Automating Distributed Domestic Heating Systems

Ka Lung Ng

A dissertation submitted to the University of Dublin,
in partial fulfilment of the requirements for the Degree of
Master of Science in Computer Science

2017

Declaration

I declare that the work described in this dissertation is, except where otherwise stated, entirely my own work and has not been submitted as an exercise for a degree at this or any other university.

Signed: _____________________________________

Ka Lung Ng

30 August 2017

Permission to lend and/or copy

I agree that Trinity College Library may lend or copy this dissertation upon request.

Signed: ______________________________________

Ka Lung Ng

30 August 2017

Acknowledgement

I would like to thank my supervisor, Professor Siobhan Clarke, for providing me support and guidance since I was selecting my dissertation topic. I am sincerely grateful for her encouragement and her knowledge in the relevant area and researching methodology.

I would also like to thank to all GridLAB-D™ developers and users whom have provided me guidance for learning the software to achieve grid simulation in this dissertation.

Lastly, I would like to deliver special thanks to my family for their support and patience throughout the process.

Abstract

Domestic heating systems are major consumers of household electricity in European countries, occupying 19% of overall use. Since a domestic heating system takes significant time and energy to heat up, an intelligent planning solution is essential to maximize its energy use efficiency. Therefore, home heating automation is a solution and its goals are to maximize occupants' comfort level and minimize energy cost.

Model Predictive Control (MPC) supports periodic recomputation of optimal solutions to defined problems. MPC is robust to uncertainties and has been used in several research approaches for controlling domestic heating systems. On the other hand, heuristic approach promotes solutions sufficient enough to solve immediate objectives in order to speed up the process of development.

This dissertation investigates and implements a heuristic baseline solution based on thermal comfort, pricing scheme and energy consumption, and a MPC solution for coordinating distributed domestic heating systems. The solution balances between minimizing electricity cost and maximizing thermal comfort of occupants. Meanwhile, the non-critical electricity consumption is shifted from peak hours to off-peak hours to achieve demand response (DR) for distributed use.

Through simulation, the performance of the two solutions is compared with a default controller, which constantly maintains the temperature at 69.8°F. The results show that the cost of a typical manual controller is around 4.20% and 25.6% more than that of the default controller under flat pricing scheme and Time of Use (TOU) scheme respectively, while the cost of the heuristic baseline automatic control proposed in this dissertation is around 9.38% and 10.7% less than that of the default control under two pricing schemes respectively. MPC can produce similar performance as baseline controller in terms of cost but it can further reduce the thermal discomfort raised by the cost reduction. Both solutions have better performance in Peak-to-Average ratio (PAR) such that it is more suitable for the distributed use when comparing with the manual control.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Smart grid technology has been gradually adopted and developed in many countries since last decade. It allows easier electricity information transfer and the whole community can benefit from the continuously improved electricity system. Smart grid also promotes the concept of smart home which enables home automation for residents. Through home automation, occupants can automatically enjoy the benefit of maximizing the efficiency of energy use while minimizing energy consumption and cost without sacrificing their comfort level.

This dissertation investigates and implements different solutions to maximize occupants' comfort level and minimize energy cost by coordinating distributed domestic heating systems in home heating automation.

1.1 Motivation

Heating systems are extensively used in households and take up approximately one-third of overall household electricity use [1]. The 2013 Report about Energy in the Residential Sector provided by Sustainable Energy Authority of Ireland (SEAI) [2] estimated that space heating in household of EU countries had occupied 19% of the overall domestic electricity end use in 2009. Hence, it shows that controlling space heating appropriately is hugely beneficial to control domestic electricity end use.

Since domestic heating systems are major consumers of household electricity and take significant time and energy to heat up, an intelligent planning solution is essential for controlling domestic heating system such that it can maximize occupants' comfort level and minimize energy cost.

1.2 Aims

The goal of this dissertation is to provide solutions for home heating automation to control distributed domestic heating systems.

The aims of this dissertation are as follows:

(a) To validate the rationale of automating domestic heating system

(b) To provide approaches for automating domestic heating system

(c) To show the advantages and disadvantages of automation approaches and manual control in domestic heating system

(d) To demonstrate the feasibility of automating distributed domestic heating system with approaches suggested in (b)

1.3 Dissertation Structure

The structure of this dissertation are organized as follows:

Chapter 2 is the State of the Art which reviews important concepts of the topic and existing approaches used in home energy management (HEM) that can be useful to automate distributed domestic heating system.

Chapter 3 is the Design which describes the evaluation criteria to evaluate the performance of controls and the designing of controllers based on Chapter 2.

Chapter 4 is the Implementation which describes how different controls can be experimented through the simulation process, such as setting up the simulation environment and creating relevant models throughout the simulation.

Chapter 5 is the Evaluation which presents and analyse the results of the in detail with regard to the evaluation criteria discussed in Chapter 3.

Chapter 6 is the Conclusion which summarizes the dissertation and its contributions and explore possible related work in the future.

Chapter 2

State of the Art

This chapter reviews all important concepts such as concerns during design, and existing approaches used in smart grid or related to this dissertation topic which can be useful to automate distributed domestic heating system.

2.1 Categories of Improving Domestic Heating System

In general, there are two major categories for improving the efficiency of domestic heating system, namely technical retrofit and human retrofit [3].

Technical retrofit refers to improvements in the physical components of the house and building [3], such as the materials and the level of insulation of walls and windows. Thybo et al. [4] suggested that the floor heating system type and the building type are the major elements which affect the effectiveness of the domestic heating system control. The building type and floor heating types can be generally classified as heavy and lightweight systems, where heavy system has larger heat capacity than lightweight system such that it usually requires more time to heat up and cool down and hence less dynamic.

On the other hand, human retrofit refers to the behaviours of occupants of the house and building [3]. For instance, Roeder et al. [3] proposed a multi-objective optimization framework which balances between energy consumption and retrofit cost of thermal comfort and productivity of occupants, while the physical design of the heating system is not considered.

Since many existing researches focus on technical retrofits [3], this dissertation aims to focus on human retrofits and consider various criteria which balances between energy consumption and satisfaction of occupants. The following sections describe the possible concepts, approaches and algorithms which may achieve the above goal.

2.2 Concepts of Home Energy Management (HEM) on Demand Side

2.2.1 Overview

The purpose of electric energy management is to keep demand and supply balanced at all times [5]. Therefore, in occupants' perspective, they can conduct home energy management (HEM) on demand side, known as demand side management (DSM).

DSM has the advantages of promoting distributed generation and enables a more flexible approach to influence a load instead of constructing a completely new energy storage if any change is required [5].

Palensky et al. [5] has provided an overview and a taxonomy for DSM in terms of timing and the impact on process quality. In general, quicker changes with less time usually tend to have less optimized impacts. There are four major categories in

DSM, namely Energy Efficiency (EE), Time of Use (TOU), Demand Response (DR) and Spinning Reserve (SR). For EE, its impact on process quality is the best optimized among four categories with permanent timing as it is an ongoing process. Energy Information System can be used to analyze hidden problems which waste energy, but it is hard for occupants to change as the EE of all electric appliances and systems are pre-set. SR is of the quickest timing among all and it can reduce or increase load when the energy grid frequency drops or rises respectively. However, this is usually used in regulating power plants and occupants are not eligible to control.

Therefore, TOU and DR are more feasible for occupants to control energy and the following subsections describe the concept and the use of TOU and DR in detail.

2.2.2 Time Of Use (TOU)

Electricity prices are commonly charged under flat pricing scheme, i.e. uniform pricing regardless the time of use. However, it is notable that electricity consumption at peak time, such as evening, is higher than off-peak time. Therefore, time of use (TOU) is introduced to change the ordinary pricing scheme.

TOU charges peak time energy consumption for higher price and off-peak time energy consumption for lower price such that occupants will have the motivation to re-arrange their time of energy use in order to minimize energy cost [5].

Although flat pricing scheme are still commonly used, many countries including Ireland, the United States, Japan and Hong Kong are implementing the use of TOU with the use of smart meter [6] – [9]. Since the energy price at off-peak hours is much lower than that during peak hours, occupants should consider TOU pricing scheme when controlling domestic heating system to reduce energy cost.

2.2.3 Demand Response (DR)

Similar to TOU, demand response (DR) also promotes to reduce the non-critical energy use at peak time [5], [10] - [13]. DR has much quicker response than TOU that a controller is usually adopted and it uses models to make reasonable decisions and control the action of electric appliances and systems [5]. There are four major benefits of using DR [10]. Firstly, participant can enjoy immediate reduction in cost together with TOU. Secondly, the infrastructure cost can be reduced by lowering high demand at peak hours. Thirdly, the reliability of energy supply can be increased, and finally the market performance increases when customers have more options to use energy.

DR has been investigated in many researches, and some possible DR actions include reducing energy consumption through strategies, moving energy consumption to off-peak hours and using onsite alternatively generated energy [11]. In occupants' perspective, the most feasible approach for them is to shift energy consumption from peak hours to off-peak hours.

To achieve the above goal, a prerequisite is that that energy consumption at peak hours should be non-critical, i.e. the user does not require to use that electric appliance or system immediately. For example, it is probably impossible to shift the energy consumption to cause delay if the occupant wants to turn on the light. Hence, the concept of DR is not suitable for all domestic energy uses.

An appropriate use of DR in domestic use is to shift the charging hours of electric vehicle appropriately from peak to off-peak hours since users typically charge the electric vehicle overnight after use and electricity use can be reduced during peak hours [12], [13].

Since domestic heating systems take significant time and energy to heat up, DR is a feasible concept for consideration to maximize occupants' comfort level and minimize energy cost.

2.3 Approaches of Home Energy Management (HEM) on Demand Side

2.3.1 Overview

This section discusses the existing approaches and algorithms to control domestic energy on demand side. These approaches and algorithms have already demonstrated their feasibility of use in heating system or home energy management. Thus, these approaches and algorithms are possible to be implemented for automating distributed domestic heating systems.

2.3.2 Direct Load Control (DLC)

Direct Load Control (DLC) is one of the earliest form of energy management system [14] - [17]. The purpose of DLC is to shape the load curve for users to control appliances and the user can control the status of the appliances [14], [15].

This approach is straightforward as the user can freely control the load, but meanwhile there are two major disadvantages [16], [17]. Firstly, the infrastructure design of the load will affect the feasibility of using DLC. This means DLC can only be used if the load has been designed for the use of DLC. Secondly, DLC has limited ability as it only supports direct control of the load and does not fully exploit operational flexibilities of appliances. For example, DLC is capable of turning on and off the heating system, but it may be hard to schedule specific temperatures at different time.

Therefore, DLC can be considered as the first step for developing more advanced approach to control domestic heating system more flexibly and accurately, as this is a relatively conventional smart control.

2.3.3 Dynamic Programming (DP)

Dynamic Programming (DP), also known as dynamic optimization, is one of the most commonly used approaches to find an optimal solution [18] - [21]. The purpose of DP is to analyse sequential decision process and reduce the complexity of a problem by converting it into multiple simpler problems [18], [19]. Besides, the solution often does not need to be calculated repeatedly once an optimal solution is found.

This approach has demonstrated satisfactory performance in HEM, particularly solving linear energy scheduling optimization [20], [21]. However, it is usually hard for DP to further improve the solution once an optimal solution is found. Since DP typically truncates time horizon into one-step ahead policy [22], so it is much harder to predict when the time horizon is longer, causing the limited ability of DP.

Therefore, based on DP, Predictive Model Control (MPC) is introduced to solve the longer time horizon problem. Details will be explained in the next subsection.

2.3.4 Model Predictive Control (MPC)

Model Predictive Control (MPC) commonly has three elements, namely prediction model, objective functions and optimization with constraints [23]. The prediction model should be able to capture all process dynamics to calculate for predictions. Afterwards, objective functions are needed to address the necessary objectives and ultimately results can be obtained after objective function optimization with regard to constraints. The difference of MPC from DP is that the whole process of MPC is in receding horizon such that the optimization is carried out on a time interval of the current time plus a prediction time horizon [24]. Hence, MPC can become more flexible and accurate than DP by freely adjusting the time horizon.

MPC has already been used in several research approaches for controlling domestic heating systems [25] - [30]. For example, Kajgaard et al. [25] created an MPC for domestic heat pump to balance the trade-off between human discomfort level and price. They discretized a continuous house model and formulated objective functions regarding comfort and power cost. For comfort, it is a cost function which penalize the difference of the current temperature from the desired temperature. For power cost, it is computed by multiplying the heat pump power consumption by the electricity price. Together with the constraints of heat pump power limits and comfort limits, an optimal solution can be found when there is a new iteration. There had been a few papers using the concept of MPC on heating, ventilating and air conditioning (HVAC) [26] – [28] before this paper has been published, but it focuses more on experimentation and takes multiple objectives into consideration. However, the possibility for distributed use has not been validated in this paper.

Sundstrom et al. [29] have further extended the use of MPC in general energy management at home. The MPC controller formulates four factors which are indoor heat transfer, water tank level, hot water consumption and state of energy of electric vehicle. The MPC is designed to minimize the weighted cost of the energy and maximum power so far used during that month. MPC is also discovered to be robust to uncertainties with the use of the predictor. By lengthening the prediction horizon of MPC, its performance can be increased such that minimal peak consumption can be achieved since the controller can better plan and distribute the energy consumption. It has also validated MPC can perform as well as DP. This paper has taken more objectives into consideration but it also makes the scenario more complicated as more electric appliances are involved and the performance of MPC on heating system specifically is slightly obscure.

Van Leeuwen et al. [30] have proposed another MPC to control a group of heat pumps which provide space heating and domestic hot water in many houses. This paper proposes three different models. The Energy System Model describes the configuration between different components of energy system, while Household Space Heating Demand Model describes the use of simulation model to learn relations between occupants' demand data. The last model, Heat Pump Model, has approximated heat pump performance on input and output during different operation modes. Afterwards, creating models for three components, the optimized control algorithm is to minimize peak electric demand by considering the electric demand of the heat pump and control state of other heat pumps. It has been validated that this novel approach has outperformed ordinary threshold control and demonstrates the use of controlling multiple heat pump. However, this approach seems to be a centralized control for a group of heat pumps and lacks of measurements to validate the possibility of distributed use.

From the above reviews, MPC has already demonstrated its practicability in controlling domestic heating system. Therefore, solutions for automating distributed domestic heating system in this dissertation is also based on MPC. However, we still need to have a general solution for using MPC and validate it for the feasibility of distributed use.

2.3.5 Heuristic Algorithms

Different from DP and MPC which find an optimal solution for a problem, heuristic algorithm is a general term to describe a solution sufficient enough to solve immediate objectives such that the process of development can be sped up [17].

Since the execution of conventional optimization in smart grid is very time consuming and makes it practically infeasible be implemented, but heuristic algorithm can overcome these problems.

Rehman et al. [17] compared three heuristic algorithms on HEM with regard to energy cost, energy consumption and Peak-to-Average Ratio (PAR). The three heuristic algorithms are namely binary particle swarm optimization (BPSO), genetic algorithm (GA) and wind driven optimization (WDO). BPSO aims to find the optimal solution within search space considering locally best position and the global position of all particles such that the global position determines the action of electric appliances. GA aims to find the optimal solution by incorporating mutation, crossover and selection until stop requirement is reached. WDO is a global optimization algorithm which generates optimal solution based on random number of solutions and meanwhile keeps updating in each iteration. These three algorithms have demonstrated their own advantages respectively.

Golpayegani et al. [13] have proposed another algorithm, namely Collaborative Parallel Monte Carlo Tree Search (CP-MCTS), for shifting non-critical energy use at peak hours to off-peak hours when charging electric vehicle. MCTS is a heuristic search method trying to find the optimal decision by forming a search tree based on random samples of decision space with four fundamental phases, namely Selection, Expansion, Simulation and Back-propagation. Parallel-MCTS (P-MCTS) is a variant of MCTS which allows every agent to run independent MCTS on their own. To avoid the bottleneck of central decision, Collaborative P-MCTS (CP-MCTS) is introduced with the use of collaboration. After carrying out P-MCTS and if violation occurs, collaboration stage consists of four steps where agents need to search for the conflicted agent, create a collaboration agenda, compare each agent current priority and carry out final decision based on the previous step. CP-MCTS has demonstrated the ability of improving final decision using collective knowledge obtained from other agents during the collaboration stage.

The above two reviews have shown that heuristic approaches are able to solve the problem based on immediate objectives although the solution may not be able to be proved to be optimal. Therefore, the heuristic concept may be useful for automating distributed domestic heating systems.

2.4 Chapter Summary

There are two major retrofits for improving domestic heating system, namely technical and human retrofit. This dissertation focuses on human retrofit and investigates solutions targeting on occupants' benefits, regarding the concepts related to TOU and DR.

MPC has been validated for the feasibility of controlling domestic heating system. Besides, heuristic approaches can be some sub-optimal solutions which are sufficient enough to solve immediate objectives to speed up the process of development and many algorithms have demonstrated their use in HEM. Therefore, this dissertation will work on these two approaches and evaluate them in the domestic and distributed use.

Chapter 3

Design

This chapter describes the objectives and evaluation criteria when designing the controllers for automating distributed domestic heating system, the system architecture of how heating system can be automated, and the controller design with different approaches which will be implemented in Chapter 4.

3.1 Objectives and Evaluation Criteria

The following are the major objectives of the solution which automates domestic heating system:

(a) Minimize energy cost

(b) Maximize thermal comfort of occupants

Apart from the major objectives which can maximize the benefits of occupants, the following objective can allow for distributed use and help energy providers provide more stable energy supply in the meanwhile:

(c) Shift the non-critical energy use from peak hours to off-peak hours

This following subsections describe the evaluation criteria of each objective.

3.1.1 Evaluation Criteria for Energy Cost

To calculate energy cost at time interval t, the following formula is used:

$$\mathrm{Cost(t)} = \mathrm{E(t)\ P(t)} \tag{1}$$

E(t) indicates the marginal energy consumption and P(t) indicates the price under particular pricing scheme at time interval t respectively. Therefore, to calculate the energy cost for a period of time, the total cost will be the summation of Cost(t) under different time intervals.

To compare the performance of different controls in terms of energy cost, the control with the lowest value of energy cost indicates the best performance as occupants need to pay less for the energy consumption.

3.1.2 Evaluation Criteria for Thermal Comfort

To calculate thermal comfort at time interval t, the following formula is used:

$$\mathrm{Disomfort(t)} = \begin{cases} (T_C(t) - T_D(t))^2, & T_c(t) < T_D(t) \\ 0, & T_c(t) \geq T_D(t) \end{cases} \tag{2}$$

$T_C(t)$ indicates the current indoor temperature and $T_D(t)$ indicates the desired indoor temperature at time interval t respectively. Therefore, the thermal discomfort level at time interval t is 0 if the current indoor temperature has already reached the desired temperature, otherwise the discomfort level will be calculated by the square of the difference. Adopting squared equation is to penalize exponentially if the current temperature deviates from the desired one too far since users will feel much more uncomfortable if there is a huge difference.

To compare the performance of different controls in terms of thermal comfort, the control with the lowest value of thermal discomfort level indicates the best performance as occupants feel less uncomfortable when the value is lower.

Apart from the above calculation, another criteria is to consider how long the occupant needs to wait until reaching the desired indoor temperature. Detailed explanation in implementation and result will be discussed in Section 5.2.2.

3.1.3 Evaluation Criteria for Distributed Use

For distributed use, shifting the non-critical energy use from peak hours to off-peak hours is an important requirement. To calculate the effectiveness of shifting the non-critical energy use from peak hours to off-peak hours, Peak-to-average Ratio (PAR) [13] can be used to measure the distribution of energy demand over a period of time:

$$\mathrm{PAR} = \frac{\mathrm{Max\ E(t)} * \mathrm{N}}{\sum_{\mathrm{t=0}}^{\mathrm{N}} \mathrm{E(t)}} \tag{3}$$

N represents the number of timeslot which takes into account for calculating PAR, E(t) indicates the marginal energy consumption at time interval t and Max E(t) indicates the highest value of E(t) among N timeslot.

To compare the performance of different controls in terms of demand response, the control with the lowest value of PAR indicates the best performance as lower value implies energy consumption demand is distributed better over the time period [13]. Therefore, lower PAR also means it is more suitable for distributed use.

Apart from PAR, a more direct consideration is the energy consumption during peak hours. Therefore, if the energy consumption during peak hours can be reduced, the control is more suitable for distributed use.

3.2 System Architecture

Figure 3.1 depicts the system architecture of the apartment design. The assumption is that the heating control system can directly control the whole heating system in the apartment such that the temperature can be raised or declined accurately according to the instructions of the heating system.

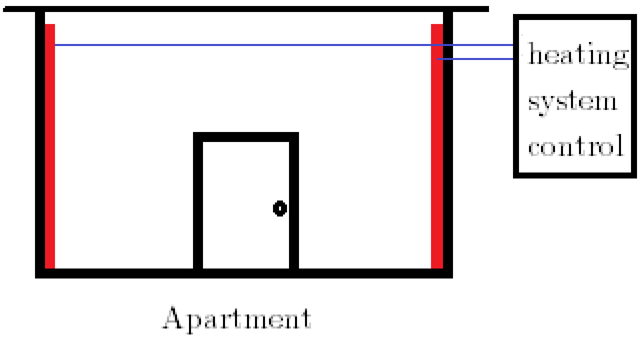

Figure 3.1: System Architecture of the Apartment Design

The instructions of the heating system are the designed schedule which are calculated by the designed controller explained in the next section.

3.3 Controller Design

The following sections describe the details of each controller design which composes of the heating system control.

3.3.1 Default Control

By default, the heating system will constantly maintain the indoor temperature at 69.8°F [31]. Therefore, regardless of the time, the heating system will be permanently turned on to maintain the indoor environment within the optimal temperature range.

However, occupants may need to pay more for the unnecessary heating. Besides, ordinary occupants probably will not turn on the heating system at all time. Therefore, the manual control described by the following subsection models the action of occupants better.

3.3.2 Manual Control

The Manual Control models the typical action of occupants. Its assumption is to consider occupants will be away from home during 9 am and 6 pm for work during weekdays, while occupants will be staying at home all day during weekends.

From the researches [31], [32], it was found that the optimal indoor temperature for occupants is approximately 65°F during sleeping time and 69.8°F for the remaining time. Therefore, on weekdays, we can assume that an occupant will turn on the heating system and set it as 69.8°F from 6 pm and set it to 65°F at 12 midnight before sleeping. Afterwards, the temperature will be set to 69.8°F from 6 am to 9 am, and finally the occupant will turn off the heating system during 9 am and 6 pm. Meanwhile, the heating system will be set as 69.8°F at all time in the weekends. Table 3.1 summarizes the temperature of the apartment under manual control.

Day	**Time**	**Temperature (°F)**
Weekdays	6 pm – 12 midnight	69.8
	12 midnight – 6 am	65
	6 am – 9 am	69.8
	9 am – 6 pm	Unknown as the heater is off
Weekends	24 hours	69.8

Table 3.1: Temperature of the Apartment under Manual Control

3.3.3 Heuristic Baseline Control

The heuristic baseline controller is to be designed for the general use for controlling domestic heating system without manual control. It considers three major concerns which are thermal comfort, pricing scheme and the relationship between the rate of increasing temperature and energy consumption.

Similar to manual control, the desired temperature of weekdays is set to be 69.8°F from 6 am to 9 am and from 6 pm to 12 midnight, 65°F from 12 midnight to 6 am, and the temperature between 9 am and 6 pm does not matter.

Apart from thermal comfort, TOU pricing scheme is also considered. The pricing scheme of SEAI of Ireland is utilized [7] and it is understood that 5 pm to 7 pm are the peak hours of energy use. Therefore, non-critical energy use during these hours should be shifted to off-peak hours, particularly energy consumed by raising temperature.

Most importantly, the relationship between the rate of increasing temperature and energy consumption is included in the design. For instance, it is found that the energy consumption of raising from 64°F to 66°F in 15 minutes and 30 minutes is different. In general, energy consumption doubles if the rate of increasing temperature doubles. Therefore, in the previous example, the energy consumption of raising from 64°F to 66°F in 15 minutes doubles the energy consumption when comparing with the scenario of raising same temperature in 30 minutes. Hence, this factor is taken into account such that the increase in temperature should not be rapid.

Although this heuristic baseline solution may not be the optimal solution, it has considered all objectives of automating distributed domestic heating system mentioned in Section 3.1. Therefore, this solution will be sufficient enough to solve the problem caused by the manual control. More detailed explanation and evaluation will be further revealed in Section 4 and 5.

3.3.4 MPC

The functionality of MPC controller is similar to the heuristic baseline controller, but MPC controller is based on the concept of MPC mentioned in section 2.3.4. It also concerns the objectives of energy cost and thermal comfort.

Based on the evaluation criteria of energy cost and thermal comfort, energy cost model and thermal comfort model are established respectively. From Equation (1) in Section 3.1.1, the energy cost model is the summation of Cost(t) over the time horizon with K samples and start from time k, noted as Equation (4).

$$\mathrm{Cost} = \sum_{t=k}^{k+K-1} \mathrm{E(t)\ P(t)} \tag{4}$$

From Equation (2) in Section 3.1.2, the thermal discomfort model is the summation of Discomfort(t) over the time horizon with K samples and start from time k, noted as Equation (5).

$$\mathrm{Discomfort} = \sum_{t=k+1}^{k+K} \mathrm{Discomfort(t)} \tag{5}$$

Therefore, the control algorithm of MPC is to minimize the functions of the energy cost model and thermal discomfort model, noted as the following:

$$\mathrm{minimize} \qquad \alpha \sum_{t=k}^{k+K-1} \mathrm{E(t)\ P(t)} + \beta \sum_{t=k+1}^{k+K} \mathrm{Discomfort(t)} \tag{6}$$

α and β are the scalar factors which balances the importance between cost and discomfort level.

3.4 Chapter Summary

This chapter discusses the performance criteria of each objective, i.e. minimizing energy cost, maximizing thermal comfort and shifting non-critical energy demand. It also describes the assumption of the design and details of each controller design. Based on the design and its consideration, its implementation will be discussed in Section 4.

Chapter 4

Implementation

This chapter describes the implementation of the design for the dissertation. This includes the software for the simulation environment, modules utilized and models created in the simulation environment and implementation of controller design.

4.1 Simulation Environment Setup

Since real world experiments with smart meter and heating system requires large space and huge cost for equipment, the implementation of this dissertation is carried out on GridLAB-D™ which is an open-source, smart grid simulator developed by the United States Department of Energy (DOE) [33].

GridLAB-D™ is a power distribution system simulation and analysis tool which can design and operate distribution systems [33]. Different from conventional simulation which need to design the system dynamics and dynamic systems, GridLAB-D™ is an agent-based simulation that agents are placed in environments and it focuses on behaviours and relationships between entities. Since this dissertation does not aim to reconstruct the whole heating system, agent-based simulation is more appropriate for this dissertation as we can create the house models with existing models and design the controllers which utilize the algorithm design discussed in Section 3.3. Table 4.1 summarizes the strengths and weaknesses of conventional simulation and agent-based simulation [34].

Type	Advantages	Disadvantages
Conventional Simulation	1. Easy to validate analytically 2. Computationally efficient	1. Difficult to scale 2. Difficult to integrate with other models 3. Difficult to modify once the system is set
Agent-based Simulation	1. Easy to Scale 2. Easy to integrate with other models	1. Require detailed model 2. Difficult to validate

Table 4.1: Comparison between Conventional Simulation and Agent-Based Simulation

Besides, GridLAB-D™ utilizes its designed files to describe simulation, namely GLM files, representing **G**rid**L**AB-D **M**odel [34]. The strengths of GLM file are easy to read and edit and able to manage multiple models. However, its weakness is incompatible with many other software tools.

4.2 Simulation Modules and Models

This section explains the structure of GLM files, including modules utilized in the GLM files and the models which can created from the modules.

```
clock {
    timezone PST+8PDT;
    starttime '2016-01-01 00:00:00';
    stoptime '2017-01-01 00:00:00';
}
```

Figure 4.1: Clock Directive of the GLM file

```
module climate;
object csv_reader {
    name my_csv_reader;
    filename "weather_Dublin_2016.csv";
}
object climate {
    name Dublin_climate_2016;
    tmyfile "weather_Dublin_2016.csv";
    reader my_csv_reader;
}
```

Figure 4.2: Climate Module and Settings in the GLM file

Firstly, the clock directive, which indicates the period of time for simulation, needs to be included in GLM file like figure 4.1

Secondly, the climate module, which indicates the climate for implementation, is included in GLM file like figure 4.2. In this dissertation, Dublin climate information in 2016 is utilized for simulation [35].

Thirdly, the powerflow module, which can be used to measure energy consumption, is included in GLM file like figure 4.3.

```
module powerflow;
object triplex_meter {
    name house_meter;
    phases AS;
    nominal_voltage 120;
}
```

Figure 4.3: Powerflow Module and Settings in the GLM file

Parameter		**Value**
Location		Dublin, Ireland
House Type		3-bedroom apartment
Dimensions & Height	Area	90 m^2
	Window-to-wall Ratio	15%
Building Envelope	Thermal Integrity Level	Medium
	Window Frame	Insulated
Heating System	Heating	Heat Pump
	Auxiliary Heating	Electric

Table 4.2: Parameters and Design of the Apartment

After setting up all essential modules, house models can be created. Table 4.2 describes the house model implemented in this dissertation. The house model shows a typical Irish apartment [36] which utilizes heat pump heating system with medium thermal integrity level and insulated frame. Noted that these variables can be changed in the GLM file. For example, thermal integrity can be changed from medium to low. For simplification purpose to evaluate the controllers, uniform house model is used.

After that, the fundamental design of the models is completed. The remaining is the implementation of different controllers and this will be explained in the next section.

4.3 Controller Implementation

The difference between different controllers in implementation is the scheduling of controlling heating system. The following subsections discuss the settings among controllers.

4.3.1 Default Control

As mentioned in section 3.3.1, default control is to constantly maintain the apartment at the optimal temperature which is 69.8°F. Therefore, the house model will be set to 69.8°F throughout the simulation process. It can be done by setting parameter "heating_setpoint" as 69.8 or setting a schedule to maintain temperature as 69.8 , as shown in figure 4.x.

```
schedule schedule1 {
    * * * * * 69.8;
}
```

Figure 4.4: Schedule for Default Control

4.3.2 Manual Control

As mentioned in section 3.3.2, the heating schedule will work in accordance with Table 3.1 to model typical actions of occupants.

```
schedule heating_schedule_manual {
    * 1-5 * 1-6,9-12 * 65;
    * 6-8 * 1-6,9-12 * 69.8;
    * 9-17 * 1-6,9-12 1-5 35;
    * 9-17 * 1-6,9-12 0,6-8 69.8;
    * 18-00 * 1-6,9-12 * 69.8;
    * 6-8,18-00 * 7-8 * 60;
    * 1-5,9-17 * 7-8 * 25;
}
```

Figure 4.5: Schedule for Manual Control

4.3.3 Heuristic Baseline Control

Day	**Time**	**Temperature (°F)**
Weekdays	5 pm – 12 midnight	69.8
	12 midnight – 6 am	65
	6 am – 9 am	69.8
	9 am – 5 pm	Does not care but will gradually reach 69.8 °F before 5 pm
Weekends	24 hours	69.8

Table 4.3: Temperature of the Apartment under Heuristic Baseline Control

The main theme of the heuristic baseline control is to consider the relationship between the rate of increasing temperature and energy consumption, meanwhile the objectives of thermal comfort and pricing scheme are considered. Therefore, based on the finding mentioned in Section 3.3.3 that energy consumption doubles if the rate of increasing temperature doubles, this approach will adopt a stepwise manner to increase temperature. More specifically, it increases 1°F every 15 minutes and ensures the apartment reaches 69°F before 5pm since TOU pricing scheme has been taken into consideration. Therefore, it means the temperature will be inclined gradually over a period of time before reaching the desired temperature at the required time.

4.3.4 MPC

As mentioned in section 3.3.4, the control algorithm of MPC is to minimize the functions of the energy cost model and thermal discomfort model. Therefore, in this dissertation, the weighting a(t), where its value is between 50 and 400, was multiplied to the energy cost model to avoid the overwhelming effect of the thermal discomfort model, as shown in equation (7).

$$\text{minimize} \quad \sum_{t=k}^{k+K-1} \mathrm{a(t)\ E(t)\ P(t)} + \sum_{t=k+1}^{k+K} (\mathrm{T}_C(\mathrm{t}) - \mathrm{T}_D(\mathrm{t}))^2 \tag{7}$$

To carry out prediction based on MPC, for P(t), reference materials [7] and [37] are used as the flat and TOU pricing scheme respectively for calculating the energy price at a particular time. For E(t), the estimation is based on the following figure.

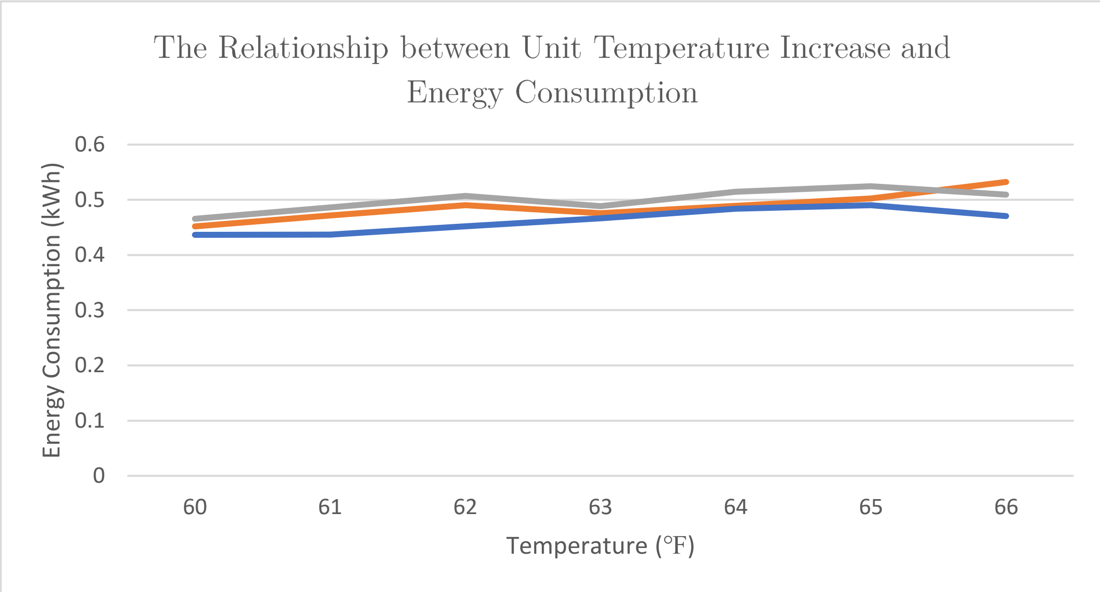

Figure 4.6: The Relationship between Unit Temperature Increase and Energy Consumption

Current Temp	Desired Temp	Manipulated Variable (°F)	Result
59 °F	69 °F	60	$400(0.41)(0.1) + (60 - 69)^2 = 116.4$
		61	$400(0.41 + 0.43)(0.1) + (61 - 69)^2 = 114.6$
		62	$400(0.41 + 0.43 + 0.45)(0.1) + (62 - 69)^2 = 115.6$
		63	$400(0.41 + 0.43 + 0.45 + 0.47)(0.1) + (63 - 69)^2 = 119.4$

Table 4.4: Example Calculation of Using MPC

Figure 4.6 is obtained from the preliminary experimentation that there is a linear relationship between unit temperature increase and energy consumption during 60°F and 66°F. Therefore, E(t) can be easily estimated from the figure in the calculation process.

Table 4.4 shows an example of calculation. If the current temperature is 59°F, the desired temperature is 69°F, the pricing scheme is 0.1€ per kWh, the best move is to set the temperature to 61°F which minimizes the equation.

In the example, the prediction horizon is 15 minutes. In this dissertation, the prediction horizon is 2.5 hours such that MPC has sufficient time to know that the energy price will rise in 2.5 hours and plan for the move. Figure 4.7 has summarized the structure of the heating system and MPC.

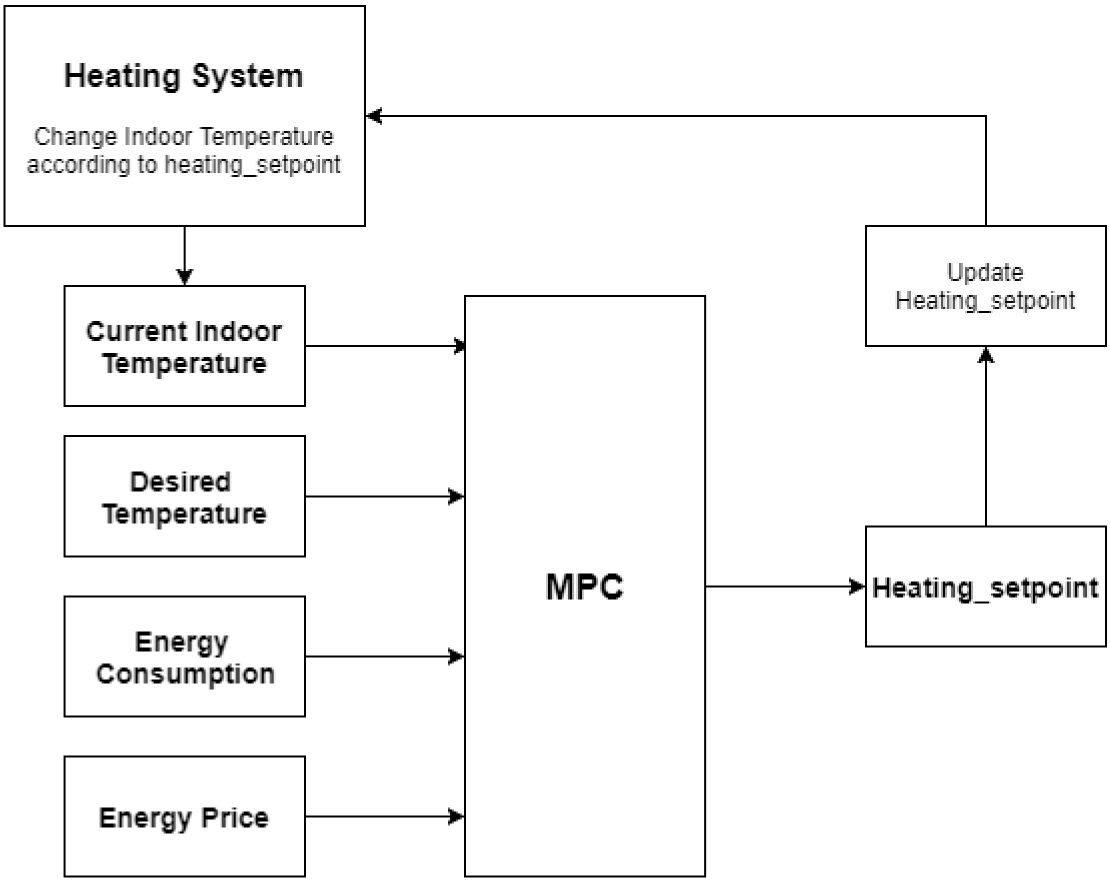

Figure 4.7: The Structure of the Heating System and MPC

4.4 Simulation Results

After implementing above details, simulation can be run to obtain the results. Firstly, gridlabd command is used to run the GLM file in GridLAB-D Console, as shown in Figure 4.8. In the GLM file, recorder module has been used, as shown in Figure 4.9. Parameters such as outdoor temperature, indoor temperature and energy consumption can be captured every 15 minutes. Therefore, a csv file can be output with the aforementioned parameters, as shown in Figure 4.10. Therefore, data processing can be carried out, such as calculating the marginal energy consumption, energy cost at each time interval, thermal comfort level and PAR value, as shown in Figure 4.11. Finally, data and graphs are obtained for interpretations in Chapter 5.

```
GridLAB-D Console
Microsoft Windows [Version 10.0.15063]
(c) 2017 Microsoft Corporation. All rights reserved.

C:¥Program Files (x86)¥GridLAB-D>cd C:¥github¥gridlab-d

C:¥github¥gridlab-d>gridlabd house_heater.glm
```

Figure 4.8: Screenshot of GridLAB-D Console

```
object recorder {
    parent house3;
    property air_temperature,outdoor_temperature, energy.real;
    interval 900;
    file "house3_withManualHeater.csv";
}
```

Figure 4.9: Recorder Module and Settings in the GLM File

# file...... house3_withManualHeater.csv			
# date...... Mon Aug 28 17:35:27 2017			
# user...... Thomson			
# host...... (null)			
# target.... house 5			
# trigger... (none)			
# interval.. 900			
# limit..... 0			
# timestamp	air_temperature	outdoor_temperature	energy.real
2016-01-01 00:00:00 PST	79.4088	34.16	0
2016-01-01 00:15:00 PST	75.0906	34.16	0
2016-01-01 00:30:00 PST	73.1746	34.16	0
2016-01-01 00:45:00 PST	71.3935	34.16	0
2016-01-01 01:00:00 PST	69.6947	34.7	0
2016-01-01 01:15:00 PST	68.125	34.7	0
2016-01-01 01:30:00 PST	66.6005	34.7	0
2016-01-01 01:45:00 PST	65.1451	34.7	0
2016-01-01 02:00:00 PST	65.7885	31.64	0.150604
2016-01-01 02:15:00 PST	64.1234	31.64	0.432162
2016-01-01 02:30:00 PST	65.9306	31.64	0.987964
2016-01-01 02:45:00 PST	64.3972	31.64	1.35545
2016-01-01 03:00:00 PST	65.9916	30.74	1.95605
2016-01-01 03:15:00 PST	64.2453	30.74	2.34836
2016-01-01 03:30:00 PST	65.6927	30.74	2.95316
2016-01-01 03:45:00 PST	64.4693	30.74	3.41267
2016-01-01 04:00:00 PST	65.2865	31.46	3.95028
2016-01-01 04:15:00 PST	64.8821	31.46	4.45422

Figure 4.10: CSV Output from Recorder Module

# file...... house3_withMPC_TOU.csv							
# date...... Mon Aug 28 17:35:27 2017							
# user...... Thomson							
# host...... (null)							
# target.... house 5							
# trigger... (none)							
# interval.. 900							
# limit..... 0							
# timestamp	air_temperature	outdoor_temperatur	energy.real	margin energy	price_TOU	price_Flat	PAR
2016-01-01 00:00:00 PST	78.6094	34.16	0	0	0	0	
2016-01-01 00:15:00 PST	74.3675	34.16	0	0	0	0	
2016-01-01 00:30:00 PST	72.4853	34.16	0	0	0	0	
2016-01-01 00:45:00 PST	70.7357	34.16	0	0	0	0	2.145399
2016-01-01 01:00:00 PST	69.0669	34.7	0	0	0	0	
2016-01-01 01:15:00 PST	67.5258	34.7	0	0	0	0	
2016-01-01 01:30:00 PST	66.0287	34.7	0	0	0	0	
2016-01-01 01:45:00 PST	64.5993	34.7	0	0	0	0	
2016-01-01 02:00:00 PST	64.2181	31.64	0.176797	0.176797	0.0176797	0.035183	
2016-01-01 02:15:00 PST	65.9419	31.64	0.691462	0.514665	0.0514665	0.102418	
2016-01-01 02:30:00 PST	64.4099	31.64	1.04432	0.352858	0.0352858	0.070219	
2016-01-01 02:45:00 PST	65.9042	31.64	1.63486	0.59054	0.059054	0.117517	
2016-01-01 03:00:00 PST	64.5995	30.74	2.02246	0.3876	0.03876	0.077132	
2016-01-01 03:15:00 PST	65.8349	30.74	2.62727	0.60481	0.060481	0.120357	
2016-01-01 03:30:00 PST	64.1686	30.74	3.04591	0.41864	0.041864	0.083309	

Figure 4.11: Data Processing on the CSV Output

4.5 Chapter Summary

This chapter describes the implementation of the dissertation. GridLAB-D™ was chosen to be the simulation environment as it provides a reliable smart grid simulator. Houses models and controllers can be built easily and the implementation can be repeated by varying different parameters. CSV file can be output as the result of the simulation such that data and graphs are obtained for interpretations.

Chapter 5

Evaluation

This chapter describes the result of the implementation on approaches which automate distributed domestic heating systems and analyzes the results. For section 5.1 and 5.2, results are described and analyzed in terms of energy cost and thermal comfort respectively based on the simulation of an apartment. For section 5.3, results are described and analysed for the feasibility of distributed use based on the simulation of 20 apartments. Based on sections 5.1 to 5.3, a further analysis is carried out in section 5.4 to compare the use of different controls, followed by a summary in section 5.5.

5.1 Energy Cost

This section discusses the energy cost of using different controllers on manipulating domestic heating system.

5.1.1 Comparison between Default Control and Manual Control

Figure 5.1 and Figure 5.2 describe the energy cost of using default control which constantly stays the indoor temperature at 69.8°F and manual control which models the typical action of occupants under Flat Pricing Scheme and TOU Pricing Scheme respectively.

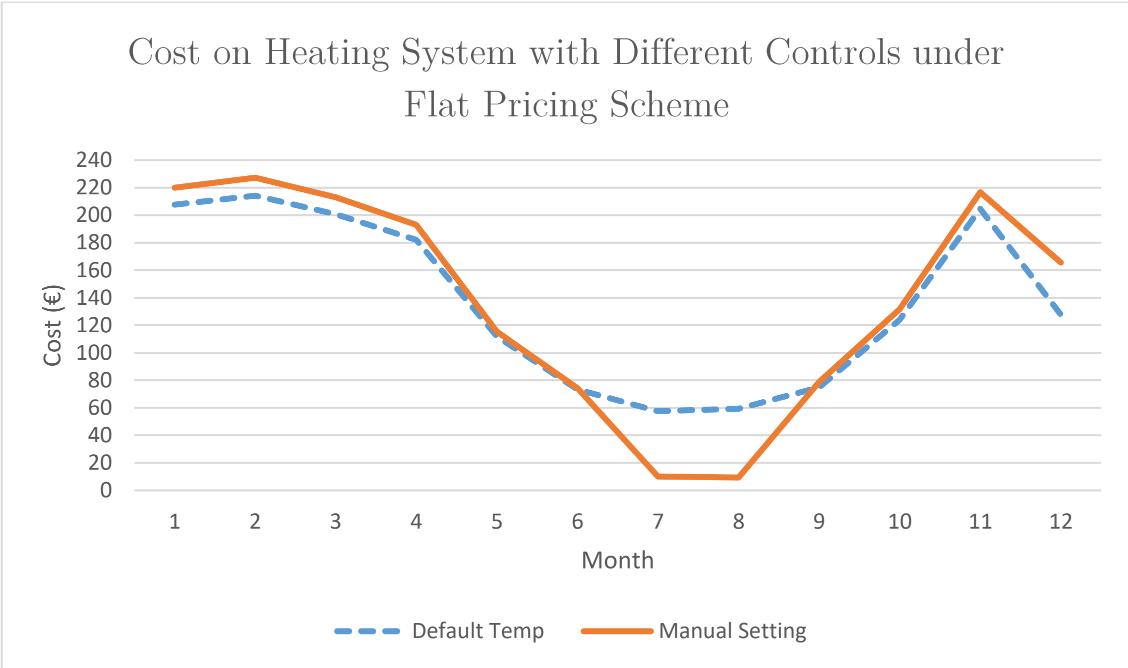

Figure 5.1: Energy Cost on Heating System with Default Temperature Control and Manual Setting Control under Flat Pricing Scheme

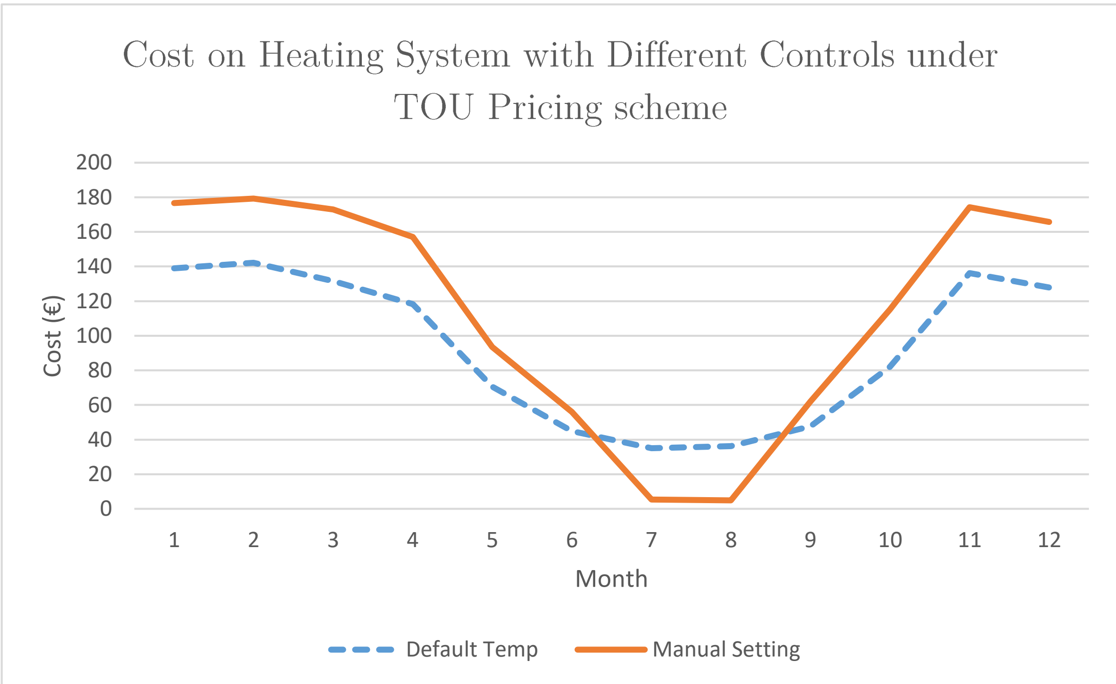

Figure 5.2: Energy Cost on Heating System with Default Temperature Control and Manual Setting Control under TOU Pricing Scheme

Blue striped lines indicate the cost and thermal cost of the default control respectively, while the orange lines indicate the cost and thermal cost of the manual control respectively.

For default control, the energy cost under flat pricing scheme dominantly ranges from 200€ to 210€ between November and March, while the energy cost under TOU pricing scheme dominantly ranges from 120€ to 140€ between November and March. For manual control, the energy cost under flat pricing scheme dominantly ranges from 210€ to 230€ between November and March, while the energy cost under TOU pricing scheme dominantly ranges from 160€ to 180€ between November and March.

Time	**Outdoor Temperature (°F)**	**Indoor Temperature (°F)**	**Energy Consumption (kWh)**
18:15	47.3	57.3758	/
18:30	47.3	60.4234	2.2511
18:45	47.3	63.2532	2.2511
19:00	47.48	65.9522	2.2511
19:15	47.48	68.5452	2.2511

Table 5.1: Extract of the Result Using Manual Control

Time	Outdoor Temperature (°F)	Indoor Temperature (°F)	Energy Consumption (kWh)
15:00	46.04	57.489	/
15:15	46.04	59.9959	0.6408
15:30	46.04	62.9175	0.7127
15:45	46.04	64.0532	0.6377
16:00	46.58	66.1976	0.764
16:15	46.58	66.1835	0.582
16:30	46.58	67.3554	0.5788
16:45	46.58	68.1579	0.5448
17:00	47.3	68.841	0.5128

Table 5.2: Extract of the Result with Gradual Temperature Increase

Since the heating system is turned off with manual control in July and August to save energy cost, the performance of manual control is compared with default control between September and June for a fairer comparison. It is found that typical manual control creates greater energy cost than that of default control. On average, the cost of a typical manual controller is around 4.20% and 25.6% more than that of the default controller under two pricing schemes respectively.

The major reason which contributes to the energy cost increase is that energy consumption increases hugely when there is a sharp increase in temperature demand. For instance, during the simulation, it takes 9 kWh energy to increase the temperature from 57.3°F to 69.5°F in 75 minutes as shown in Table 5.1. However, it only takes 4.9736 kWh energy to increase the temperature from 57.4℉ to 69.8℉ in 135 minutes as shown in Table 5.2, and the energy consumption only halves the former scenario. Meanwhile, maintaining the temperature around 69.8℉ only takes around 0.51 kWh per fifteen minutes such that only 2.04 kWh energy is required to maintain optimal temperature in 75 minutes and the energy consumption is only one-fifth of the former case. Since energy consumption has a direct relationship with energy cost, a sudden increase in temperature has used up more energy consumption, leading to higher energy cost. It is also discovered that maintaining temperature at optimal level may be even cheaper than using manual control where occupants turn on and off the heating system according to their preference.

Besides, it is discovered that there is a more obvious difference in default control and manual control in terms of energy cost under TOU scheme than that in flat pricing scheme. The reason to account for that is because a typical user will probably start heating up around 6 pm after work, and TOU pricing scheme charges user more for the energy use during 5 pm and 7 pm as this period is peak hours. Therefore, the factors of higher cost per energy unit and rapid temperature increase has led to much higher energy cost under TOU pricing scheme than flat pricing scheme.

Hence, this also validates why home heating automation is necessary as ordinary manual control can be more costly than simply staying the domestic heating system at constant temperature if the occupant does not have the concept of TOU pricing scheme and controlling heating system appropriately.

5.1.2 Comparison between Heuristic Baseline Control and Manual Control

Figure 5.3 and Figure 5.4 describe the energy cost of using different controls under Flat Pricing Scheme and TOU Pricing Scheme respectively. These two figures are the extended version of Figure 5.1 and Figure 5.2 respectively.

The grey line in Figure 5.3 and Figure 5.4 indicates the energy cost of the heuristic baseline control. For the heuristic baseline control, the energy cost under flat pricing scheme dominantly ranges from 180€ to 190€ between November and March, while the energy cost under TOU pricing scheme dominantly ranges from 115€ to 130€ between November and March.

Since the heating system is turned off with both manual control and heuristic baseline control in July and August to save energy cost, the performance of heuristic baseline control is compared with manual control between September and June only as the control does not affect the performance on heating system during July and August. It is found that heuristic baseline control can reduce the energy cost when comparing with manual control. The cost of the heuristic baseline control is around 9.38% and 10.7% less than that of the default controller under flat pricing scheme and TOU pricing scheme on average respectively.

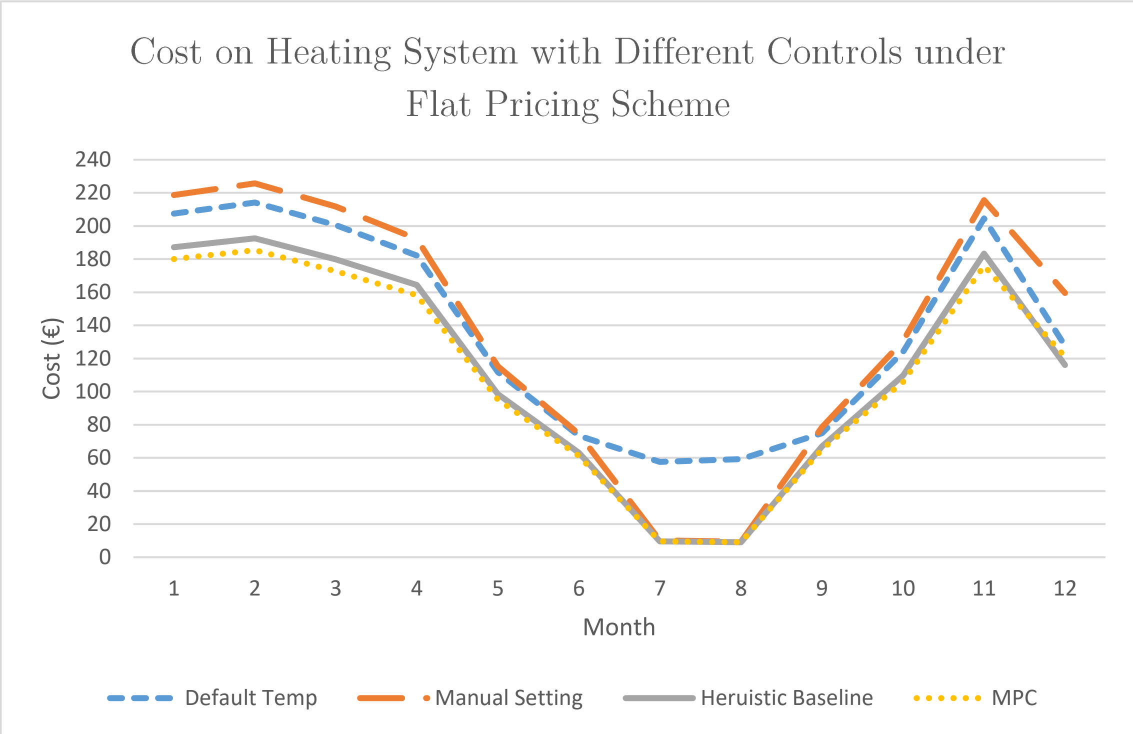

Figure 5.3: Energy Cost on Heating System with Different Controls under Flat Pricing Scheme

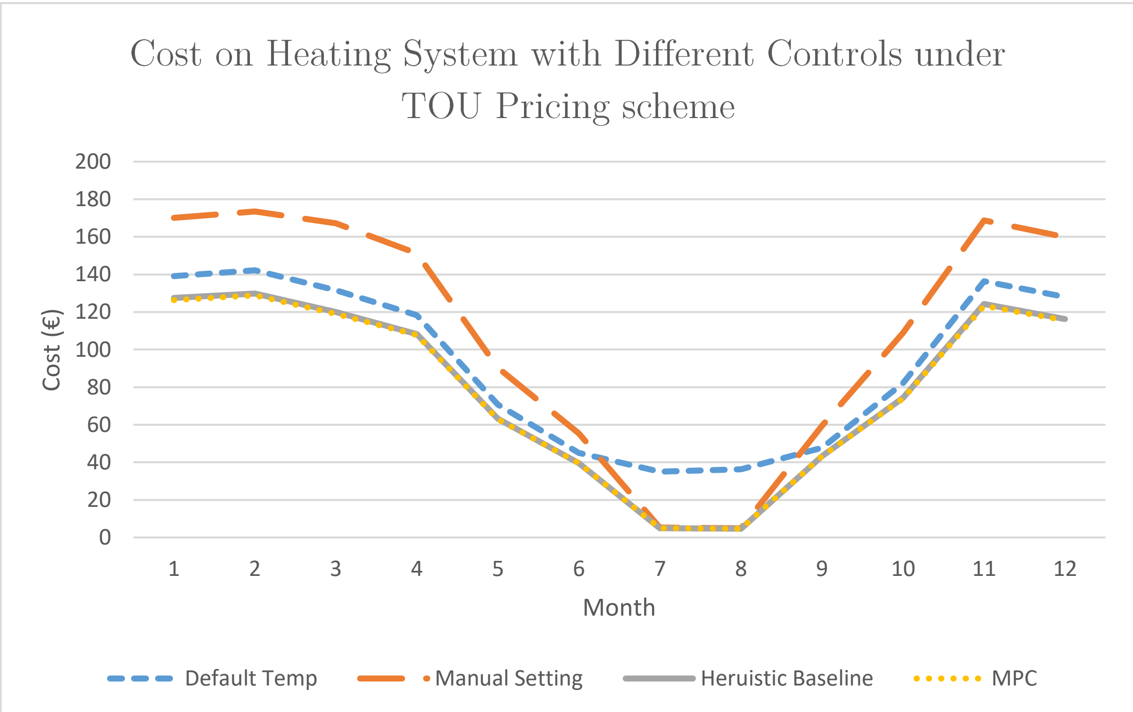

Figure 5.4: Energy Cost on Heating System with Different Controls under TOU Pricing Scheme

This is because the relationship between the rate of increasing temperature and energy consumption has been taken into account such that an abrupt change in temperature is avoided. For instance, the example mentioned in Section 5.1.1, manual control uses 9 kWh energy to increase the temperature from 57.3°F to 69.5°F in 75 minute, but the energy consumption only halves to rise the same amount of temperature in 135 minutes. Since the baseline control has increased the temperature in a stepwise manner, there is an energy cost earning from the baseline control.

Besides, with taking TOU pricing scheme into account, temperature is maintained at 69°F during 5pm and 7pm to reduce energy cost due to unplanned temperature increase. Therefore, there is a further cost reduction when using heuristic baseline control under TOU pricing scheme.

5.1.3 Comparison between MPC and Manual Control

The yellow dotted line in Figure 5.3 and Figure 5.4 indicates the energy cost of the MPC. For the MPC, the energy cost under flat pricing scheme dominantly ranges from 175€ to 185€ between November and March, while the energy cost under TOU pricing scheme dominantly ranges from 115€ to 130€ between November and March.

Similar to the comparison of manual control and heuristic baseline control, the heating system is turned off with both manual control and MPC in July and August to save energy cost, the performance of MPC control is only compared with manual control between September and June. It is found that heuristic baseline control can reduce the energy cost when comparing with manual control. The cost of the MPC is around 9.86% and 13.2% less than that of the default controller under flat pricing scheme and TOU pricing scheme on average respectively.

Through the design, thermal comfort and the energy cost such as energy cost per energy unit and pricing scheme have been taken into account. Therefore, similar to the heuristic baseline control, an abrupt change in temperature is avoided.

Besides, temperature is always maintained at 69.8°F after 5pm under TOU pricing scheme as MPC comprehends that the energy unit rice will rise in the coming time horizon. However, under flat pricing scheme, temperature will only be maintained at 69.8°F after 6pm as the energy cost per unit is constant at all time such that raising temperature between 5 pm and 6 pm does not incur extra cost. Therefore, to reduce energy cost, MPC only ensures that heating system is at 69.8°F from 6 pm, i.e. the time when the occupant wants to use the heating system.

5.2 Thermal Comfort

This section discusses the thermal comfort of using different controllers on manipulating domestic heating system based on thermal discomfort level and investigating the time each control takes to raise the temperature to optimal level.

5.2.1 Thermal Discomfort Level Comparison between Different Controls

According to Table 3.1 which describes which models the typical desired temperature of occupants, all controls (i.e. default control, manual control, heuristic baseline control and MPC) have successfully met all requirements without thermal discomfort according to the specific temperature during specific time.

However, when considering that the occupant may not follow typical action and may stay at the apartment unexpectedly, here is the quantitative analysis, provided by equation (8), which constantly states the desired temperature as 69.8°F since 69.8°F is an optimal temperature under all indoor occasions.

$$\sum_{t=k+1}^{k+K}(T_C(t) - 69.8)^2 \tag{8}$$

From Figure 5.5, heuristic baseline control and MPC have much smaller thermal discomfort level than manual control under this requirement, particularly during winter. On average, heuristic baseline control and MPC under TOU pricing scheme can create 57.1% and 51.3% decrease in thermal discomfort level each month respectively between September and June.

Meanwhile, MPC under flat pricing scheme can only create 25.6% decrease in thermal discomfort level because MPC under TOU pricing scheme will foresee the increasing price during peak hours and hence increase the temperature earlier. Therefore, the period of time of the apartment under optimal temperature will be shorter for MPC under flat pricing scheme.

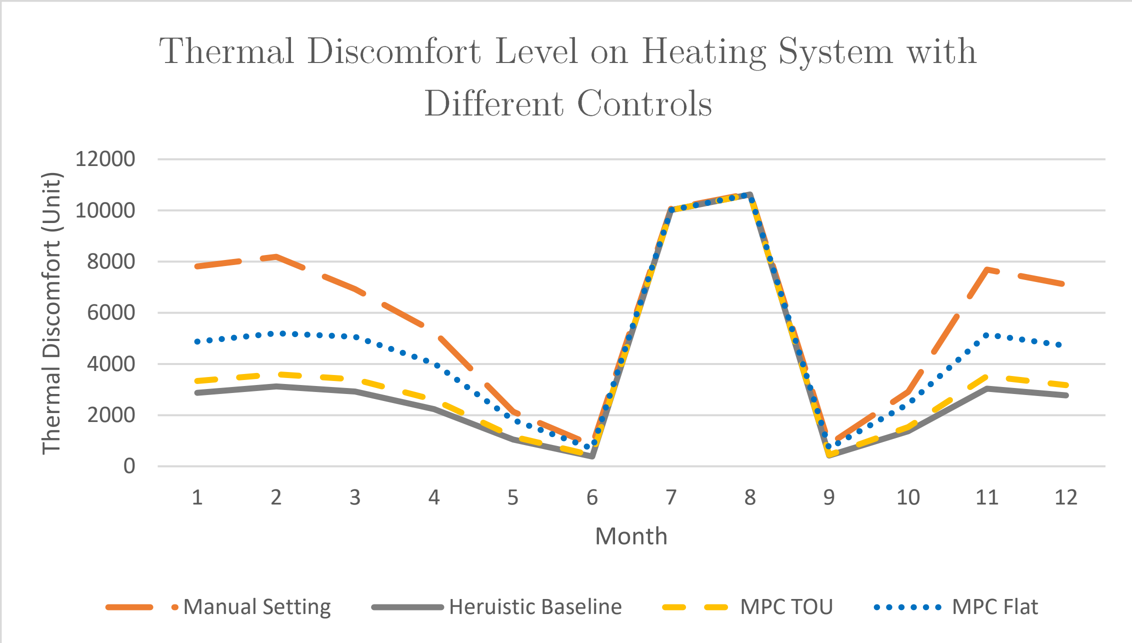

Figure 5.5: Thermal Discomfort Level on Heating System with Different Controls

5.2.2 Case Study Comparison between Different Controls

Figure 5.5 has shown the quantitative analysis based on thermal discomfort level. However, it may not be fair to manual control because the apartment probably does not need to maintain 69.8°F at all time. Therefore, a case study on how long the heating system takes to raise the apartment to 69.8°F at an unexpected time is carried out. Table 5.1 summarizes the result of the time each control takes.

Control Mode	**Time (hour)**
Manual Control	1.75
Heuristic Baseline Control	3.25
MPC	2.25

Table 5.3: Time Taken to Raise the Temperature until 69.8°F at an Unexpected Time with Different Controls

From Table 5.1, Manual Control has sacrificed energy cost in exchange for immediate thermal comfort so that it takes the minimal time among three controls. Heuristic Baseline Control weighs more on the energy cost and takes a stepwise temperature increase such that the time to increase temperature up to optimal level is the longest among all. Since MPC balances between thermal comfort and energy cost, it outperforms the baseline control in this perspective but it still needs 30 minutes more to reach the optimal temperature when comparing with manual control.

5.3 Feasibility of Distributed Use

This section discusses the feasibility of deploying different controllers in the distributed use. To experiment on that, different controllers were implemented in a small community of 20 apartments respectively. To measure their performance in distributed use, Peak-to-Average Ratio (PAR) and energy consumption during peak hours were measured.

5.3.1 Peak-to-Average Ratio (PAR) Comparison between Different Controls

Section 3.1.3 has discussed about how PAR is related to DR and shifting non-critical energy use from peak to off-peak hours can provide more stable energy supply to end users, benefiting distributed use.

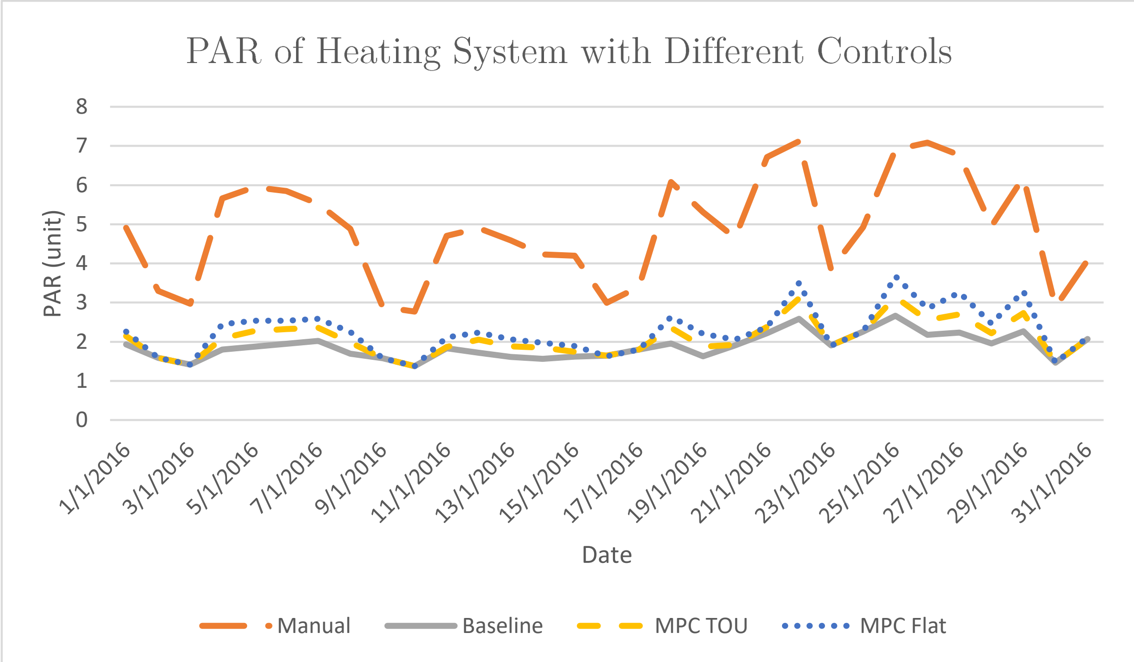

Figure 5.6: Peak-to-Average Ratio (PAR) of Heating System with Different Controls

Figure 5.6 depicts PAR of heating system with different controls in January. Manual control has the highest PAR among all controls and the PAR value fluctuates between 3 and 7. This is because manual control adopt a greedy approach such that shifting energy consumption has not been considered and hence the energy consumption pattern is the least distributed.

On the other hand, heuristic baseline control has the lowest PAR among all with averaged value 1.88 and the PAR value ranges from 1.5 to 2.5. This is mainly because stepwise temperature increase is adopted such that the occurrence of rapid temperature increase is hugely reduced. Hence, energy consumption will be the most distributed over the period.

Besides, MPC has slightly higher PAR comparing with the baseline control, with values mainly ranging from 1.5 to 3. Since MPC balances between thermal comfort and energy cost, its response is quicker than the baseline control such that the energy consumption may be slightly higher during some time intervals. Hence, it is slightly less distributed as the baseline control.

Moreover, noted that MPC under flat pricing scheme has slightly higher PAR than that in MPC under TOU pricing scheme. It is because MPC under flat pricing scheme takes the advantage of flat pricing and inclines temperature at a later time, while MPC under TOU pricing scheme needs to avoid the expensive pricing during peak hours and inclines temperature at an earlier time. Hence, MPC are more favourable for distributed use under TOU pricing scheme.

5.3.2 Energy Consumption during Peak Hours Comparison between Different Controls

Apart from PAR, a more direct consideration is the energy consumption during peak hours. Here denotes peak hours as 5 pm to 7pm according to the definition provided by the TOU pricing scheme [7].

From Figure 5.7, energy consumption of heating system during peak hours with manual control is the highest among all approaches. It is because energy usually has been spent to raise the temperature between peak hours with manual control. There are four troughs in the graph because temperature has been maintained at

69.8℉ constantly in the weekends such that energy are only consumed for maintaining temperature and without the need to raise the temperature.

On the other hand, energy consumption of heating system during peak hours with the baseline control and MPC under TOU pricing scheme are the lowest among all approaches, and only half the energy consumption when using manual control. This is because energy are consumed for maintaining temperature and avoid the need to raise the temperature during this period.

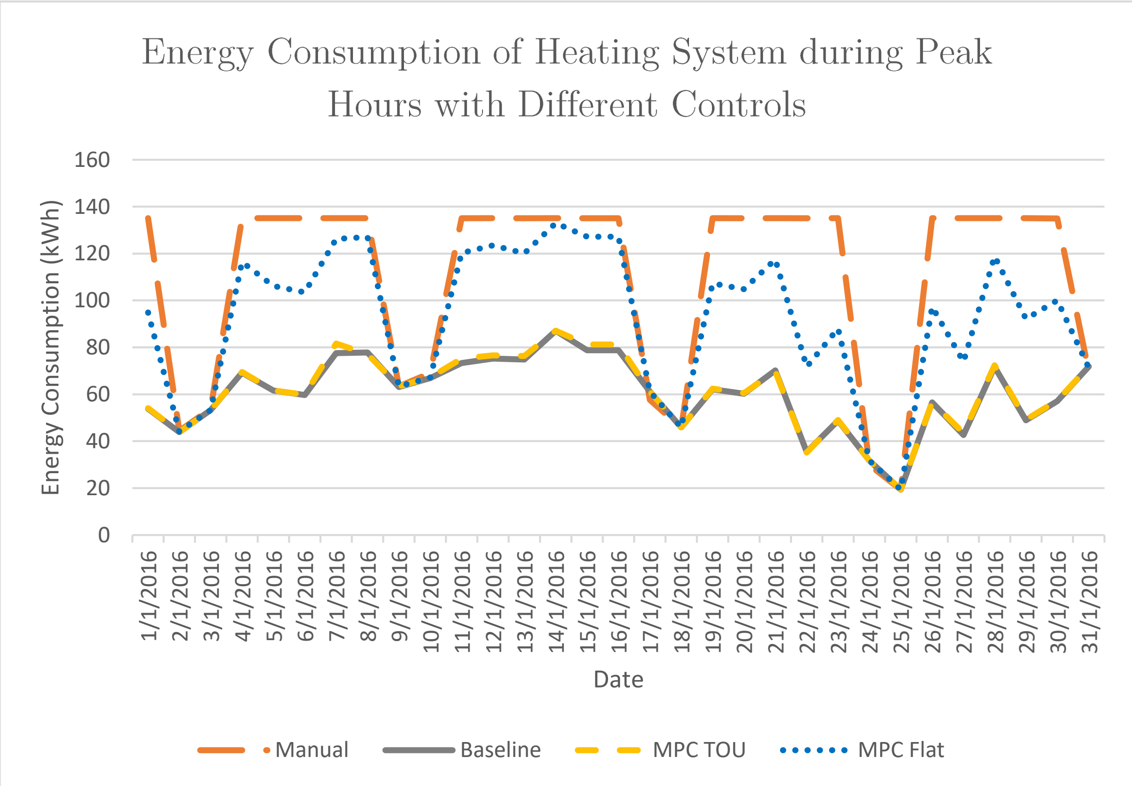

Figure 5.7: Energy Consumption of Heating System of 20 Apartments during Peak Hours with Different Controls

For MPC under flat pricing scheme, although it has satisfactory performance in PAR, its energy consumption is around three-fourth of that with manual control, and is higher than the baseline control and MPC under TOU pricing scheme. It is because there is no advantage to avoid energy consumption during peak hours under flat price, as explained in the last part of Section 5.1.3. Therefore, with gradually increasing the temperature, its energy consumption is comparatively lower than manual control, but higher than the baseline control and MPC under TOU pricing scheme.

5.4 Further Analysis

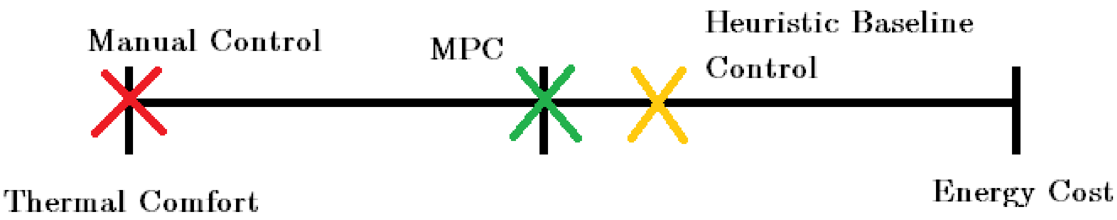

Figure 5.8: Analysis of Different Controls Based on Evaluation Criteria

Figure 5.8 has visualized the evaluation of different controls based on evaluation criteria. Thermal comfort has an indirect relationship with energy cost such that a balance always needs to be obtained in between. Manual control focuses on thermal comfort of occupants as occupants typically control domestic heating system according to their preference, so energy cost has been sacrificed. On the other hand, heuristic baseline control has shown its effectiveness in reducing energy cost, it relatively takes more time to raise the temperature to optimal level. Finally, MPC performs the best among all, particularly under TOU pricing scheme. It can reduce energy cost as the baseline control, meanwhile retaining thermal comfort with similar performance as manual control. Therefore, this also provides users for choices to automate heating system according to their preference over thermal comfort or energy cost.

5.5 Chapter Summary

Based on energy cost in section 5.1, thermal comfort in section 5.2 and feasibility of distributed use in 5.3, table 5.4 summarizes each evaluation criteria and the performance of each control in the respective criteria.

From Table 5.4, manual control has the worst performance in four areas, while its unique advantage is minimal time to raise temperature at an unexpected time. On the contrary, heuristic baseline control has excellent performance in most of the area except it needs the maximal time among all controls to raise temperature at an unexpected time. For MPC, it performs the best under TOU pricing scheme with excellent performance in most of the areas. It also have satisfactory performance in most areas under flat pricing scheme.

Thus, it also validates heuristic baseline control and MPC can be used for automating their domestic heating system as they can bring out benefits where ordinary manual control cannot achieve.

<table>
<tr><th colspan="2" rowspan="2">Criteria</th><th colspan="3">Performance</th></tr>
<tr><th>Good</th><th>Normal</th><th>Bad</th></tr>
<tr><td colspan="2">Energy Cost</td><td>HB
MPC (Flat)
MPC (TOU)</td><td>/</td><td>MC</td></tr>
<tr><td rowspan="2">Thermal Comfort</td><td>Thermal Discomfort Level</td><td>HB
MPC (TOU)</td><td>MPC (Flat)</td><td>MC</td></tr>
<tr><td>Time taken to raise to Optimal Temperature</td><td>MC</td><td>MPC (Flat)
MPC (TOU)</td><td>HB</td></tr>
<tr><td rowspan="2">Feasibility of Distributed Use</td><td>PAR</td><td>HB
MPC (Flat)
MPC (TOU)</td><td>/</td><td>MC</td></tr>
<tr><td>Energy Consumption during Peak Hours</td><td>HB
MPC (TOU)</td><td>MPC (Flat)</td><td>MC</td></tr>
</table>

MC: Manual Control

HB: Heuristic Baseline Control

MPC (TOU): MPC under TOU Pricing Scheme

MPC (Flat): MPC under Flat Pricing Scheme

Table 5.4: Evaluation Criteria and Performance of Different Controls

Chapter 6

Conclusion

This Chapter summarizes the findings of this dissertation in the Project Overview Section, as well as addressing the contribution of this dissertation in the Contribution Section. This dissertation ends with suggestions of possible future work in the Future Work Section.

6.1 Project Overview

This dissertation starts with addressing the importance of controlling domestic heating system in Chapter 1. Therefore, concerns and concepts related to control domestic heating system and existing approaches which can be used in HEM have been reviewed in Chapter 2.

Hence, the heuristic concept and MPC algorithm, which have been learnt in Chapter 2, are used to design for automating distributed domestic heating system in Chapter 3. Besides, Chapter 3 have also listed out the evaluation criteria which consider the energy cost and the thermal comfort of occupants, and the feasibility for distributed use.

By implementing the design in Chapter 4, Chapter 5 evaluated different controls based on the evaluation criteria discussed in Chapter 3. It is found that both heuristic baseline control and MPC have improvements when comparing with manual control. Since manual control typically put the focus on thermal comfort and neglect the factor of energy cost, heuristic baseline control and MPC can approximately reduce 10% of energy cost caused by manual control. In the meanwhile, only very slight thermal comfort need to be sacrificed when using MPC. Most importantly, heuristic baseline control and MPC are suitable to be utilized for distributed use since they have achieved lower PAR than manual control, validating their feasibility of automating distributed domestic heating system.

6.2 Contribution

Firstly, this dissertation has provided justification of the necessity of automating distributed domestic heating system as manual control can cost more than automation if the user raise the indoor temperature rapidly.

This dissertation provides two approaches for automating domestic heating system. The approaches have balanced between energy cost and occupants' thermal comfort. Hence, these system do not require mandatory occupants' preference. Therefore, occupants can utilize these approaches for maximizing their benefits.

Moreover, both approaches have demonstrated their feasibility on the use over distributed domestic heating system when comparing typical manual control by experimenting in 20 apartments. Therefore, future work can be established based on these approaches for further improvements.

6.3 Future Work

This dissertation have demonstrated two approaches for automating distributed domestic heating systems. Therefore, more advanced researches can continue to be carried out in the future, such as adopting a hybrid control. In this dissertation, the action of the controllers is based on the typical activity of occupants and no sensor and external data except weather are involved in calculation. Therefore, if sensor data like detecting the presence of occupant is introduced, a hybrid control of combining heuristic baseline control and manual control may be feasible as the manual control can override the baseline control if the occupant is present and the baseline control is used if the occupant is absent from the apartment.

Another possible research direction is to add additional features to MPC in order to improve it for distributed use, such as adding “collaborative, parallel” features which have been mentioned in CP-MCTS in Section 2.3.5. In this dissertation, “parallel” feature has been experimented as 20 apartments were running MPC at the same time when evaluating the feasibility of distributed use. However, “collaborative” feature may probably be added to the use of MPC. For example, agents in each apartment can collaborate, such as giving priority to apartments with lower thermal comfort, if there is high energy demand in each apartment.

Appendix A

Abbreviations

BPSO	Binary Particle Swarm Optimization
CP-MCTS	Collaborative, Parallel Monte Carlo Tree Search
DLC	Direct Load Control
DOE	Department of Energy
DP	Dynamic Programming
DR	Demand Response
DSM	Demand Side Management
EE	Energy Efficiency
EU	European Union
GA	Genetic Algorithm
GLM	GridLAB-D Model
HB	Heuristic Baseline Control
HEM	Home Energy Management
HVAC	Heating, Ventilating and Air Conditioning
KWh	Kilowatt Hour
MC	Manual Control
MCTS	Monte Carlo Tree Search
MPC	Model Predictive Control
MPC (Flat)	MPC under Flat Pricing Scheme
MPC (TOU)	MPC under TOU Pricing Scheme

P-MCTS	Parallel Monte Carlo Tree Search
PAR	Peak-to-Average Ratio
SEAI	Sustainable Energy Authority of Ireland
SR	Spinning Reserve
TOU	Time of Use
WDO	Wind Driven Optimization

Bibliography

[1] United States Energy Information Administration, "Energy Use in Homes - Energy Explained, Your Guide to Understanding Energy - Energy Information Administration", January 2013. [Online]. Available: http://www.eia.gov/energyexplained/index.cfm/data/index.cfm?page=us_energy_homes. [Accessed: 13- Feb- 2017].

[2] Sustainable Energy Authority of Ireland, "Energy in the Residential Sector 2013 Report", September 2013. [Online]. Available: https://www.seai.ie/Publications/Statistics_Publications/Energy-in-the-Residential-Sector/Energy-in-the-Residential-Sector-2013.pdf. [Accessed: 28-Jul-2017].

[3] S. Papadopoulos and E. Azar, "Optimizing HVAC operation in commercial buildings: A genetic algorithm multi-objective optimization framework," in *Proceedings of the 2016 Winter Simulation Conference (WSC)*, December 2016, Washington, US, pp. 1725-1735.

[4] H. Thybo, L. F. S. Larsen, and P. Weitzmann, "Control challenges in domestic heating systems," in *Proceedings of the 2007 European Control Conference (ECC)*, July 2007, Kos, Greece, pp. 2895-2901.

[5] P. Palensky and D. Dietrich, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," in *IEEE Transactions on Industrial Informatics*, vol. 7, no. 3, pp. 381-388, August 2011.

[6] B. Spiller, "All Electricity is Not Priced Equally: Time-Variant Pricing 101", September 2013. [Online]. Available: http://blogs.edf.org/energyexchange/2015/01/27/all-electricity-is-not-priced-equally-time-variant-pricing-101/. [Accessed: 28-Jul-2017].

[7] Sustainable Energy Authority of Ireland, "SEAI - Time-varying Electricity Price", August 2010. [Online]. Available: http://www.seai.ie/Renewables/Smart_Grids/The_Smart_Grid_for_the_Consumer/Home_Consumer/Smart_Meter/Time_varying_electricity_price/. [Accessed: 28-Jul-2017].

[8] Calmac, "Time-of-use rates can help grid operators and businesses to control their costs", December 2015. [Online]. Available: http://www.calmac.com/energy-storage-article-time-of-use-rates-can-help-grid-operators-and-businesses-to-control-their-costs. [Accessed: 28-Jul-2017].

[9] China Light and Power Corporate, "CLP launches Smart Energy Programme to help turn Hong Kong into a Smart City", June 2017. [Online]. Available: https://www.clpgroup.com/en/Media-Resources-site/Current%20Releases/20170615_en.pdf. [Accessed: 28-Jul-2017].

[10] P. Siano, "Demand response and smart grids - A survey," *Elsevier Renewable and Sustainable Energy Reviews,* vol. 30, pp. 461-478, February 2014.

[11] M. H. Albadi and E. F. El-Saadany, "A summary of demand response in electricity markets," *Elsevier Electric Power Systems Research,* vol. 78, no. 11, pp. 1989-1996, November 2008.

[12] I. Dusparic, A. Taylor, A. Marinescu, V. Cahill, and S. Clarke, "Maximizing renewable energy use with decentralized residential demand response," in *Proceedings of the 2015 IEEE First International Smart Cities Conference (ISC2)*, October 2015, Guadalajara, Mexico, pp. 346-351.

[13] F. Golpayegani, I. Dusparic, and S. Clarke, "Collaborative, parallel Monte Carlo Tree Search for autonomous electricity demand management," in *Proceedings of the 2015 Sustainable Internet and ICT for Sustainability*

(SustainIT), April 2015, Madrid, Spain, pp. 17-24.

[14] K. Bhattacharyya and M. L. Crow, "A fuzzy based load model for power system direct load control," in *Proceedings of the International Conference on Control Applications*, September 1995, Albany, New York, pp. 27-32.

[15] C. O'Dwyer, "Modelling Demand Response in the Residential Sector," M.E. thesis, University College Dublin, Dublin, Ireland, August 2011.

[16] C. Chen, J. Wang, and S. Kishore, "A Distributed Direct Load Control Approach for Large-Scale Residential Demand Response," in *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2219-2228, September 2014.

[17] N. u. Rehman, H. Rahim, A. Ahmad, Z. A. Khan, U. Qasim, and N. Javaid, "Heuristic Algorithm based Energy Management System in Smart Grid," in *Proceedings of the 2016 10th International Conference on Complex, Intelligent, and Software Intensive Systems (CISIS)*, July 2016, Fukuoka, Japan, pp. 396-402.

[18] E. V. Denardo, "Dynamic Programming: Models and Applications," Upper Saddle River, New Jersey: Prentice-Hall, March 1984.

[19] R. Bellman, "Dynamic Programming," Mineola, New York: Dover Publications, March 2003.

[20] H. Tischer and G. Verbic, "Towards a smart home energy management system - A dynamic programming approach," in *Proceedings of Innovative Smart Grid Technologies Asia (ISGT) 2011 IEEE PES*, November 2011, Perth, Australia, pp. 153-159.

[21] F. De angelis, M. Boaro, D. Fuselli, S. Squartini, and F. Piazza, Francesco,

"A Comparison Between Different Optimization Techniques for Energy Scheduling in Smart Home Environment," *22nd Italian Workshop on Neural Nets*, May 2012, Vietri sul Mare, Italy, pp. 311-320.

[22] D. P. Bertsekas, "Dynamic Programming and Suboptimal Control: A Survey from ADP to MPC," *Elsevier European Journal of Control,* vol. 11, no. 4-5, pp. 310-334, June 2005.

[23] E. F. Camacho and C. Bordons, "Model Predictive Control," London, Great Britain: Springer-Verlag London, November 1998.

[24] J. B. Rawlings and K. R. Muske, "Stability of constrained receding horizon," in *IEEE Transactions on Automatic Control*, vol. 38, no. 10, pp. 1512-1516, October 1993.

[25] M. U. Kajgaard, J. Mogensen, A. Wittendorff, A. T. Veress, and B. Biegel, "Model predictive control of domestic heat pump," in *Proceedings of the 2013 American Control Conference*, June 2013, Washington, USA, pp. 2013-2018.

[26] R. Z. Freire, G. H. C. Oliveira, and N. Mendes, "Predictive controllers for thermal comfort optimization and energy savings," *Elsevier Energy and Buildings*, vol. 40, no. 7, pp. 1353 – 1365, December 2008.

[27] M. Gwerder, B. Lehmann, J. Todtli, V. Dorer, and F. Renggli, "Control of thermally activated building systems,"*Elsevier Applied Energy*, vol. 85, no. 7, pp. 565 – 581, July 2008.

[28] S. Privara, J. Siroky, L. Ferkl, and J. Cigler, "Model predictive control of a building heating system: The first experience," *Elsevier Energy and Buildings*, vol. 43, no. 2-3, pp. 564 – 572, February – March 2011.

[29] C. Sundstrom, D. Jung, and A. Blom, "Analysis of optimal energy management in smart homes using MPC," in *Proceedings of the 2016 European Control Conference (ECC),* June 2016, Aalborg, Denmark, pp. 2066-2071.

[30] R. P. van Leeuwen, J. Fink, and G. J. M. Smit, "Central model predictive control of a group of domestic heat pumps case study for a small district," in *Proceedings of the 2015 International Conference on Smart Cities and Green ICT Systems (SMARTGREENS)*, May 2015, Lisbon, Portgual, pp. 136-148.

[31] H. E. Burroughs and S. J. Hansen, "Managing Indoor Air Quality," 5th ed. Lilburn, Georgia: Fairmont Press, April 2011.

[32] J. S. Lewinski, "The Best Room Temperature for Sleeping", *Men's Health*, August 2015. [Online]. Available: http://www.menshealth.com/health/best-sleeping-temperature. [Accessed: 28-Jul-2017].

[33] GridLAB-D, "GridLAB-D Simulation Software", December 2012. [Online]. Available: http://www.gridlabd.org/. [Accessed: 28-Jul-2017].

[34] GridLAB-D, "GridLAB-D OnlineTutorial", *Sourceforge*, 2017. [Online]. Available: https://sourceforge.net/p/gridlab-d/code/3889/tree/course/OnlineTutorial_v22/. [Accessed: 28-Jul-2017].

[35] Met Éireann, "Download Historical Climate Data - Met Éireann - The Irish Meteorological Service Online", August 2017. [Online]. Available: http://www.met.ie/climate-request/. [Accessed: 28-Jul-2017].

[36] "New guidelines to allow for smaller apartments", *RTE*, December 2015. [Online]. Available: https://www.rte.ie/news/business/2015/1222/755594-apartment-sizes/. [Accessed: 28-Jul-2017].

[37] Sustainable Energy Authority of Ireland, "Electricity & Gas Prices in Ireland 2nd Semester (July-December) 2016", June 2017. [Online]. Available: http://www.seai.ie/Publications/Statistics_Publications/Electricity_and_Gas_Prices/Price-Directive-2nd-Semester-2016.pdf. [Accessed: 28-Jul-2017].