include Augmented Lagrangian method ([18],[20]), Branch and Bound[18], Dynamic Programming ([18],[20]), Travelling Salesman algorithm[18], Newton's method[18], Nonlinear Programming ([18],[20]), Greedy Algorithm[18]. This thesis uses Model Predictive Control [20] to minimize energy usage by the building. This optimization based control technique is explained in the subsequent section.

3.3 Model Predictive Control using Receding Horizon Control Method

The section 3.2 explains the basics of optimization. The traditional methods of optimization are methods in which all the actual values of necessary data are known all at once and the optimization is carried out offline. In some cases, the actual values of data cannot be known beforehand; they need to be predicted one or few at a time and optimization needs to be performed in real time (online optimization). Such optimization wherein the optimal solution is evaluated based on some predicted values of necessary data and a mathematical optimization model (Section 3.2), is called Model Predictive Control (MPC). Sometimes input to the model is predicted and optimal output is calculated while in some other cases, disturbances in the model are predicted and optimal inputs along with optimal outputs are evaluated. The period for which MPC is implemented is a called a *control horizon*. The period for which data is predicted at a time is called the *prediction horizon*. A control horizon comprises of one or many prediction horizons. The difference between traditional (offline) optimization and MPC (online optimization) can be understood from the schematics in Figure 3.1 and Figure 3.2.

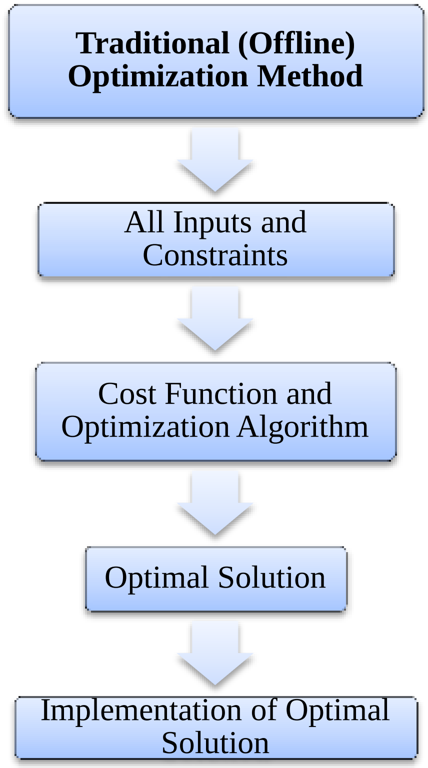

Figure 3.1: Schematic of Traditional Optimization Method

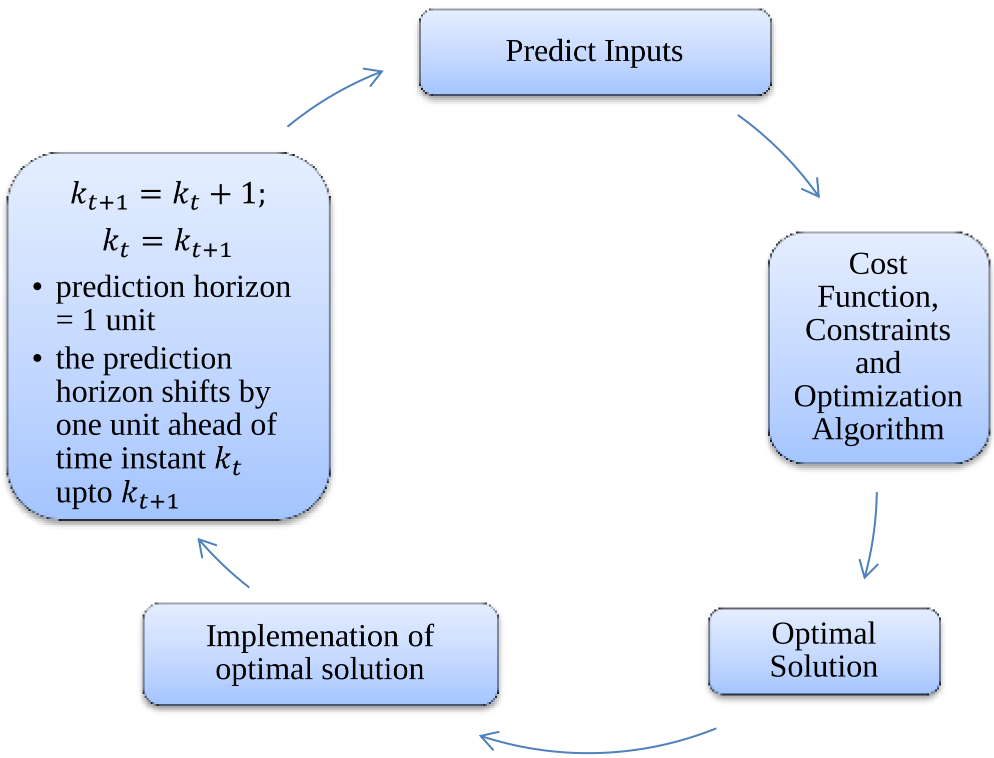

Figure 3.2: Schematic of MPC (Receding horizon control method)

The prediction horizon as per the algorithm in the schematic of MPC shifts by one unit after every cycle of optimization. Thus such an algorithm is called receding horizon control method. To understand receding horizon control method, let us assume our control horizon to be three units of time and sample time for data predicted/optimized is one unit. Then the control horizon will consist of three prediction horizons. Inputs are predicted for the first prediction horizon based on the known data from the previous one unit of time (it could be an hour or a day, etc.). Optimization is carried out using these predicted values and the optimal solution is implemented. After implementing the solution, the prediction horizon shifts by one unit of time. The inputs are again predicted based on the data collected during the previous prediction horizon. Optimization is carried out; the optimal solution is implemented and data is gathered to predict inputs for the next prediction horizon. This kind of online optimization helps in gaining more efficient control over certain activities. For example, as explained in Chapter 1 section 1.3.2, receding horizon control method is used to minimize the cost of electricity. Price of electricity is predicted based on the previous prediction horizon data for load and frequency. The predicted price is used as input to determine the amount of electricity to be used in the upcoming prediction horizon. If the predicted price is high, then low priority devices are turned off and are scheduled to run when the price drops. Thus the receding horizon control helps reduce the cost of electricity in real time.

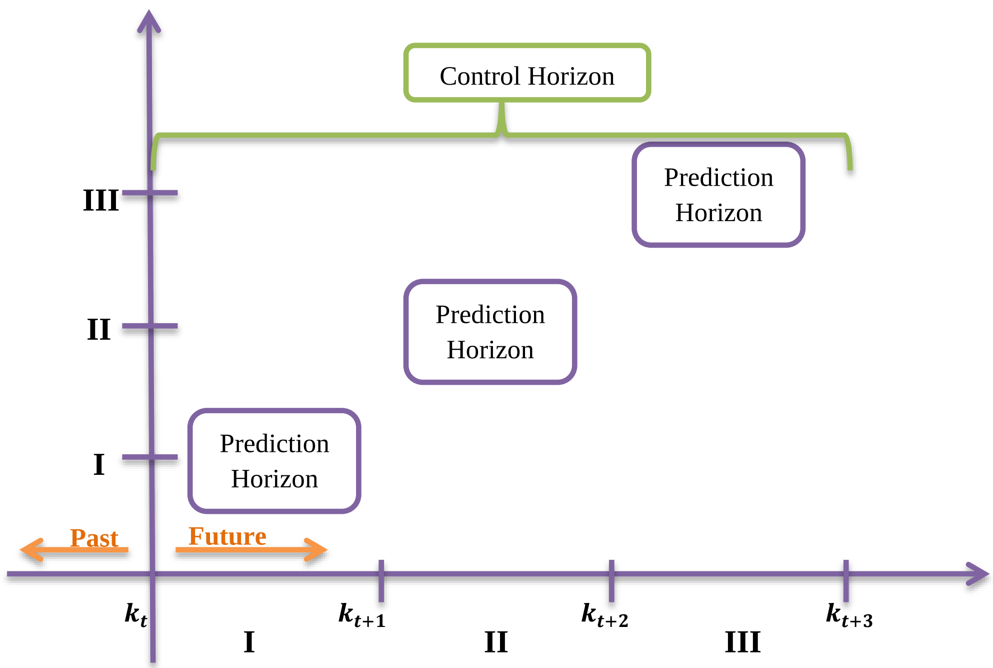

Figure 3.3: Schematic of receding horizon control method using control horizon and prediction horizon

The following chapter uses MPC with receding horizon control to minimize the energy used by the room under consideration.

3.4 Optimization Problem Formulation

In Chapter 2, an energy model was developed for a room in the Lakeshore Centre. To formulate an optimization problem for the room, we first formulate the cost function. Our aim is to minimize the energy/electricity consumption by the room in one day. Thus the equation for the cost function must be an equation which calculates the electricity consumption by the room. The energy model in Chapter 2 is based on the energy transfer equation that is stated in equation (2.8) again.

$$\dot{E}_{in} - \dot{E}_{out} = C\frac{dT}{dt} \tag{3.15}$$

For a heat pump, electricity utilized is given by equation (2.22).

$$\dot{W} = \dot{E}_{in}/COP \tag{3.16}$$

where $\dot{W}$ = electricity power utilized by the heat pump,

$\dot{E}_{in}$ = heat flow rate supplied by the heat pump to the room,

COP = coefficient of performance of the heat pump.

Heat supplied to the room by the heat pump is given by equation (2.23).

$$\dot{E}_{in} = \dot{m} \times C_p \times (T_s - T_r) \tag{3.17}$$

Thus, for a 24 hour optimization problem, our cost function is given as:

$$\min \sum_{k \in N} \dot{W}_k \tag{3.18}$$

$$where\ \dot{W}_k = \frac{\left[\dot{m} \times C_p \times \left(|T_{s_k} - T_{r_k}|\right)\right]}{COP} \tag{3.19}$$

$$and\ N\ is\ a\ 24\ hour\ horizon$$

The COP for the heat pump under consideration is 3.2. The mass flow rate of air, $\dot{m}$ is 0.52 kg/sec.

The inequality constraints that are considered for the optimization of energy are the constraints for room temperature (T_r) and supply temperature (T_s). The bounds on the room temperature are not constant throughout the 24 hours since the room is not occupied during the night time. According to ASHRAE standard [21], the thermal comfort zone for a typical winter day is between 20°C to 23.5°C. This comfort zone is based on factors given in Table 3.1.

Table 3.1: Factors determining the comfort zone for the room [21]

Relative humidity	60%
Typical winter clothing	0.8-1.2 clo
Activity level	1.2 met
Air speed	0.05-0.25 m/sec.

Since the actual set point in the Lakeshore room is 21°C, during the day, the operating temperature range considered for optimization is 20°C to 22°C. The room is usually occupied from morning 8 o'clock till evening 6 o'clock. The heat pump takes an hour to heat up the room to the set point, so the heat pump is started at 5 o'clock in the morning. This allows sufficient time for the room to get heated and then for the room temperature to stabilize. For optimization purposes, the operating temperature range is kept different for the day and the night. Since the ASHRAE standards do not specify a thermal zone when a room is not occupied, the operating temperature range during occupied hours is relaxed by 2°C on both ends for the unoccupied hours. Thus the room temperature bounds are as given in Table 3.2.

Table 3.2: Operating bounds on room temperature

Time of the day	Operating temperature range
7 a.m. – 8 p.m.	20°C - 22°C
9 p.m.	19°C - 23°C
10 p.m. – 5 a.m.	18°C - 24°C
6 a.m.	19°C - 23°C

The bounds for room temperature can be seen as in Figure 3.4.

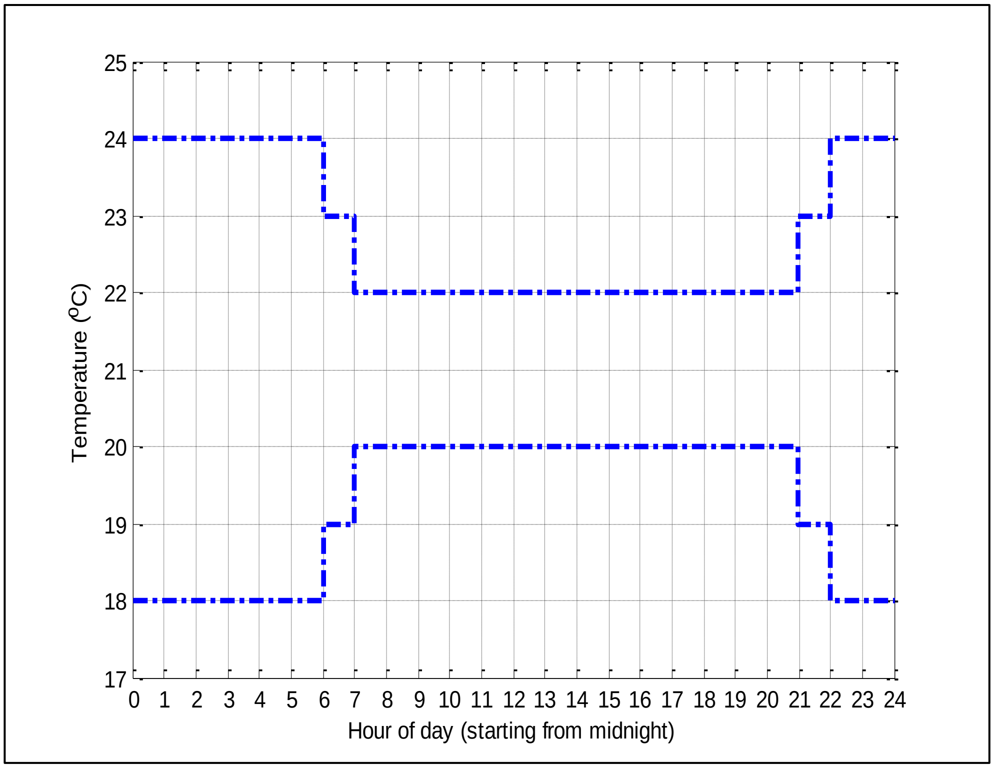

Figure 3.4: Operating limits for room temperature

The supply temperature's upper limit is 32°C based on the model of the heat pump that is used for the room. Supply temperature is supposed to be either equal to or greater than the room temperature for effective heating. Thus for optimization sake, for every iteration, the lower limit on supply temperature is taken to be the value of room temperature obtained in previous iteration.

The energy model of the room developed in the Chapter 2 is a continuous model. Since receding horizon control method is used for optimization, the continuous energy model is converted to a discrete model. The equations of this discrete model act as the equality constraints for optimization problem. The equations are in the form of state space equation similar to equation (3.20).

$$x_{k+1} = Ax_k + Bu_k + Fd_k \tag{3.20}$$

where, x_{k+1} = states of the model being predicted over one unit time of prediction horizon

u_k = input to the model (T_{s_k}) [which is also predicted in our optimization]

d_k = predicted disturbances

The states of the model x are the room and the wall temperatures at the nodes ($[T_{r_k}, T_{w1_k}, T_{w2_k}, T_{w3_k}, T_{w4_k}]$ at instant k). The input to the model is the supply temperature (T_{s_k}) which is also predicted. The predicted variables for the MPC are taken as the four temperatures outside the four walls of the room (T_{dj_k}; j= 1 to 4 at time instant k). The operating conditions for these predicted variables are taken to be the same as those taken for validation of continuous model in Chapter 2. Room temperature bounds are relaxed by a small value 'ε' called the slack variable giving more flexibilty to the algorithm.

Thus the optimization problem can be stated as:

$$\min \sum_{k \in N} \dot{W}_k \tag{3.21}$$

$$where\ \dot{W}_k = \frac{\left[\dot{m} \times C_p \times \left(|T_{s_k} - T_{r_k}|\right)\right]}{COP} \tag{3.22}$$

$$and\ N\ is\ a\ 24\ hour\ horizon$$

$$s.t. \qquad x_{k+1} = Ax_k + Bu_k + Fd_k \tag{3.23}$$

$$T_{r_k} \leq u_k \leq 32°C \tag{3.24}$$

$$T_{r_{lb}}^k - \varepsilon_{lb_k} \leq T_{r_k} \leq T_{r_{ub}}^k + \varepsilon_{ub_k} \tag{3.25}$$

$$\varepsilon_{lb_k} \geq 0;\ \varepsilon_{ub_k} \geq 0 \tag{3.26}$$

where $T_{r_{lb}}^k$ and $T_{r_{ub}}^k$ are lower and upper bounds for room temperature, respectively (Table 3.2); $k = 0\ to\ N-1$; $\varepsilon_{lb}\ and\ \varepsilon_{ub}$ are slack variables for lower and upper bounds for room temperature, respectively.

Thus we have an optimization model for the room.

3.5 Optimization Results

The YALMIP tool [22] in MATLAB® is used for the optimization of the room energy consumption. Since receding horizon control method is used, the receding horizon limit is chosen as one hour. On simulating the model in YALMIP, initial optimization results are obtained as shown in Figure 3.5.

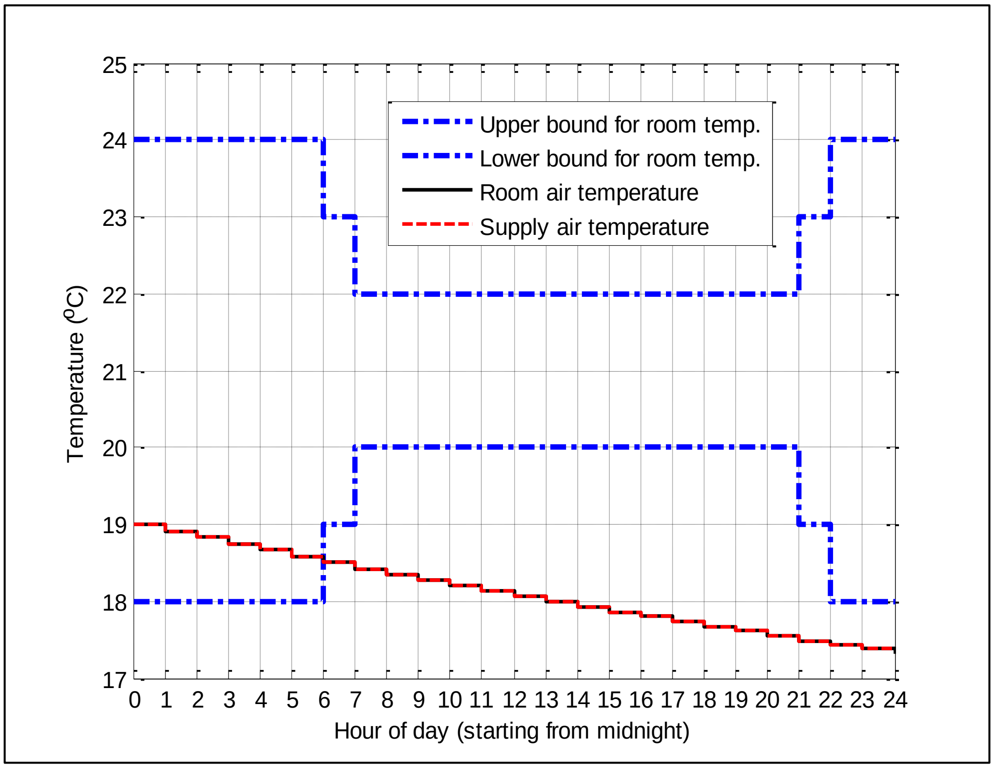

Figure 3.5: Optimization of energy used by the room using unconditioned optimization model for the room

As can be seen in Figure 3.5, a feasible solution was not found. Room temperature and supply temperature coincide with each other indicating heat pump never started. To get the room and supply tempertaures within their respective bounds, a term is added in the objective function so that the weight on the bounds for the room temperature is dominant. This weight is called the penalty for violation on room temperature comfort bounds indicated by ρ. Thus optimization problem can be reframed as shown in equation from (3.27) to (3.32).

$$\min \sum_{k \in N} \dot{W}_k \tag{3.27}$$

$$where\ \dot{W}_k = \frac{\left[\dot{m} \times C_p \times \left(|T_{s_k} - T_{r_k}|\right)\right]}{COP} + \rho\left[|\varepsilon_{lb_k}| + |\varepsilon_{ub_k}|\right] \tag{3.28}$$
$$and\ N\ is\ a\ 24\ hour\ horizon$$

$$s.t. \qquad x_{k+1} = Ax_k + Bu_k + Fd_k \tag{3.29}$$

$$T_{r_k} \leq u_k \leq 32°C \tag{3.30}$$

$$T_{r_{lb}}^k - \varepsilon_{lb_k} \leq T_{r_k} \leq T_{r_{ub}}^k + \varepsilon_{ub_k} \tag{3.31}$$

$$\varepsilon_{lb_k} \geq 0;\ \varepsilon_{ub_k} \geq 0 \tag{3.32}$$

where ρ = penalty for violation of room temperature comfort bounds

$k = 0\ to\ N - 1$

The value of ρ needs to be tuned until the room temperature lies within its bounds as well as the energy consumed is the least.

Figure 3.6 shows the simulation result with ρ=10.

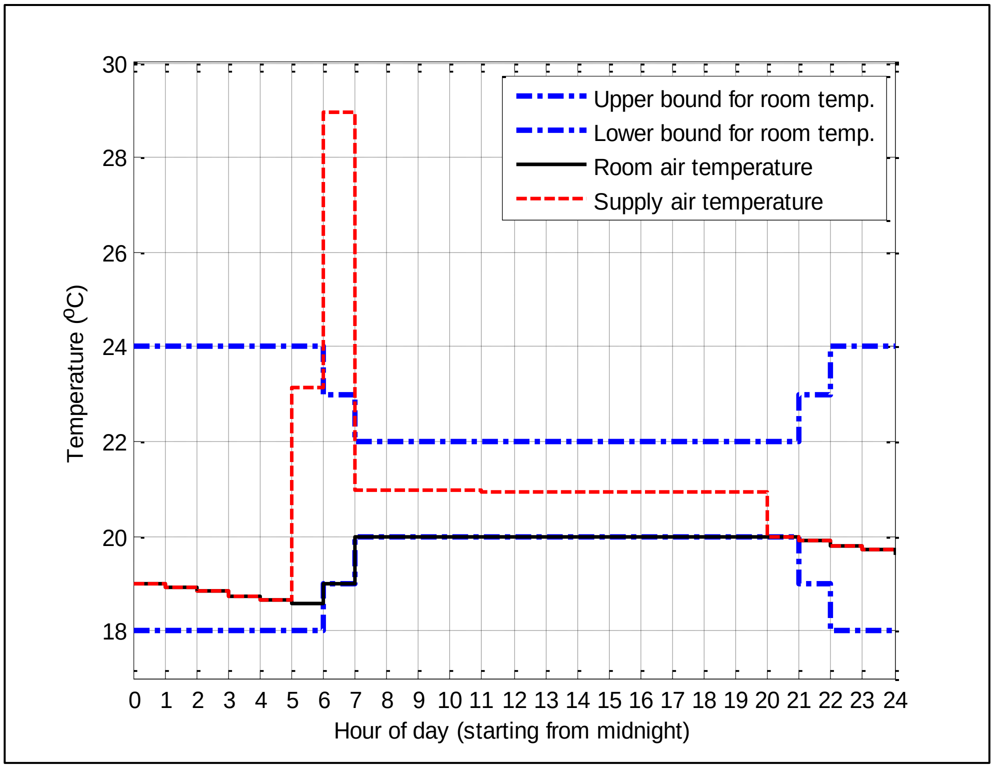

Figure 3.6: Optimization of energy used by the room using conditioned optimization model for the room with ρ=10

From Figure 3.6, it can be seen that the room temperature as well as the supply temperature lie within their respective bounds. The optimized electricity consumption by the heat pump is 4.4 kW/day. When the electricity consumption is calculated using the measured data (from the Lakeshore room using temperature sensors; section 2.3) and heat pump specifications data (Table 2.1), it is 5.3 kW/day. Thus the electricity consumption is reduced. The room temperature coincides with the lower bound from the sixth hour till the twentieth hour. The room and supply temperatures coincide in the first 4 hours and 21st to 23rd hours of the plot, thus giving zero energy consumption for that period. This behaviour of the optimized room temperature explains the decrease in the power consumption. The percent saving in the power utilization is 16.9% in a day or in a month.

Different values of ρ are tested to determine a feasible range of ρ which gives the desirable power consumption (less than 5.3 kW/day). Table 3.3 summarizes the results.

Table 3.3: Power used by the heat pump for different values of ρ

ρ	Daily Power (kW)
500	4.4
2,000	4.4
20,000	4.4

The plots for all the values of ρ are exactly the same as the Figure 3.6. From Table 3.3, we can conclude that any value for ρ greater than 10 till 20,000 gives the desirable result. For the energy minimization in this section, we will use ρ=2000 to significantly penalize any violation from room comfort temperature bounds.

Now that we have the optimization model for the room, we will test it for different conditions of the outside environmental temperature. The data used in simulations in Figure 3.6, consists of the outside environmental temperature (T_{d4}) of 0°C ±2°C which will be regarded as the base case in this chapter here onwards. The simulations for different environmental conditions are shown in Figure 3.7, Figure 3.8 and Figure 3.9.

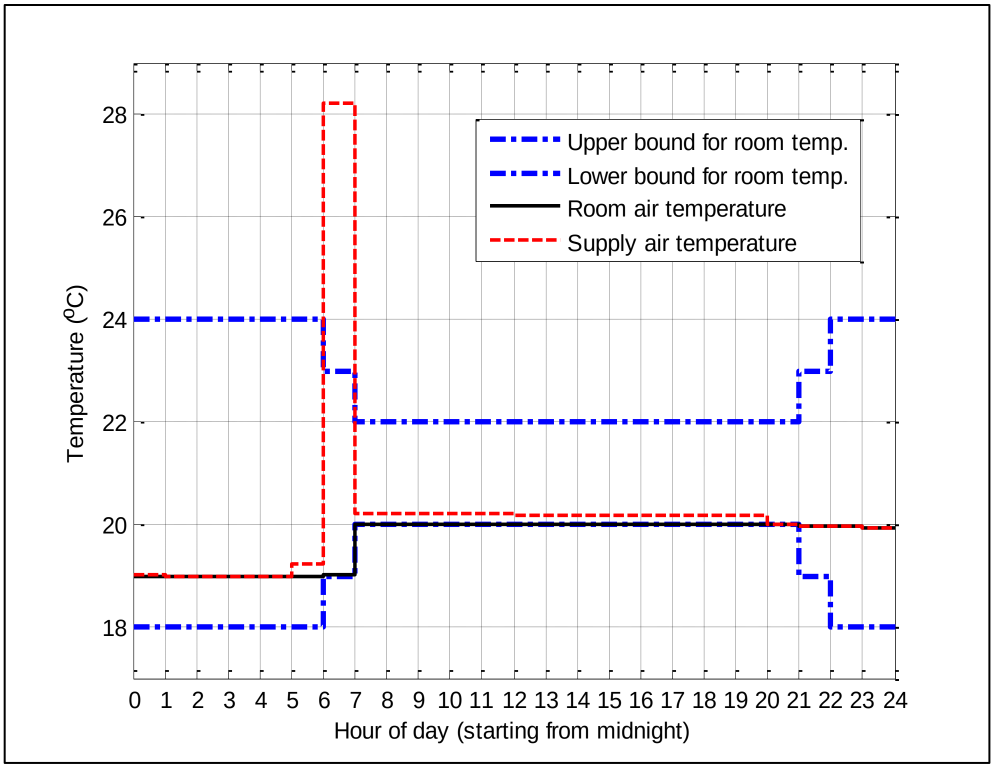

Figure 3.7: Optimization of energy used by the room on a mild day with T_{d4} within 15°C ±2°C.

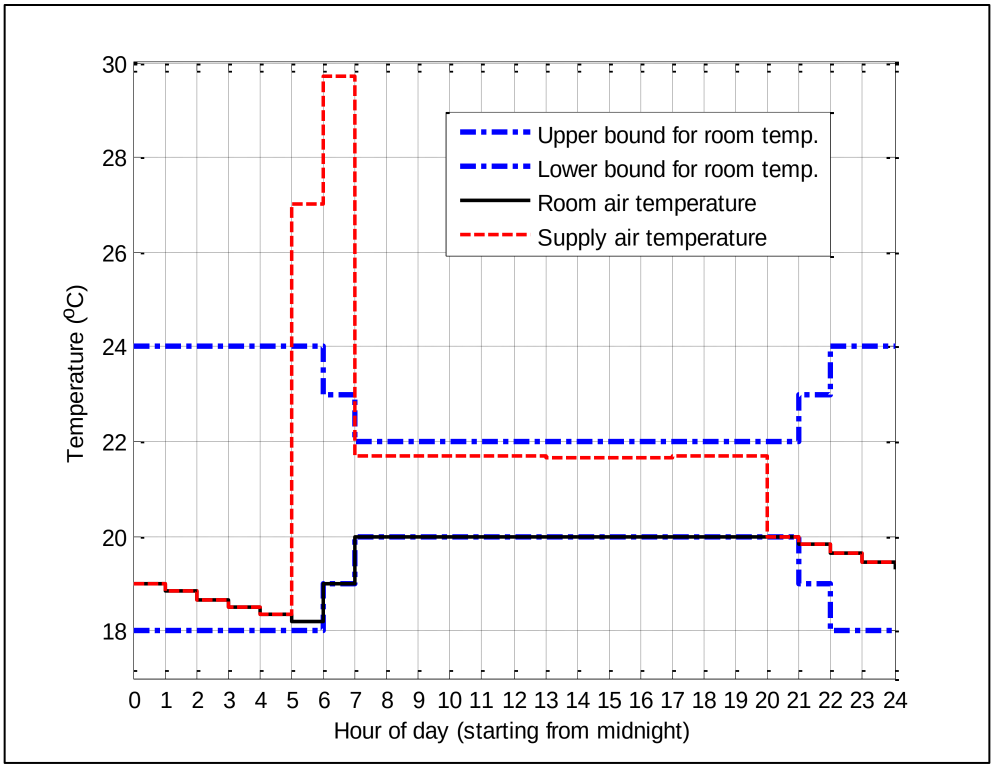

Figure 3.8: Optimization of energy used by the room on a colder day with T_{d4} within -15°C ±2°C.

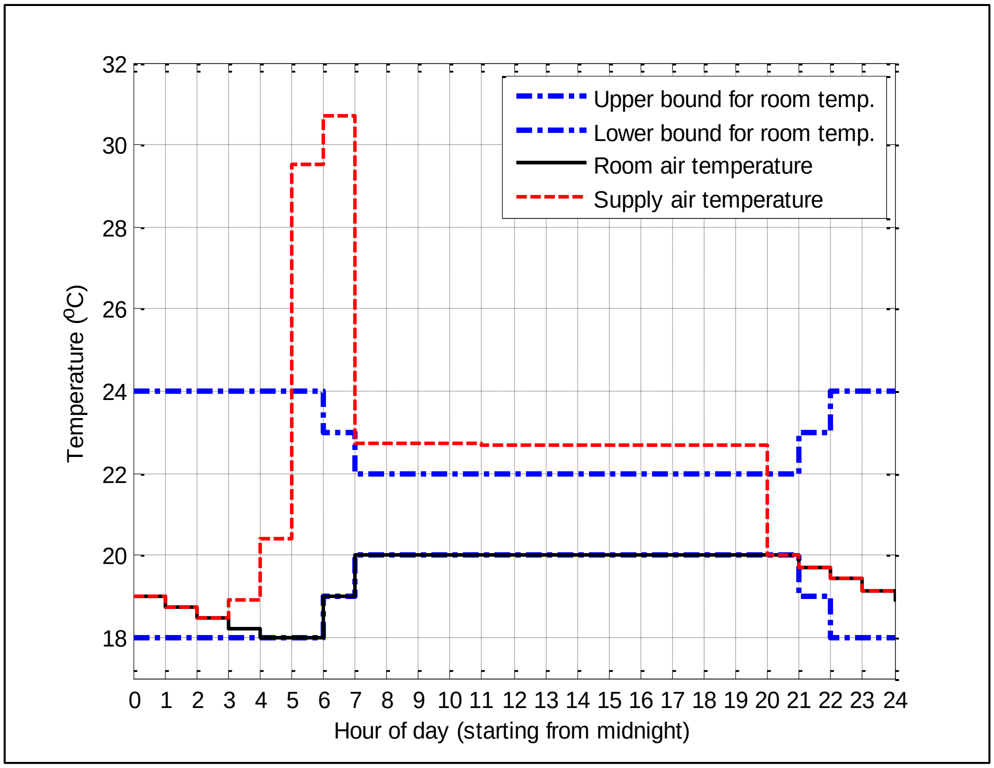

Figure 3.9: Optimization of energy used by the room on an extremely cold day with T_{d4} within -35°C ±2°C.

It is observed that for all three cases of different environmental conditions, the room temperature and the supply temperature lie within their respective bounds. The room temperature coincides with its lower bound from 7th to 20th hour for all three cases and varying number of hours during the night for each case. The room temperature and supply temperature coincide for different number of hours for each case during the night. This behaviour of the room and supply temperatures is similar to the base case in Figure 3.6. Thus such behaviour gives us a pattern to expect during the optimization of the room model for any environmental temperature range lying between -35°C to 15°C. The different cases along with the original case (base case) are summarized in Table 3.4. As expected the power consumed by the heat pump increases as the outside temperature drops.

Table 3.4: Temperature ranges and power used by heat pump for each type of environmental condition

Case	Outside Temperature (°C)	Daily power consumed (kW)	Monthly power consumed (kW)
Mild day	15 ± 2	1.9	57
Cold day (base case)	0 ± 2	4.4	132
Colder day	-15 ± 2	6.7	201
Extremely cold day	-35 ± 2	10	300

3.6 Comparison of MPC with Existing Controller

On validating the MPC model, we need to compare the MPC model with the existing controller in Lakeshore Centre and analyse if MPC really optimizes the energy usage in the room. The existing controller is also applied to the same discrete model of the room as that developed for MPC. The limits for the room temperature during the day in MPC were decided based on ASHRAE guidelines [21]. The room temperature limits for existing controller during the day lie within the ASHRAE limits but have a smaller range. For existing controller the room temperature bounds and the sample time are similar to those used in MPC.

Existing controller is an ON/OFF controller. On/off controller has a simple algorithm. Indoor temperature in buildings is maintained within a small range. The range for indoor temperature has a lower limit and an upper limit. When the indoor temperature drops below the lower limit of its range, the compressor of the heat pump is switched ON. The heat pump remains ON till the indoor temperature exceeds the upper limit of the thermal comfort range. The moment the indoor temperature above the upper limit is sensed, the heat pump is switched OFF. The heat pump then remains OFF till the indoor temperature drops below the lower limit of the thermal comfort range. Due to such behaviour, the controller is also called as a hysteresis controller.

The OFF state of heat pump is included in the algorithm for the controller in the form of supply temperature equal to room temperature and hence there will be no heat transfer between the two. Using this algorithm, the simulation result is shown in Figure 3.10.

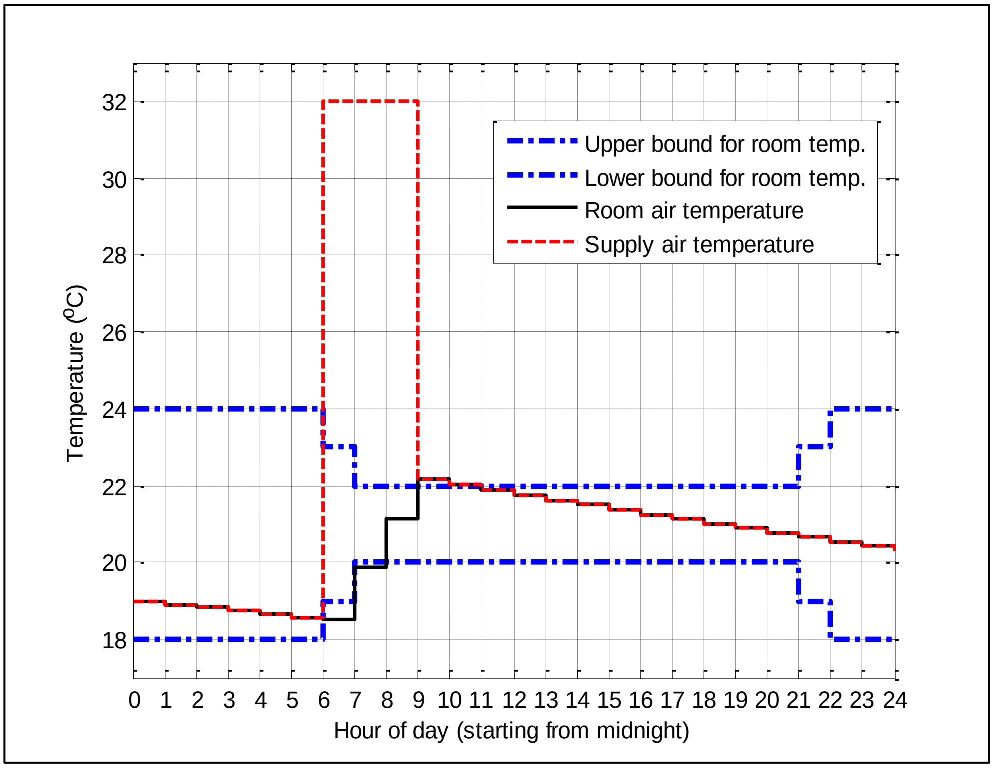

Figure 3.10: Simulation for performance of the Existing Controller with T_{d4} within 0°C ±2°C

The data for outside temperature used for the simulation in Figure 3.10, is the same as that used for the cold day case in MPC called the base case. The energy used per day by the existing controller is 5.9 kW. Thus on comparing the cold case of both controllers, we observe that MPC consumes less power than the existing controller.

Table 3.5: Comparison of MPC and Existing Controller

Controller	Daily power consumed (kW)	Monthly power consumed (kW)	% Power Saving by MPC over Existing Controller
MPC	4.4	132	25.4% (base case)
Existing	5.9	177	

The MPC does save power if used in place of existing controller for a cold day case. But it needs to be validated if MPC consumes lesser power compared to existing controller in any environmental condition. The simulation results for the existing controller in other environmental conditions are shown in Figure 3.11, Figure 3.12 and Figure 3.13.

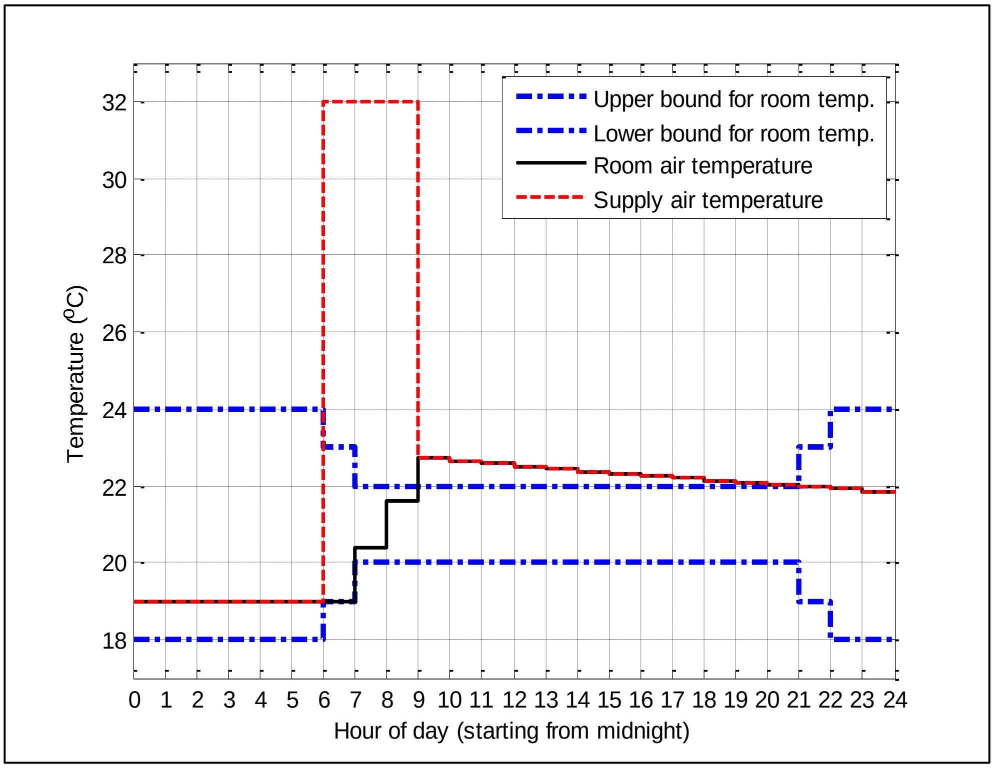

Figure 3.11: Simulation of Existing Controller on a mild day with T_{d4} within 15°C ±2°C.

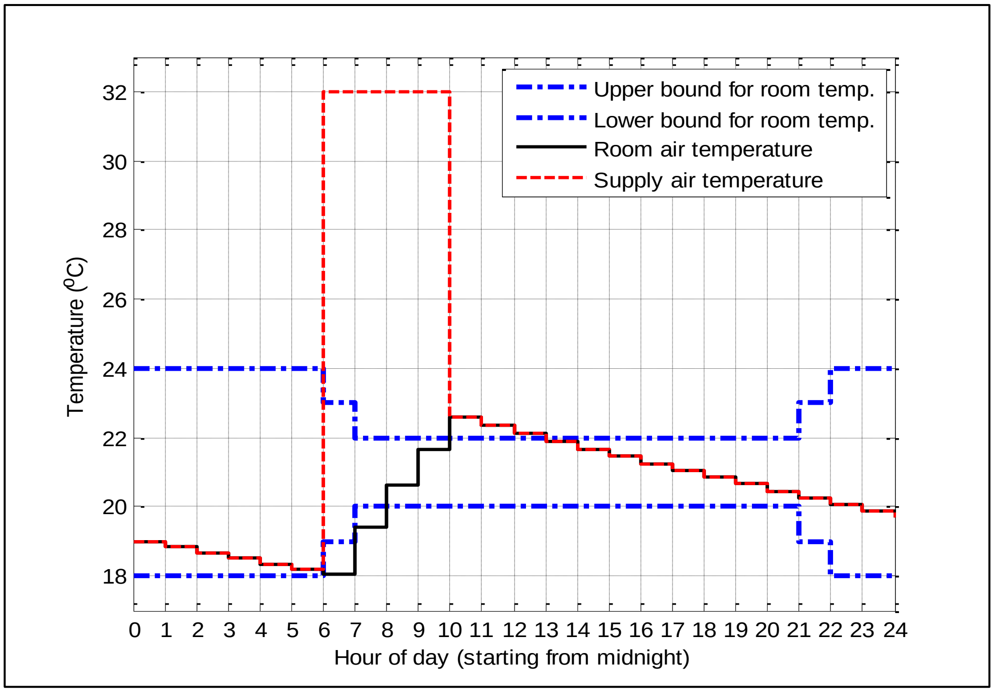

Figure 3.12: Simulation of Existing Controller on a colder day with T_{d4} having values -15°C ±2°C.

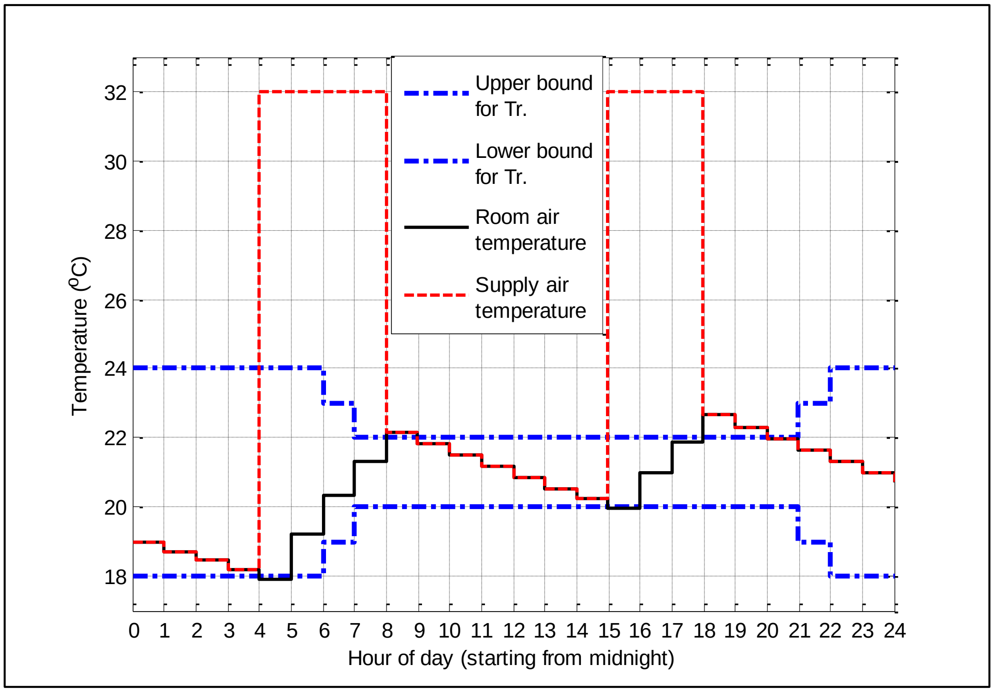

Figure 3.13: Simulation of Existing Controller on an extremely cold day with T_{d4} within -35°C ±2°C.

On tabulating the results, we can compare the MPC and existing controller energy consumption for different environmental conditions. Table 3.6 summarizes the comparative results.

Table 3.6: Comparison of MPC and Existing Controller for different environmental conditions

Case	Outside Temper -ature (°C)	**MPC**		**Existing Controller**		% Power Saving by MPC over Existing Controller
		Daily power consumed (kW)	Monthly power consu-med (kW)	Daily power consumed (kW)	Monthly power consu-med (kW)	
Mild day	15 ± 2	1.9	57	5.7	171	66.6%
Cold day (base case)	0 ± 2	4.4	132	5.9	177	25.4%
Colder day	-15 ± 2	6.7	201	7.8	234	14.1%
Extremely cold day	-35 ± 2	10	300	13.5	405	25.9%

Thus it is observed that MPC saves a lot of power if used in place of the existing controller. As seen in Table 3.6, the power saving percentage decreases from 66.6% to 14.1% but increases again for an extremely cold day. The reason for this is the existing controller over heats the room. With rise in outside temperature, the overheating by existing controller does not decrease significantly whereas the heat supplied by MPC drops significantly. The percentage saving increases for extremely cold day case compared to colder day case because the heat supplied by MPC increases only by 100 kW while for existing controller it increases by 171 kW which means existing controller is overheating the room again.

Thus MPC saves power significantly in a wide range of environmental conditions. This leads to the conclusion that MPC is an appropriate choice for energy minimization in the Lakeshore building.

Chapter 4

4 Energy Cost Minimization and Energy Profile Peak Constraining

Chapter 3 introduced and explained how MPC helps optimizing the power consumption in a building. MPC is a better algorithm than On/Off controller in minimizing the energy used up. Apart from the amount of energy used, one main concern for the consumers is the cost they are paying for the used energy. Chapter 1 explained the different types of energy metering and dynamic pricing.

Cost of electricity has two parts namely, a fixed part and a variable part. The fixed part is decided by the supplier side and the variable part is determined by the consumer side. The fixed cost of electricity [23] is determined by the cost of fuel used to produce electricity, season, type of zone supplied (residential or commercial or industrial), government policies, market status, maximum allowable load to be supplied to the zone, etc. The variable cost of electricity [24] is determined by how much, when (time of day) and for what purposes the electricity is used by the consumer.

There are different plans for electricity pricing suitable for different types of consumers. The fixed rate plan for electricity pricing provides a fixed rate for a period of time and no changes are made in the rate even if the cost of electricity changes in the market. This type of plan is suitable for consumers with a fixed or limited budget and this way they can determine the price they will have to pay for the power they will use during the period of their contract. The disadvantage of this plan is that, if the cost of electricity drops in the market, the consumer is stuck with the initial higher price till his contract gets over. Another plan is the variable pricing of electricity which is mostly used by commercial businesses and industries. This plan provides rates based on whole sale prices. If the prices in the market go up, consumers pay more, if the prices in the market drop, consumers pay less. One of the examples of variable pricing [24] is time of use pricing. For time of use pricing, prices are fixed for a particular period of time and change in prices is as frequent as twice per year. The prices are high for a particular period if it is known that the use of power is high during that period. The prices are low for a particular period if it is known that the use of power is less during that period.

Another example of variable pricing is the real time pricing [24]. It is also called *dynamic pricing* since the frequency at which the prices change is as high as every hour of the day. Based on previous usage of power, the prices are determined for the consequent hour and provided to the consumer in advance. It helps consumers to manage their power consumption according to the cost of electricity provided. The consumer can schedule the low priority devices during the period in which the cost is low. This predicted profile for cost of electricity is useful in Model Predictive Control (MPC) algorithm which is implemented to reduce the power consumption as well as cost of power used.

This chapter deals with the MPC algorithm to reduce the cost of electricity used by the consumer. Appropriate objective function is determined leading to lowest cost for the consumer. The second contribution from this chapter is to design an MPC algorithm for power peak shaving of building load. Thus the building peak power load will not exceed a maximum allowable load from the distribution power grid. To this end, the MPC algorithm is extended to all the heating zones connected to the node which supplies power to the Lakeshore Centre. An optimized energy profile is obtained which lies within the maximum allowable load profile at the node for the Lakeshore Centre.

4.1 Cost of Energy by Energy Minimization

In Chapter 2, an energy model for a room was developed and in Chapter 3, the energy model was used to form MPC model with energy minimization as the objective function. The output of base case MPC optimization (section 3.5) is the room temperature and supply temperature profiles which are used to determine the amount of power (kWh/day) consumed. The power calculated in each hour can be multiplied by the electricity pricing data to determine total cost the consumer has to pay for the power used per day. The pricing data used in this thesis is the dynamic pricing predicted over every hour, the data for which was obtained from Midcontinent Independent System Operator (MISO) Inc. [25]. The pricing data for Michigan hub for 24 hours is shown in Figure 4.1.

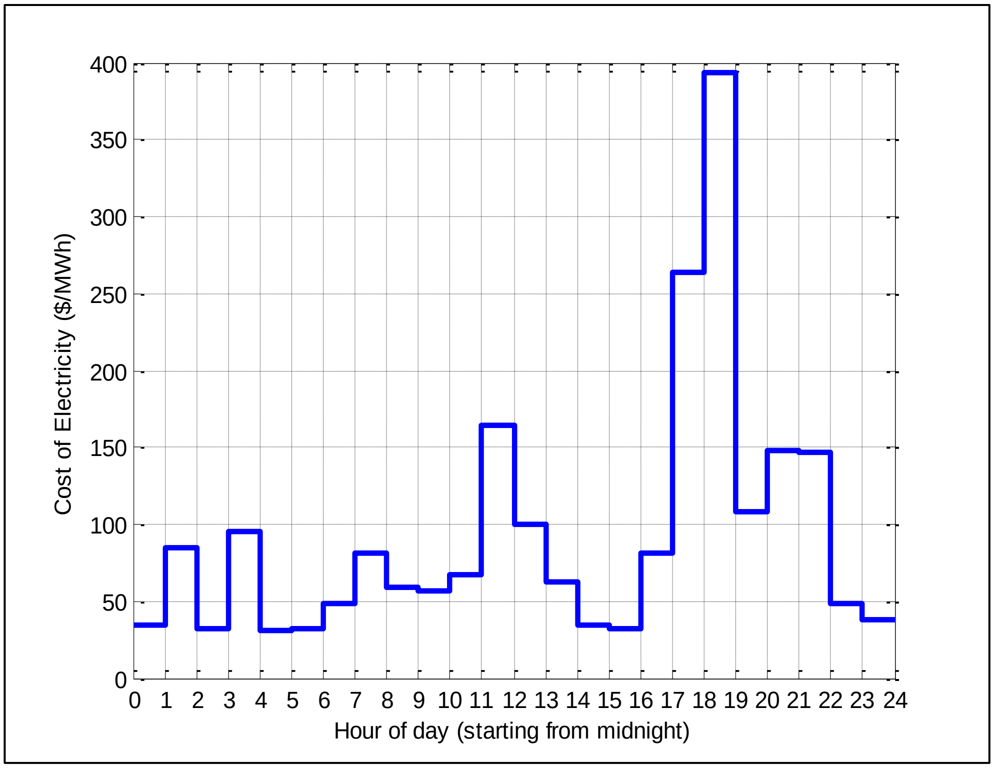

Figure 4.1: Dynamic Pricing data for Michigan hub for 24 hours [25]

To get the cost close to real cost, 100W power is added to the power profile obtained in base case of section 3.5 (Figure 3.6) since the fan of the heat pump keeps running continuously even though the compressor turns on and off. When pricing data from [25] is multiplied by the energy profile (including fan energy) for 24 hours, the total cost obtained with energy minimization is $0.56 per day for one room. So the monthly cost for the consumer for one room is $16.8. This is the cost of electricity obtained when MPC uses energy equation as its objective function and dynamic pricing data is used after optimization result is obtained for minimizing energy consumption. The next section deals with MPC problem with dynamic pricing data included in the objective function itself.

Chapter 3 included existing On/Off controller which was proved to use more power than MPC. This existing On/Off controller not only uses more power but when combined with dynamic pricing gives more cost. For example, if the energy profile obtained in base case of section 3.6 (adding 100W of fan power to it) is multiplied by dynamic pricing profile for 24 hours, it gives $0.59 per day and monthly room energy cost is $17.7 which is more than the cost obtained in energy minimization by

MPC. Thus for reducing power usage as well as its cost, MPC is better than existing On/Off controller.

4.2 Cost of Energy by Cost Minimization

MPC using energy minimization was proved to be a better algorithm to minimize energy in Chapter 3. Now to determine if energy minimization gives lower cost of energy for the consumer, we determine cost of energy using a different objective function. In the section 4.1, dynamic pricing was used after optimization was completed. In this section, dynamic pricing is used in the objective function leading to cost minimizing MPC algorithm.

The cost minimizing MPC problem has the same structure as the energy minimizing MPC problem in section 3.4 from equations (3.21) to (3.26) except the objective function for cost minimization is:

$$\min \sum_{k \in N} Cost_k \tag{4.1}$$

$$Cost_k = \frac{\left[\dot{m} \times C_p \times \left(|T_{s_k}|\right)\right] \times P_r}{COP \times 10^6} \times \alpha + \rho\left[|\varepsilon_{lb_k}| + |\varepsilon_{ub_k}|\right] \tag{4.2}$$
$$and\ N\ is\ a\ 24\ hour\ horizon$$

where $Cost_k$ = cost of electricity as per power usage in k^{th} hour.

P_r = predicted cost of electricity for k^{th} hour per MWh ($/MWh)

α = weight on dynamic pricing term = 1

The cost is calculated based on the heat supplied by the heat pump to the room. Thus the objective function is a function of T_{s_k} and P_r only and not a function of room temperature T_{r_k}. When optimization is carried out, the result obtained is shown in Figure 4.2. The cost calculated throughout the rest of this chapter includes 100W fan power as mentioned in section 4.1.

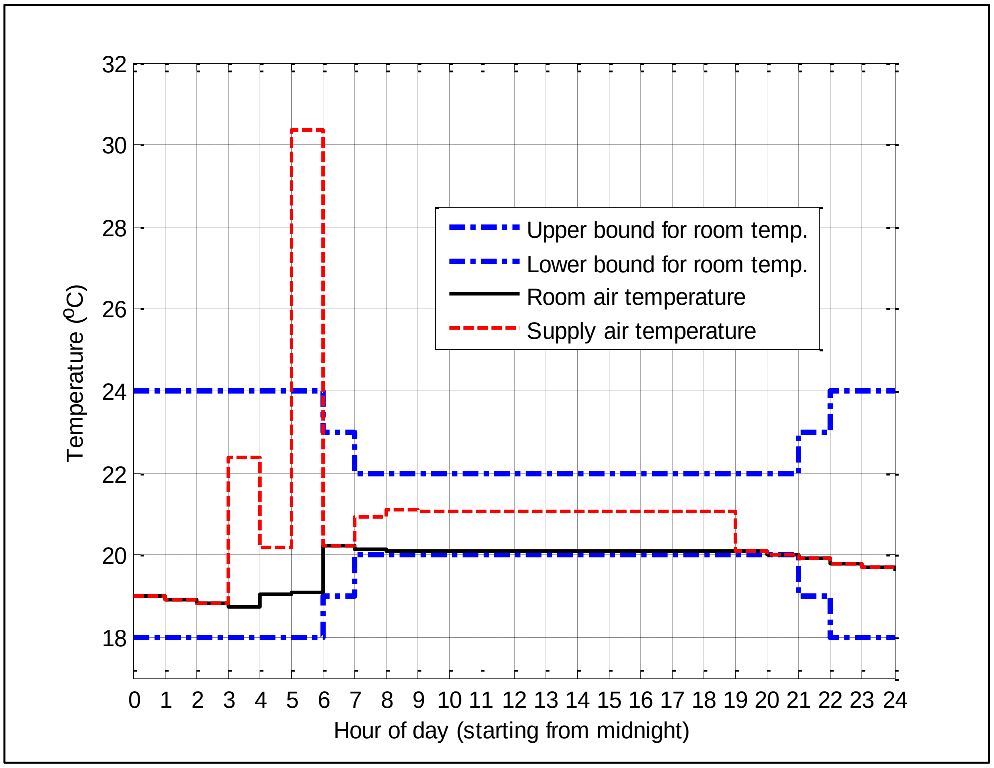

Figure 4.2: Room temperature and supply temperature profiles after optimizing the MPC model for cost minimization.

As can be seen from Figure 4.2, the solution is feasible. The cost of power used in 24 hours is $0.56 per day which is the same as that obtained after energy minimization. In equation (4.2), the weight α on the dynamic pricing term in the objective function is increased to 10, to see if it affects the end cost of power. On optimizing this new objective function, the result obtained is shown in Figure 4.3.

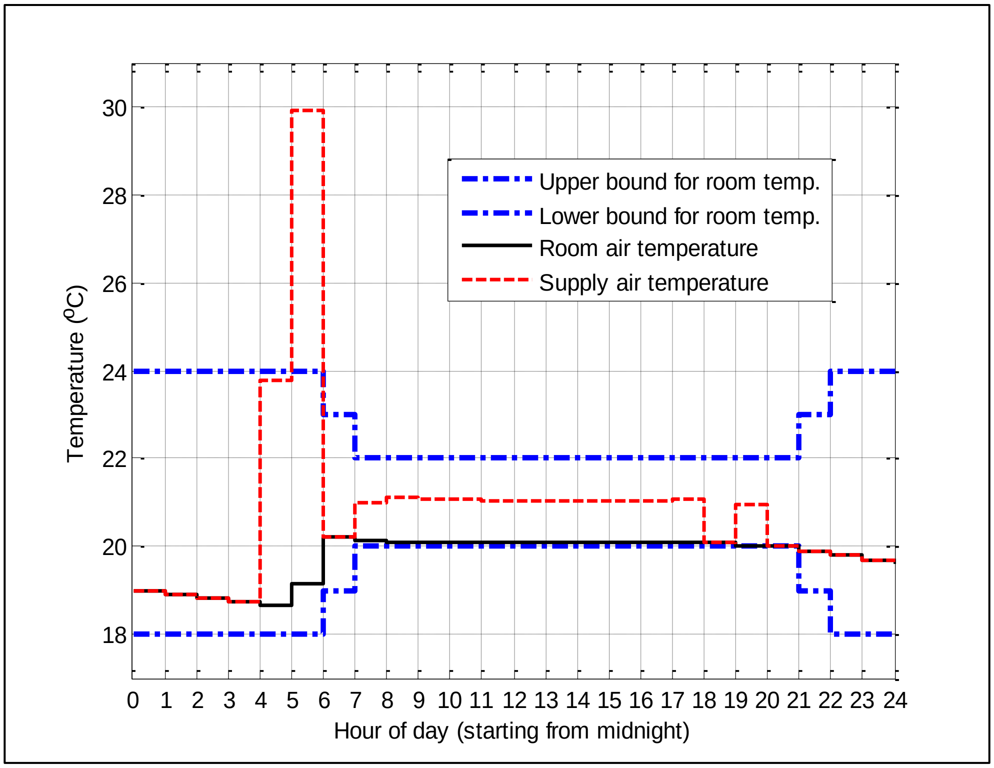

Figure 4.3: Room temperature and supply temperature profiles after optimizing the MPC model for cost minimization with dynamic pricing weight α = 10.

As can be seen from Figure 4.3, on increasing the weight on dynamic pricing, we still get a feasible solution with cost of power for 24 hours equal to $0.47. This leads to a monthly cost of $14.1 for one heating zone. This cost is less than that obtained after energy minimization which was $16.8 per month for one heating zone. Figure 4.4 gives the optimization result if the weight α on dynamic pricing is increased to 50. It gives an infeasible solution. If α is changed to 15, it gives the result shown in Figure 4.5 and the cost as $0.48 per day. The Figure 4.5 shows that the room temperature violates the lower bound between 20^{th} and 21^{st} hour. In addition, the cost is higher than that when α is 10. Thus value of α equal to 10 is chosen.

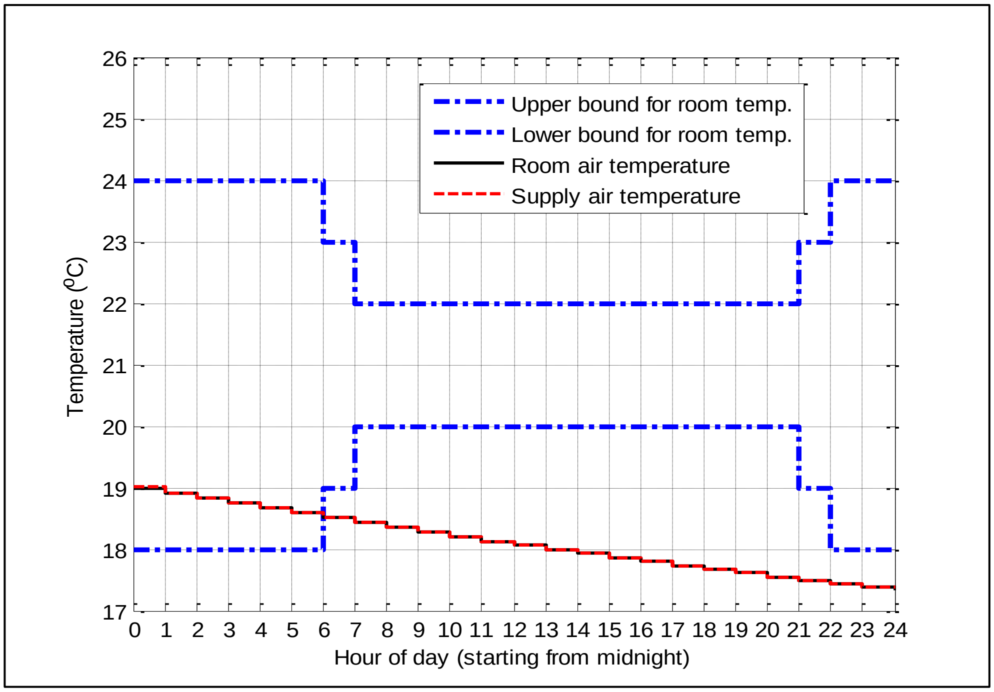

Figure 4.4: Room temperature and supply temperature profiles after optimizing the MPC model for cost minimization with dynamic pricing weight α = 50.

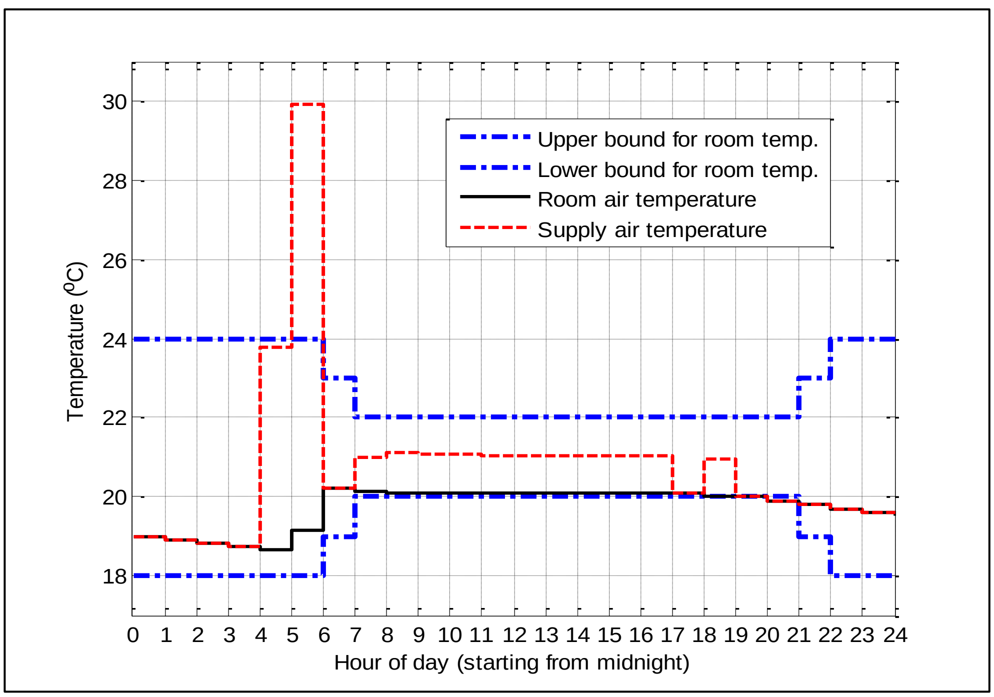

Figure 4.5: Room temperature and supply temperature profiles after optimizing the MPC model for cost minimization with dynamic pricing weight α = 15.

The resulting MPC objective function for cost minimization is the one given in equations (4.1) and (4.2) with α=10.

4.3 Comparison with On/Off Controller

Table 4.1 compares the energy cost by the existing On/Off controller (section 3.6) with MPC. The result shows existing On/Off controller gives the highest cost for power consumption. Table 4.1 shows that using price of electricity in the objective function itself, reduces the cost compared to using only energy equation in the objective function. Figure 4.6 shows the comparison of cost profiles of all three controllers. The dynamic pricing inclusive cost function gives supply temperature and room temperature values in such a way that more power is used when the price is low and less power is used when the prices are higher. Hence it results in lower end cost of electricity compared to that in section 4.1. Figure 4.7 shows that MPC resulted in higher power consumption when price is low and lower power consumption when price is higher. The power consumption also depends if the room temperature is within the comfort zone or not. For example, in first four hours, even though the price is very low, power used is close to zero Watt since the room temperature is within the comfort zone. At the fifth hour, the lower limit of the comfort zone rises and hence to raise the room temperature, the power consumed is the highest at the fifth hour.

Table 4.1: Comparison of end cost of electricity consumed in one room i.e. one heating zone through different controllers. Existing On/Off controller gives the highest cost. Including dynamic pricing in objective function reduces cost as against using it post optimization as done in energy minimization.

Controller	Daily Cost ($)	Monthly Cost ($)
Existing On/Off Controller	0.59	17.7
MPC - Energy minimization	0.56	16.8
MPC - Price minimization	0.47	14.1

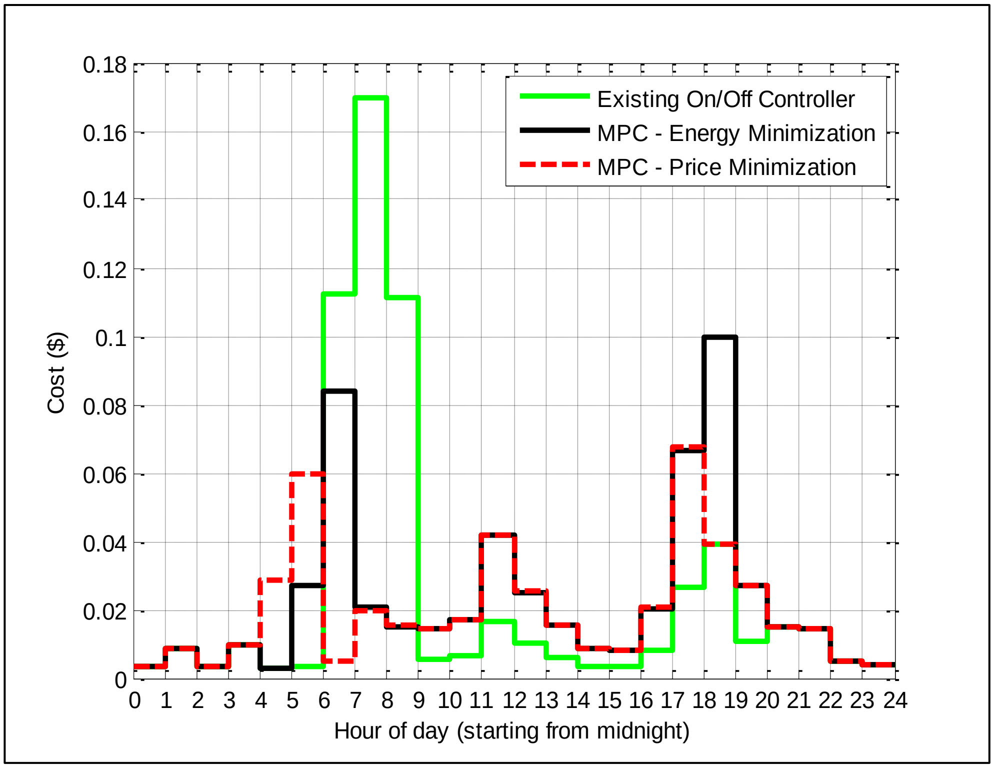

Figure 4.6: Comparison of cost profiles of existing On/Off controller, MPC with energy minimization and MPC with price minimization. Existing On/Off controller shows the highest peaks while MPC with price minimization shows the lowest lying peaks.

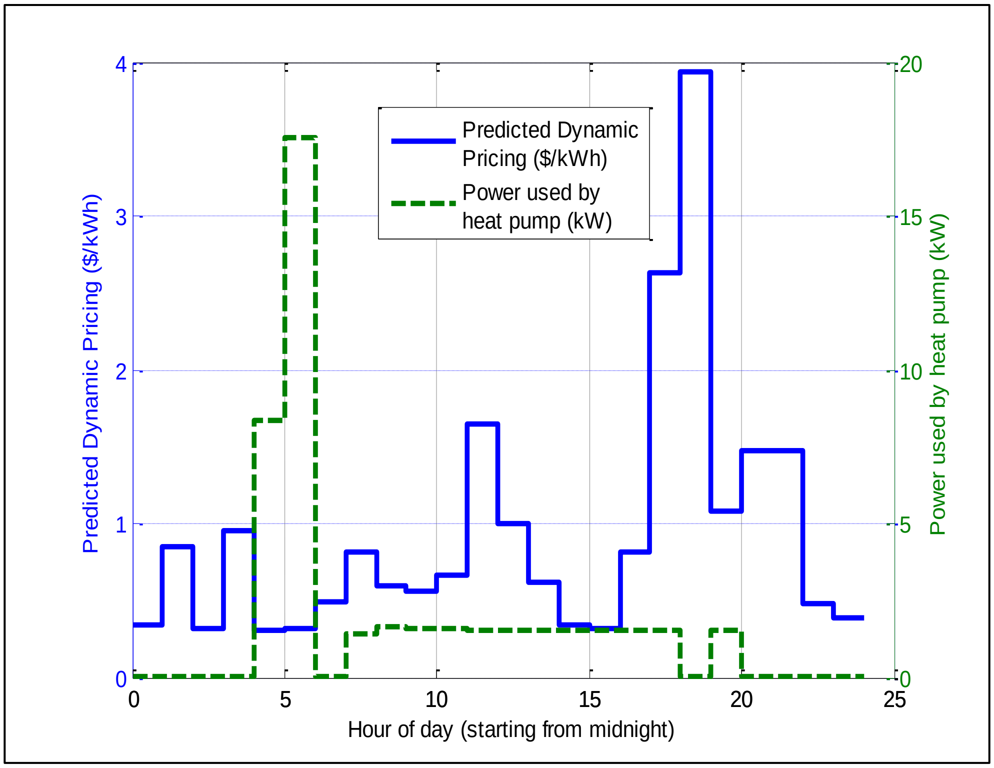

Figure 4.7: Trend of power consumption using price minimizing algorithm in comparison with the Dynamic Pricing.

4.4 MPC and Energy Profile Peak Constraining for a Building

A grid supplying electricity has many nodes. Each node can be connected to different loads such as buildings. The distribution network consisting of nodes helps in management of loads. By information exchange, between distribution grid and building energy management system (BMS), buildings can ensure that they will not violate maximum allowable load from the grid. Here a case study is presented to illustrate how BMS can use optimization of HVAC loads to avoid violation of maximum allowable load. To this end, it is assumed that Lakeshore Centre is connected to node 18 in the 33-node standard IEEE distribution feeder [19]. Results from reference [19] are used to determine maximum allowable load for Lakeshore Centre. While optimizing the building load according to predicted dynamic pricing, care must be taken that the load at the node during low price period does not exceed the maximum allowable load at that particular node. Figure 4.8 shows the maximum allowable load [19] developed for the node at which Lakeshore Centre is connected. It is assumed that the node supplies power to six buildings with 20 heating zones each.

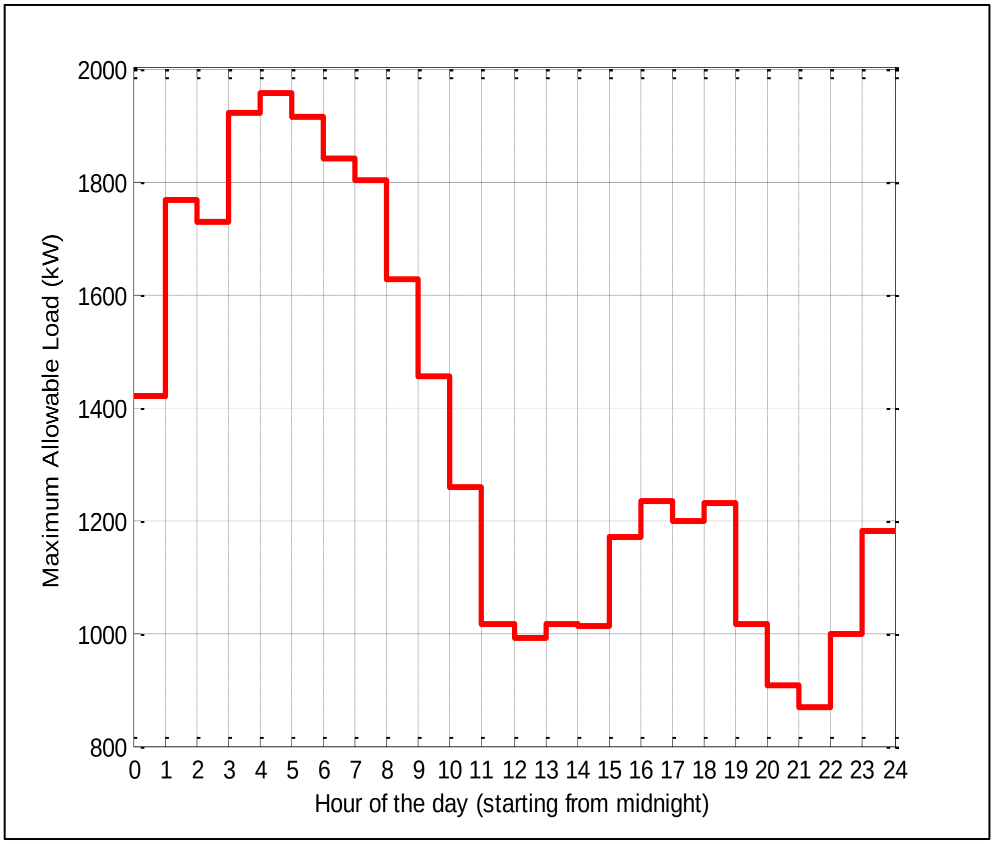

Figure 4.8: Maximum allowable load at the node at which Lakeshore Centre is connected [19].

Throughout the thesis till previous section 4.2, the energy model represents one room, i.e. one heating zone. A scale factor of 20 is used to scale up the energy model to a building. A further scale factor of six is used to represent power consumption by six buildings at node 18. In addition to the HVAC load predicted by MPC, lighting and other appliances load is also considered in order to compare the total load of buildings with the maximum allowable load. For lighting and other appliances load, the distribution is adapted from [19] as shown in Figure 4.9.

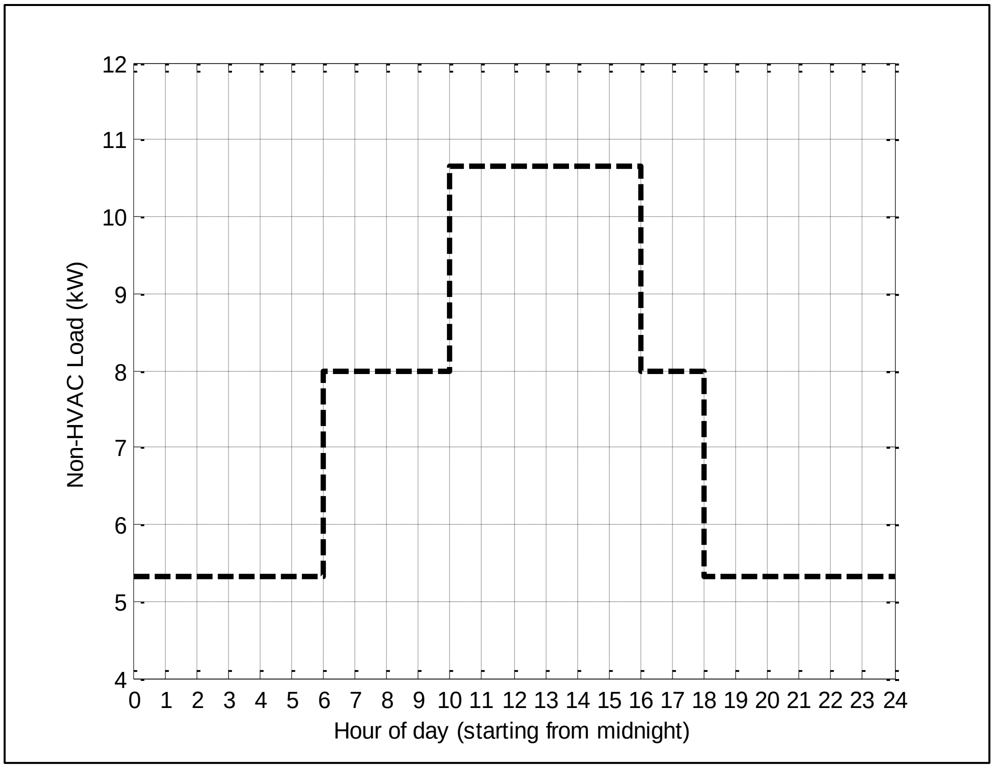

Figure 4.9: Profile of the non-HVAC load i.e. lighting and other appliances load for 24 hours adapted from [19]

On scaling up the model, the HVAC load for Lakeshore Centre is obtained through MPC algorithm, and then added to the non-HVAC load to give the profile for total load. This total load of the building is then used to compare the demand side load with the maximum allowable load at the node. Figure 4.10 shows the total load profile for Lakeshore Centre.

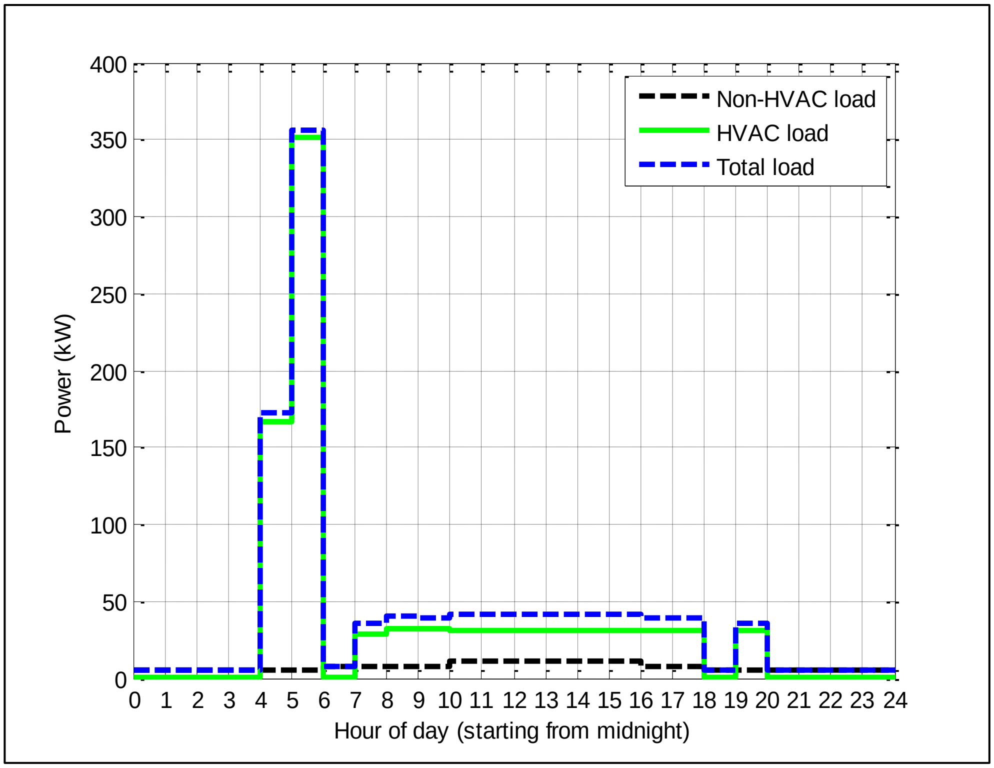

Figure 4.10: HVAC load (MPC) and non-HVAC load profiles for one building (Lakeshore Centre) are added to obtain total building load. Data in this figure is for one building, so this load is multiplied by six to determine total load at node#18.

Figure 4.11 shows the total optimized load of six buildings in comparison with maximum allowable load at the node. As seen from the figure, the total load exceeds the maximum allowable load from fifth to sixth hour. HVAC optimization is run by adding a new constraint, i.e. maximum allowable load. It is found that violation of maximum load can be avoided if the room temperature constraints are relaxed. On relaxing the room temperature constraints, the total load of all six buildings together lies within the maximum allowable load. The minimum relaxation in room temperature that brings building loads within the maximum allowable load is 0.7°C as shown in Figure 4.12. This shows the benefit of exchange between the distribution grid and optimizer of building HVAC systems.

The room temperature profile obtained upon relaxing room temperature constraints by 0.7°C is shown in comparison with original room temperature constraints in Figure 4.13. The figure shows the amount of violation in room temperature that is allowed in order to shave the peaks in building loads.

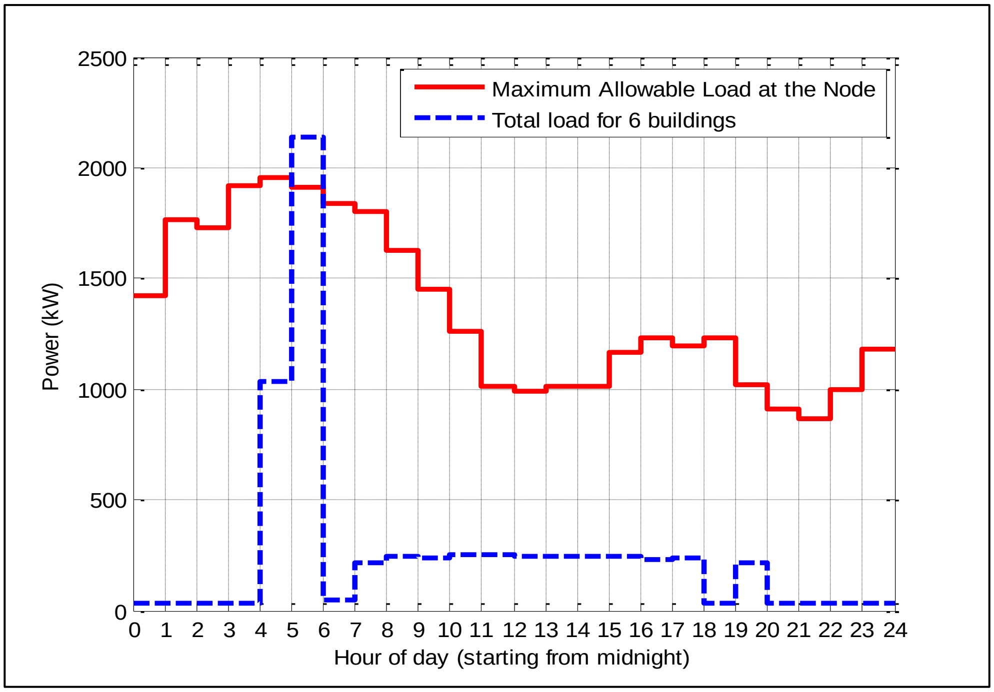

Figure 4.11: Total optimized load of six buildings exceeds the maximum allowable load from fifth to sixth hour since the dynamic pricing is very low during that period.

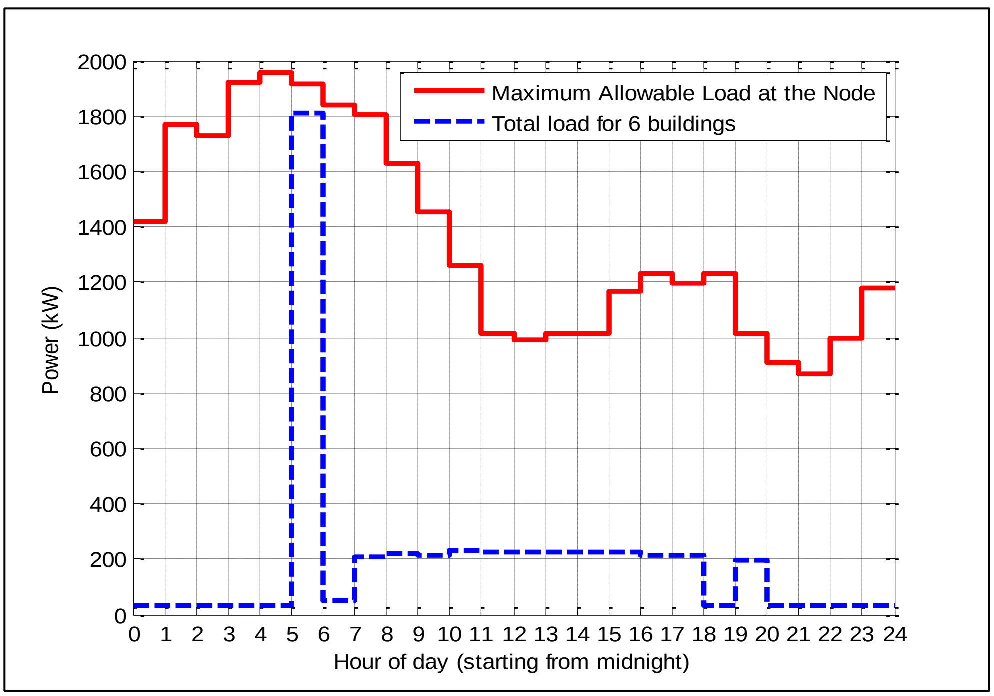

Figure 4.12: Total optimized load of six buildings lies within the maximum allowable load after relaxing the indoor temperature constraints by 0.7°C.

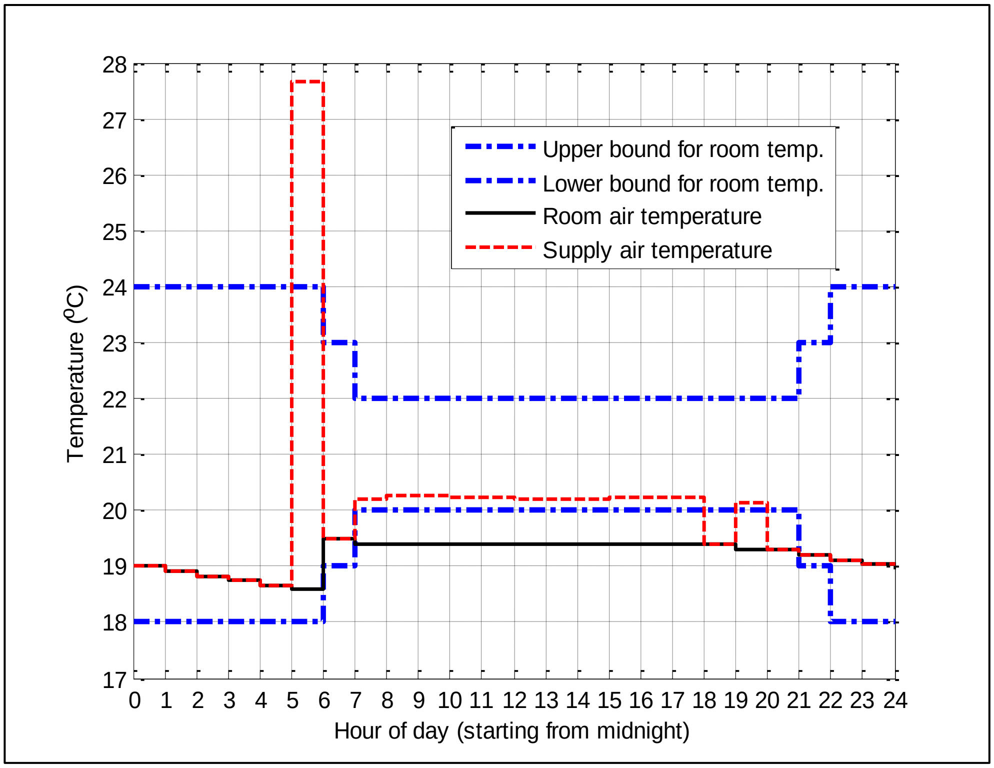

Figure 4.13: Room temperature and supply temperature profiles obtained upon relaxing room temperature bounds by 0.7°C are shown along with original room temperature constraints.

Thus over a series of steps an MPC algorithm was developed considering one goal at a time in the order of energy minimization, cost minimization and lastly considering maximum allowable load profile to avoid overloading of electricity power distribution grid.

Chapter 5

5 Conclusions and Future Work

Model Predictive Control was implemented successfully by predicting an energy profile for a building in order to optimize the power consumption and reduce the cost of power consumption. This chapter summarizes all the conclusions from this thesis and future work is recommended.

5.1 Conclusions

- Smart building in a smart grid is capable of adjusting its power consumption according to the load on the grid and the predicted price of electricity. When power consumption is at its peak, the price of electricity rises because of large consumption while the prices drop in low power consumption period. The controller in a smart building can adjust controllable load (of HVAC) to use less energy during peak period and schedules maximum power usage in low price period.
- A discrete state space resistance-capacitance (RC) model representing the thermal circuit was developed for a room with a ground source heat pump. On simulation of the model using input as supply temperature by heat pump and disturbance as outside environmental temperature, the resultant room temperature had a deviation of less than 1°C from the measured room temperature. This validated the model.
- A sensitivity analysis was carried out for the model to determine the parameters that affect the room temperature the most when changed by 10%. The parameters surface area of window, conductivity of outside wall, thickness of outside wall and convection coefficient for inner three walls are found to have a significant effect on the room temperature.

- Room temperature has a positive sensitivity with respect to thickness of outside wall whereas a negative sensitivity with respect to conductivity of outside wall, surface area of window and convection coefficient of inner three walls.
- In order to reduce/optimize the energy consumption of the room, Model Predictive Control (MPC) using Receding Horizon Control method was implemented. A predicted data for outside temperature was used. A prediction horizon of one hour was considered. Receding horizon control method determines room temperature and supply temperature through optimization for a prediction horizon based on the outside temperature predicted for that particular horizon and then proceeds to next prediction horizon. The objective function for minimizing the energy consumption is the energy equation for heat used by the room. For optimization constraints, room temperature limits were determined by ASHRAE standards [21]. MPC result was compared with existing On/Off controller for different environmental conditions; on a typical cold day (0°C ± 2°C), MPC uses 25.4% less power than existing On/Off controller. It was proved that MPC results in minimum power consumption in all environmental conditions. Thus MPC is consistent irrespective of outside conditions.
- To achieve reduction in total cost of power consumption, it was proved that using dynamic pricing data in the objective function itself is more effective than using it after optimization of energy. The energy used is high when dynamic pricing is low and energy used is low when the price is high. On a typical cold day (0°C ± 2°C), for a room, the cost function including dynamic pricing gives a daily cost of $0.47 which is less than that given by MPC with energy minimization algorithm ($0.56) and the one given by existing On/Off controller ($0.59).
- On obtaining the most suitable controller for one room, the model and algorithm was scaled up to first represent a building with 20 heating zones and then six buildings with 20 heating zones each. All the six buildings were connected at the same node in the grid. The HVAC profile obtained for six buildings by MPC with price minimization along with non-HVAC load (adopted from [19]), was compared with the maximum allowable load at the node. One of the peaks from the demand side profile exceeds the maximum allowable load. To get the peak within the maximum allowable load, indoor thermal comfort limits were relaxed by 0.7°C. Thus a profile for demand

side load with optimized power consumption reduced total cost of energy and also constrained peaks in demand side load

.

5.2 Future Work

Some recommendations for future work are,

- The room temperature control achieved in the thesis is by controlling the supply temperature provided by the heat pump while keeping the mass flow rate of air into the room constant. Room temperature control can also be achieved by varying the mass flow rate of air keeping a constant temperature of air supplied by heat pump.
- Radiation and internal heat generation can be considered in the building HVAC model to improve accuracy of building model.
- Convection coefficient of heat transfer for outside air is assumed to be constant. A convective heat coefficient varying according to outside conditions (e.g. wind, relative humidity, etc.) can be considered to make the building model more practical.
- The COP considered in this thesis is constant (i.e., COP= 3.2) since ground source heat pump is used in this thesis (ground temperature is almost constant). Given the dependence of heat pump's COP on the outside temperature, COP should be considered variable for air-source heat pumps. As an extension to the work in this thesis, a general heat pump model with varying COP for air-source heat pumps can be developed and its effect on optimization can be studied.
- The MPC framework from this thesis can be experimentally implemented on Michigan Tech's Lakeshore Centre.

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Appendix A

The state space matrices for building energy model are specified in this section.

- State matrix:

$$A = \begin{matrix} g_0 & \frac{T_{sample}}{C_r \times R_{w1_{in}}} & \frac{T_{sample}}{C_r \times R_{w2_{in}}} & \frac{T_{sample}}{C_r \times R_{w3_{in}}} & \frac{T_{sample}}{C_r \times R_{w4_{in}}} \\ \frac{T_{sample}}{C_{w1} \times R_{w1_{in}}} & g_1 & 0 & 0 & 0 \\ \frac{T_{sample}}{C_{w2} \times R_{w2_{in}}} & 0 & g_2 & 0 & 0 \\ \frac{T_{sample}}{C_{w3} \times R_{w3_{in}}} & 0 & 0 & g_3 & 0 \\ \frac{T_{sample}}{C_{w4} \times R_{w4_{in}}} & 0 & 0 & 0 & g_4 \end{matrix}$$

where,

$$g_0 = \frac{T_{sample}}{C_r} \times \left[\frac{-1}{R_{w1_{in}}} + \frac{-1}{R_{w2_{in}}} + \frac{-1}{R_{w3_{in}}} + \frac{-1}{R_{w4_{in}}} + \left(\dot{m} \times C_p\right) + \frac{-1}{R_{win}} + \frac{C_r}{T_{sample}}\right]$$

$$g_1 = \frac{T_{sample}}{C_{w1}} \times \left[\frac{-1}{R_{w1_{in}}} + \frac{-1}{R_{w1_{out}}} + \frac{C_r}{T_{sample}}\right]$$

$$g_2 = \frac{T_{sample}}{C_{w2}} \times \left[\frac{-1}{R_{w2_{in}}} + \frac{-1}{R_{w2_{out}}} + \frac{C_r}{T_{sample}}\right]$$

$$g_3 = \frac{T_{sample}}{C_{w3}} \times \left[\frac{-1}{R_{w3_{in}}} + \frac{-1}{R_{w3_{out}}} + \frac{C_r}{T_{sample}}\right]$$

$$g_4 = \frac{T_{sample}}{C_{w4}} \times \left[\frac{-1}{R_{w4_{in}}} + \frac{-1}{R_{w4_{out}}} + \frac{C_r}{T_{sample}}\right]$$

- Input matrix:

$$B = \begin{matrix} \dfrac{T_{sample}}{C_r \times \dot{m} \times C_p} \\ 0 \\ 0 \\ 0 \\ 0 \end{matrix}$$

- Disturbance matrix:

$$F = \begin{matrix} 0 & 0 & 0 & \dfrac{T_{sample}}{C_r \times R_{win}} \\ \dfrac{T_{sample}}{C_r \times R_{w1_{out}}} & 0 & 0 & 0 \\ 0 & \dfrac{T_{sample}}{C_r \times R_{w2_{out}}} & 0 & 0 \\ 0 & 0 & \dfrac{T_{sample}}{C_r \times R_{w3_{out}}} & 0 \\ 0 & 0 & 0 & \dfrac{T_{sample}}{C_r \times R_{w4_{out}}} \end{matrix}$$

- Output matrix:

$$C = 1 \quad 0 \quad 0 \quad 0 \quad 0$$

Appendix B

Bidirectional Optimal Operation of Smart Building-to-Grid Systems [19]

This section gives a brief description of the paper by Razmara, M., et. al. This paper presents bidirectional optimization of energy, i.e. from the building side as well as from the grid side. The objective function chosen is minimizing the cost of energy consumed on the building side while on the grid side it is maximizing the load penetration by maximizing the load factor.

The test bed for demand side optimization is the Lakeshore Centre, at Michigan Technological University. This building uses ground source heat pumps with nominal COP as 3.2. A resistance-capacitance state space model was developed for the building and validated using the data obtained from Building Management System (BMS) as well as the temperature sensors in the building (accuracy ±2°C). The states of the model are the temperature of the nodes in the model (room and the four walls), the input is the air mass flow rate and the supply air temperature from the heat pump and the disturbance is the temperatures outside the four walls. The state space equations act as the equality constraints in the optimization model of the building. The inequality constraints for optimization are the room air temperature limits, supply air temperature limits and load limits from the grid during bidirectional optimization.

The model of the grid is developed by considering standard single phase 12.66 kV, 33-node distribution feeder. A 32-step regulator (tap position ranging from -16 to +16) and capacitor banks connected at 2 nodes of the grid are considered as control equipment in the distribution grid. The distribution feeder consists of the distribution lines, capacitor banks, regulators and the loads. The loads that are used in the model are constant current load, constant impedance load and constant power load.

The models for the building as well as the grid were implemented in the optimization process with the assumptions, (1) 4 arbitrary nodes from the grid are considered for optimization, (2) number of buildings connected at the nodes is 6, 3, 5 and 8 respectively, and (3) each building has 20 heating zones; all buildings have same load profiles and indoor comfort limits. The optimization is carried out using Model Predictive Control (MPC) methodology since predicted dynamic pricing and weather forecast are used. Optimization on the demand side (building) was carried out using YALMIP toolbox from MATLAB and the supply side (grid) optimization was carried out using GAMS. The results for optimization are discussed only for one node, i.e. node #18. The demand side optimization results are compared with the existing On/Off controller in the building and it was concluded that a 26% cost saving and 16% energy saving occurred due to MPC compared to unoptimized On/Off controller.

The bidirectional optimization process is shown schematically in the Figure B.1. The process has four optimizations. The process starts with building optimization I for cost minimization using the building load requirements (equality constraints) and the temperature bounds (inequality constraints). The resultant optimized load profile is used to check if it is within the grid operational limits. If the demand side load is not within grid limits, a grid optimization I is carried out for maximizing load penetration. The resultant load profile is the *maximum allowable load* for the demand side. Using this maximum allowable load as one of the constraints, building optimization II is carried out for cost minimization. If the solution is infeasible, the building load requirements are modified by either changing the temperature bounds or utilizing energy from the energy storage system of the building and thereafter building optimization I is carried out again. At any point in the iterative process, if the results of building optimization I and II are feasible, the process proceeds to grid optimization II to maximize the load factor.

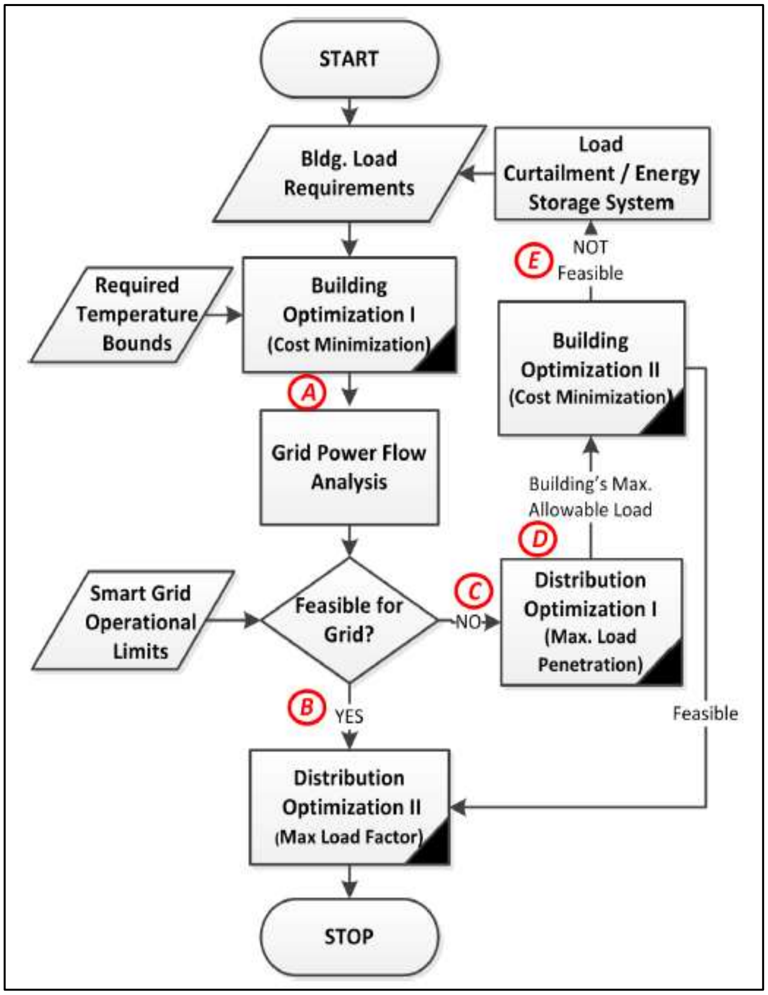

Figure B.1: Flow chart for B2G bidirectional optimization [© [2015] IEEE]

On comparing bidirectional optimization results with the existing On/Off controller, it was observed that due to bidirectional control, the building cost saving was 25% and building energy saving was 17%. By using bidirectional control in place of demand side optimization control, the building cost saving decreased by 1% while building energy saving increased by 1%.

YALMIP Toolbox and Basics [22]

YALMIP is a toolbox in MATLAB which provides a platform to develop and solve optimization problems for levels simple to tough. The toolbox was developed in the first place to solve semidefinite programming (SDP) and linear matrix inequalities (LMI). Later the toolbox was evolved so that it can be used for other types of optimization programming such as linear programming, mixed integer programming, quadratic programming, etc. YALMIP interfaces external solvers in order to obtain feasible solution for different optimization applications. Based on the type of problem defined, YALMIP chooses a solver on its own and executes it. If YALMIP does not have a certain solver needed to evaluate an optimization, it converts the optimization problem from one form to other (for example, from second order cone constraints to LMIs), and solves it with the available solver. The different solvers used in YALMIP are SeDuMi, SDPT3, PENNON, CPLEX, branch and bound (inbuilt solver in YALMIP), etc.

An optimization problem can be defined in YALMIP in three steps namely, (1)defining parameters and variables, (2)defining objective function and constraints, (3)using a command to solve the problem.

The standard MATLAB commands and syntax can be used in YALMIP. Thus parameters can be defined by basic MATLAB declaration syntax. The decision variables can be defined by using the command ‘sdpvar’. The syntax to define a symmetric *P* matrix with dimension *b* using this command is as shown below,

$$P = sdpvar(b, b,' symmetric',' real'); \tag{B.1}$$

If the matrix *P* is a real square matrix, the command does not require specifying symmetric and real and can be simply written as,

$$P = sdpvar(b, b); \tag{B.2}$$

If the matrix contains complex numbers, then real in equation (B.1) can be replaced by complex. If the matrix is fully parameterized, the terms $'symmetric'$ and $'real'$ in equation (B.1) are replaced by $'full'$.

If receding horizon control is being used during optimization, the objective function and the constraints are specified in a *for* loop. The constraints can be specified in a matrix using MATLAB syntax or sdpvar command. The operators > and < can also be used to represent semidefinite constraints (≥ and ≤ respectively). To solve the optimization problem for every prediction horizon, the command used is '*solvesdp*'. In the beginning solvesdp used to solve only semidefinite problems but now, it can be used for linear programming, quadratic programming, second order cone programming, etc. The structure of a receding horizon control for a control horizon of 24 hours in YALMIP can be shown as,

>> define parameters and matrices using standard MATLAB syntax;

>> for j=1:24

>> u= sdpvar(repmat(1,1,24),repmat(1,1,24)); % input variable

>> objective = 0;

>> constraints = [ ];

>> for k=1:24

>> $x_k = Ax_k + Bu_k + Fd_k$;

>> objective = objective + $f(x)_k$;

>> constraints = [constraints, $x_{lower\ bound} \leq x_k \leq x_{upper\ bound}$];

>> constraints = [constraints, $u_{lower\ bound} \leq u_k \leq u_{upper\ bound}$];

>> constraints = [constraints];

>> end;

>> solvesdp(constraints,objective);

>> $x_{k+1} = Ax_k + Bu_k + Fd_k$;

>> $x_k = x_{k+1}$;

>> end;

One can add more parameters to store the values of the resultant variable in a matrix/vector form. The command *repmat(1,1,24)* produces a 24×24 tiling of (1,1).

Appendix C

Letters of Permission:

Letter from Mr. Gregory Kaurala:

Michigan Technological University

1400 Townsend Drive, Houghton, Michigan 49931-1295

Facilities Management
Office of the Director
906/487-2303
FAX: 906/487-3291

Ms. Paranjape,

I hereby grant permission to Madura Paranjape to use the two images of Michigan Technological University's Lakeshore as well as data she has collected about the dimensions of the room and any data she obtained from using our building management system.

Sincerely,

Gregory Kaurala
Manager, Central Energy Plant

Permission Email from Meysam Razmara:

Dear Madhura,

I hereby grant permission to you for using the RC model schematic diagram, non-HVAC load profile, nodal information from the electrical distribution feeder and related data of the experimental setup Lakeshore Center from the paper entitled: "Bidirectional Optimal Operation of Smart Building-to-Grid Systems" submitted to 2015 American Control Conference, in your MS thesis.

Sincerely,

Meysam Razmara

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Appendix D

Thesis Files Summary

Following files were used for this thesis. Data is arranged in form of tables.

Table D.1: Excel files for experimental data and MATLAB simulation output data

Sr. #	File Name	Description
1.	Lakeshore_sensor_data	Experimental data from temperature sensors in Lakeshore Centre
2.	Dynamic_Pricing_data	Dynamic pricing data for Michigan hub [25]
3.	Maximum_allowable_load_node18	Maximum allowable load for Node#18 [19]
4.	Sensitivity_data	Sensitivity of room temperature against various parameters and variable obtained through simulations

Table D.2: MATLAB workspace data required to compare cost profiles of MPC and On/Off controllers

Sr. #	File Name	Description
1.	existing_on_off_cost_profile	Output data from existing On/Off controller simulation
2.	energy_min_cost_profile	Output data from MPC with energy minimization simulation
3.	price_min_cost_profile	Output data from MPC with price minimization simulation

Table D.3: MATLAB scripts for building model validation, simulation of MPC and On/Off controllers, plotting cost profiles and sensitivities

Sr. #	File Name	Description
1.	validation	Contains discrete model of room and its simulation
2.	sensitivity	Plots sensitivity of room temperature with respect to various parameters and variables
3.	existing_controller	Contains existing On/Off controller
4.	MPC_for_energy_and_price	Contains MPC for energy minimization as well as price minimization
5.	cost_profile_comparison	Plots cost profiles of existing controller, MPC with energy and price minimization for comparison