Framework for a User-centric Post-design Space Heating Energy Management System for Multi-family Residential Buildings in Cold Regions

by

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ABSTRACT

Building construction and operation are collectively responsible for over a third of the world's energy consumption. Space heating is the highest energy consumer in the operation of residential buildings in cold regions; in order to reduce energy consumption within the building sector, energy saving measures for efficient space heating operation cannot be ignored. However, the current practice in multi-family residential facility's space heating control systems is event-driven rather than user-centric and does not take into account the varying nature of occupant activity patterns. This research hypothesizes that integrating the uncertainties related to occupant load, along with weather disturbance and thermal performance of building envelope, in space heating management systems of multi-family residential facilities may contribute to increased energy efficiency. Hence, the present study develops a sensor-based user-centric post-design space heating control framework for multi-family residential facilities with a focus on efficient energy performance of the space heating system under occupancy. To demonstrate the proposed framework, a multi-family residential building in Fort McMurray, Alberta, is chosen as a case study. In this building, the existing space heating system is operated considering current outdoor climatic condition only. This research provides facility managers with a systematic, holistic framework to optimize multi-family residential facility's space heating control system (e.g., producing heating energy by considering occupant demand, weather load, and the facility's physical characteristics) in an endeavor to reduce the energy consumption from the building sector.

DEDICATION

This thesis is dedicated with love to my
dearest mother (Meherun Nessa Ahmed) and grandmother (Nurun Nahar).
I am who I am today because of their unconditional love and countless prayers.

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Chapter 1 : INTRODUCTION

1.1 Background and Motivation

The considerable amount of energy used in building construction, maintenance, and operation makes the building sector the largest consumer of natural resources (Straube 2006), contributing over 30% of total global greenhouse gas (GHG) emissions (Natural Resources Canada 2006). Statistics indicate that, compared to other sectors, the building sector is seeing growth in energy consumption and GHG emissions at a more advanced rate (Akashi and Hanaoka 2012), a fact which entails that the building sector has significant potential for energy savings and energy-related carbon dioxide (CO_2) emissions reduction (Gökçe and Gökçe 2013). The International Energy Agency (IEA) suggests that an estimated energy savings of 1,509 Mtoe (millions of tonnes of oil equivalent) can be attained by 2050 through reduced energy consumption from the building sector. Furthermore, energy-efficient building design can reduce CO_2 emissions—possibly mitigating 12.6 Gt (gigatonnes) of CO_2 emissions by 2050 (IEA 2010).

Natural Resources Canada (NRCan) observes that building operation is responsible for 79% of the overall energy consumption from the building sector. According to Statistics Canada, Canadian households consumed a total of 1,368,955 terajoules (TJ) of energy in 2007, and 2011 saw a 4% increase to 1,425,185 TJ (Statistics Canada 2011; 2007). Of all the energy consumed in a facility's operation, the largest proportion is directed toward the space heating system. According to NRCan, 63% of the operational energy consumption of facilities is devoted to indoor climate control—heating, ventilation and air conditioning (HVAC) systems (NRCan 2007). Researchers also identify that a significant share of total energy consumption is due to improper use of facilities' energy systems (US DOE Energy Information Administration 2003). The improvement of HVAC control systems to gauge climate control requirements and adjust accordingly can result in energy savings of 15% (Brambley et al. 2005).

To ensure optimal functioning of the space heating system in a facility, efficient facility management is required, coupled with a well-organized operational/control framework (Cong et al. 2009). Energy Conservation (2014) states that, "some of the simplest and most cost-effective conservation is accomplished through energy-efficient operations/control system". However, despite there being great potential to save energy, the idea of energy conservation through proper facility management and system control has not garnered significant attention or development to date (Energy Conservation 2014). The lack of awareness of the potential economic benefits that would be brought by a sophisticated user-oriented control system may be another contributing factor to the limited levels of implementation of such a system. Hence, more emphasis needs to be placed on energy efficiency of facility space heating energy management and control systems (Quartermaine 2012).

Many recent studies have observed discrepancies between the actual energy usage and its associated costs for a building and the energy usage projected at the design stage. These discrepancies affect the overall operational performance. The reason actual post-occupancy energy performance largely differs from the estimated performance is that the latter ignores the occupant influence on the space heating energy performance within the facility (Rose 2010). Despite the fact that inhabited spaces are dynamic in nature, according to the literature occupancy profiles are still typically in the form of mixed schedules or fixed profiles when used for the space heating control scheme of a facility (mostly focusing on commercial facilities). Many researchers note that even the use of fixed or mixed occupancy information can significantly reduce energy consumption (Glicksman and Taub 1997; Brohus et al. 2010). However, the idea of integrating the occupancy profiles in space heating management of multi-family residential facilities has not yet been thoroughly explored. Therefore, the motivation underlying this study is to develop a framework for user-centric space heating control systems in multi-family residential facilities that integrates energy usage patterns of residential occupants in order to promote sustainable building operation.

1.2 Hypothesis and Research Objective

The present research is built upon the following hypothesis:

Integrating multi-family residential facility's predictive occupant load pattern (along with predictive information about outdoor weather and thermal performance of the facility's envelope) with residential facilities' space heating control strategy may reduce energy consumption while sustaining indoor environmental quality.

This research develops a decision-making framework to provide facility managers with a user-centric post-design space heating operational/control model that addresses the uncertainty in the multi-family residential facility occupants' energy usage pattern, outdoor weather conditions, and thermal performance of building envelope for improved energy performance. This research thus undertakes the following specific objectives:

1. Develop a sensor-based monitoring system and monitor the energy usage pattern of a multi-family residential facility in a cold region under occupancy. Then identify (through sensor-based

real-time data analysis) the influencing factors (facility's physical parameters, energy usage patterns of occupants, outdoor climate, operational strategy) that significantly affect the space heating energy consumption of the facility, and define the scope in order to reduce space heating energy consumption from a multi-family residential facility.

2. Develop a mathematical model that can simulate the thermodynamic performance of a building system and can be integrated with control strategies to simulate energy performance.

3. Develop a methodological approach to learning multi-family residential facility occupants' energy usage patterns and to predicting occupant load (from previously measured real-time sensor-based data) for the purpose of integrating the predictive knowledge into the space heating operational/control system of the facility.

4. Develop an integrated user-centric post-design predictive control model for optimizing the space heating energy generation/production based on actual energy needs by addressing the uncertainty of occupant heating demand, weather, and thermodynamic performance of the facility while maintaining indoor comfort level.

5. Evaluate different potential design alternatives (for future reference in design) for improved thermal performance to reduce space heating energy consumption.

6. Validate the hypothesis by comparing the simulation results of the proposed optimization control model with those of the traditional control system.

1.3 Thesis Organization

This thesis is divided into six chapters. A brief introduction of the motivation for this subject is given in Chapter 1, and Chapter 2 provides a review of the literature. Facility management and monitoring approaches in the context of energy management, space heating control strategies, and occupant pattern/profile models are discussed in Chapter 2 to provide a knowledge base for establishing the current needs, which informs the design of the methodology presented in Chapter 3. Chapter 4 implements the framework designed in Chapter 3 to optimize the space heating energy consumption through a user-centric control strategy. It reports the findings from the sensor-based monitoring of a four-storey multi-family residential building in Fort McMurray, Alberta. This chapter aids understanding of the issues surrounding space heating energy management in the given context, and defines the scope of space heating energy management strategies for this study. It also presents the development of a mathematical model of the thermodynamic and space heating control system of the case study, and validates the model with real-time measured sensor data. This chapter also helps with understanding and predicting occupant load by developing an occupant pattern prediction model considering the previously measured real-time sensor data, and describes the development of an integrated user-centric post-design predictive space heating control model. A simulation is conducted on the case study unit in Chapter 4 to investigate the impact of building envelope on efforts to reduce energy load from mechanical means (while maintaining occupant comfort) through different design alternatives. Chapter 5 presents an investigation of the performance of an integrated user-centric predictive space heating control model, and also compares the result with those of the traditional control model developed in Chapter 4. Finally, Chapter 6 summarizes the findings of the research, first by enumerating the identified problem areas, and then by giving some indicative suggestions to alleviate these problems. The chapter concludes by identifying research areas that warrant further investigation subsequent to this study.

Chapter 2 : LITERATURE REVIEW

As mentioned in chapter 1, despite there being great potential to save energy through efficient operation of a facility's space heating system, the idea of energy conservation through holistic user-centric facility management (FM) has not yet been readily explored (Energy Conservation 2014). This may be the reason that facility managers often observe discrepancies between measured and estimated energy performance due to inadequate or incomplete building information and lack of cross-domain data sharing interfaces for building data (Rose 2010). Liu et al. (2003) note that if and when structured and well planned methods are applied by facility managers, a result in energy saving of over 20% of total energy costs and over 30% of heating and cooling costs can be expected. On the other hand, lack of relevant information hinders facility managers from utilizing improved energy saving mechanisms, and the lack of information and the obsolescence of the management tools at hand result in FM making decisions that are often *ad hoc*, arbitrary, and incomplete (Neumann and Jacob 2010).

Due to the complexity and scale of the endeavor, there are few studies that discuss the implementation and merits of such a holistic user-centric predictive space heating control/operational system. This section reviews in four parts the existing studies in the domain of facility space heating energy management: Part 1 is an overview of facility management in the context of energy management; Part 2 is an overview of monitoring approaches in the context of facility energy management; Part 3 looks at facility space heating control systems; and Part 4 reviews occupant energy usage pattern/profile models.

2.1 Facility Management in Context of Energy Management

The conventional definition of FM has been constricted to the simple management of buildings and building services. Thompson (1991) (cited in Amaratunga 2001) describes an idealized FM department as having four primary functions: Real estate and building construction; Building operations and maintenance; Facility planning; and General/office services. Barrett and David (1995) describes FM as "an integrated approach to maintaining, improving and adapting the buildings of an organisation in order to create an environment that strongly supports the primary objectives of that organisation". Akhlaghi (1996) describes FM as a hybrid discipline, a perspective which is corroborated by Barrett (1995), who characterizes FM as a platform that comprises both a physical workplace and people and that requires a multi-skill approach. Alexander (1996) underscores the importance of FM in maintaining building systems and services, supporting the core operations and processes while continuously updating itself to meet new challenges. A study by Atkin and Brooks (2000), like those preceding it, attempts to form an overall definition for FM as "an integrated approach to operating, maintaining, improving and adapting the buildings and infrastructure of an organization in order to create an environment that strongly supports the primary objectives of that organisation".

However, due to the diversity in technical background and application, FM has in practice departed from these definitions, and the role of facility managers has changed along with it. In the present context, the most popular and widely accepted definition of FM in the industry is "the practice of coordinating the physical workplace with the people and the work of the organization, integrating the principles of administration, architecture, and the behavioural and engineering science" (US Library of Congress 1983 in Svensson 1998 cited in Maria 2000). Teicholz and Takehiko (1995) conclude, based on a survey conducted in the United States, that the Operation and Maintenance (O&M) function is the most strategic one in facility management (Maria 2000).

The function of O&M in facility management is described by Chanter and Swallow (1996) as "work which enables the building to continue to efficiently perform the functions for which it was designed". O&M is a two-part definition, where the operation includes activities performed to provide comfortable working and living environments, and maintenance involves equipment upkeep to prevent functional failure. Due to O&M having such a large area of concern in relation to the facility and occupants, the United States Department of Energy (U.S. DOE) elaborates on the need for keeping up-to-date with operational procedures, documentations, and information for efficient operation of the built environment (U.S. DOE 2006).

Strategies and systems have been developed over the years to enable facility managers to identify and address sources of energy inefficiency which are in line with the requirements of O&M. According to Méndez (2006), O&M is concerned with two main factors: the energy efficiency of the building, and the comfort levels provided by the facility to its occupants. Méndez (2006) further argues in favour of implementing a monitoring program that measures the performance of building systems in order to identify potential problems and point to potential preventive measures. Cost and performance tracking analysis; "HVAC systems and equipment; indoor air quality systems and equipment; and cleaning equipment and products, materials, water fixtures and systems, waste systems, and landscape maintenance" are identified as elements that an effective O&M program will address. In this research, monitoring and the operation management aspects of FM with regard to a facility's space heating system are established as the problem domain.

2.2 Monitoring in Context of Facility's Energy Management

This section of the research reviews previous work accomplished in the context of monitoring and management of energy performance. Although energy saving measures are important to owners and to the facility manager, relevant energy information based upon which energy efficiency strategies would be formulated is often not available. Though there is a large amount of available information, there is a lack of coherent, actionable information to inform potential improvements by executives/owners/facility managers. In many cases, even after energy initiatives have been implemented the benefits are not realized due to waning commitment in monitoring and maintenance over time. The key factor in developing and maintaining an energy conservation strategy is the availability of relevant information to the parties concerned. It is therefore important to keep those responsible for building management apprised of the possible economic benefits of simple and inexpensive changes to the system. The key to facility energy management is the actionable measures deployed by the FM as realized by the owners.

Top-level energy metrics are the culmination of daily operations and many decisions, processes, and technology. Thus, by the time a top-level issue is recognized, it can already have become very costly. Therefore, the focus of improvements should be on the long-term improvements and benefits for the facility's operation. Energy sustainability has to be achieved through implementation, feedback, and improvement on those initial strategies. Since it is a continuous and lengthy process, commitment from managers and owners is essential, in the form of investment in new and advanced methodologies for monitoring, analysis, or reporting of building performance. Furthermore, occupied spaces are dynamic in nature and thus are one of the often-neglected aspects of monitoring and control due to their complexity. The dynamic nature of the built environment is the result of the constantly changing needs of occupants, and thus the unpredictable nature of energy usage at different times of the day or over the course of a year. According to the Monitoring Energy Use report (2011), typical one-time energy audits are only able to capture a snapshot of energy use. It states that "bill comparison is simply comparing the current bill with the previous month's or year's bill. This method will indicate how a program is performing but does not usually deliver information about which individual measures are still working. It shows overall performance of large projects or those with interrelated improvements; however, it will not show what other effects are occurring". The report argues that there should be strategies in place able to predict any problem before it arises, allowing the FM to develop precautionary measures and thereby prevent loss of function and reduce costs. The report further states that energy monitoring is a verified solution that uses technology to gather and report on a facility's energy data in addition to using expertise to advise on appropriate actions, revealing cost-saving potential, and providing a framework to continuously improve performance.

Researchers have developed a number of strategies to assist facility manager to identify sources of energy waste. O'Gallachoir (2007) and Hitchcock (2003) suggest rudimentary performance metrics, ASHRAE (1996) suggest building commissioning. The emphasis on gathering accurate energy data is also considered by those who suggest implementing automated fault detection and diagnostics (Katipamula 2005). Further ideas regarding preventive maintenance are also developed in Neumann (2010) for using energy signatures representing typical system performance relationships, while Piette et al. (2001), Granderson et al. (2009), Granderson et al. (2012), Crawley (2008), and Claridge (2004) go further to suggest monitoring system performance using energy information systems and energy simulations.

Energy monitoring has already proven itself as a solution for understanding system performance (Monitoring Energy Use 2011). Modern technologies (e.g., increase in computational power, availability of low-cost sensors, high-quality weather predictions, and advanced control techniques) enable new possibilities for energy-efficient facility management (ASHRAE 2003; Löfberg 2003; Wang and Ma 2008). Real-time energy performance and monitoring are significant from the perspective of real-time feedback for energy-saving behaviour. Ornstein (2005) demonstrates, through case studies of maintenance processes, how the feedback from monitoring systems can be used as a powerful instrument for decision makers. Ornstein attempts to show how this feedback can provide pertinent data for the design, construction, maintenance, use, and facility management phases. The information collected can then be further analyzed from different perspectives as required and then a diagnosis of the system can be conducted. The diagnosis can then be used as a primary document in forming new FM strategies. Continuing with the focus on the need for monitoring systems, Berardi (2012) identifies observation of building energy performance as a prime indicator to assess the sustainability of building operation. Performance monitoring enables facility managers to continuously supervise energy efficiency schemes and their effectiveness, and provides information by which to determine appropriate improvements to be undertaken. Proper targeting, monitoring of energy consumption, and continuous energy management can be effective strategies for improved energy performance of buildings and can result in reduction of operating costs for facilities (Sapri and Muhammad 2010; Lee and Augenbroe 2007). This enables the cost-effective introduction of sophisticated building automation systems and building energy management control systems in order to facilitate effective operation, maintenance, and monitoring of building systems.

Research studies examining the effect of energy feedback information on occupant behaviour have shown that real-time feedback can be a powerful catalyst for behavioural change. Continuous energy feedback was first tested by McClelland and Cook (1980), who showed that homes with continuous electricity usage feedback have, on average, 12% lower electricity use than similar homes with no usage feedback system. Hutton et al. (1986) installed the Energy Cost Indicator in 25 households in three cities, with over 75% of subjects indicating that the feedback provided by the monitoring helped them to conserve energy (as cited in Allen and Janda 2006). A technical research university has monitored energy usage to reduce energy costs through an energy awareness program that offered departments a chance to receive payments of up to 30% of the savings achieved. The departments had accomplished energy savings (saving about $300,000 per year) after one-and-a-half years of monitoring through improved operations and maintenance procedures and reduced their usage from about 44 million kWh to 40 million kWh (U.S. Environmental Protection Agency 2002). Another shows how the city of Boston, MA, by installing meters, was able to reduce the proportion of unaccounted-for water in its municipal water system from 50% to 36% (Grisham and Fleming 1989). Other studies show that an effective energy management system can identify problems in an operating system that may not otherwise have been identified (Mills and Mathew 2009). An effective system can also provide a comfortable building environment with high energy efficiency (Yang and Wang 2013).

A review of a variety of feedback mechanisms offered in the literature in the last ten years shows resultant energy reductions ranging from 0% to 20% (Abrahamse et al. 2005). Despite the fact that providing appropriate feedback to building occupants can significantly reduce the overall energy consumption, relying only on occupant awareness and behavioural change may not be an effective approach. In a study by Jiang et al. (2009), wireless AC plug-load meters and light sensors are deployed in a laboratory inside a computer science department as a case study in energy monitoring. The study reports that energy savings of more than 30% is achieved immediately after installing a monitoring system, but that the savings are subsequently reduced to less than 4% of the week one level by the fourth week of the study. An effective solution for reducing energy consumption could be an automated energy management system, in conjunction with user cooperation (Jiang et al. 2009). Jiang et al. (2009) argues that progress toward greater awareness of energy consumption has been made in recent years, and they show that advanced measurement of energy usage enables reduction of energy consumption.

The monitoring strategies implemented to study facilities and deliver information allow the facility managers to analyze and take appropriate action in order to better balance energy use and, over time, reduce it by building efficient systems (Monitoring Energy Use 2011). While the approach of monitoring energy usage is useful to achieve financial benefits, a holistic monitoring system (including occupant patterns) can extend these benefits by identifying the factors influencing a facility's space heating energy consumption. This is precisely what the present study aims to emphasize and concentrate upon. Any information pertaining to a facility's energy consumption (heating load demand, appliance usage pattern for internal heat gain) can contribute to facility management systems intended to support operational improvement, and can also provide the information needed to encourage behavioural and operational changes by building occupants and managers.

2.3 Space Heating Control Systems of Facilities

This section discusses previously conducted research on facility space heating control strategies, such as On/Off room temperature control, weather-compensated control, Direct Digital Control (DDC), Proportional-Integral-Derivative (PID) control, and Model Predictive Control (MPC).

The *traditional method* of controlling space heating systems is established in one of two ways: (1) deciding the On/Off state of the system, or (2) limiting the activation levels of different components of the HVAC system, thereby providing low-level control. On/Off room temperature control is considered the simplest type of control. Here control system turns the HVAC system On/Off according to a set room temperature. However, holistic space heating system dynamics are not included in this simple feedback control, and thus this type of control system is unable to account for many of the real-time changes that occur (Prívara et al. 2011). Continuing with traditional control systems, the theory of "if condition, then action" is followed in Rule Based Control (RBC). For efficient performance, this system requires defining and tuning of a large number of thresholds and parameters (Oldewurtela et al. 2012), a task which can become very intricate with larger and more complex heating systems.

To minimize total energy cost, House et al. (1995) present an optimal On/Off control of a fan and a heating coil. An early dynamic control of an HVAC unit, where hourly electricity usage is implemented as a control variable, is presented in a study by Daryanian and Norford (1994). Zaheeruddin and Zheng (2000) present an optimal multistage daily operation of HVAC using the conventional control variables, which are the flow rates of hot water and of air. However, the control systems presented are very application-specific and their effectiveness may suffer when translated for use in larger and more complex building control systems. Furthermore, Section 17.1 of the ASHRAE Handbook of Fundamentals (2009) states that traditional control systems are designed for the worst-case scenario under static conditions, without any consideration of solar or internal gains or storage.

Prívara et al. (2011) remark that conventional *weather compensated control* fails to make use of the energy supplied in a building by solar gain. They further elaborate on how this feed-forward control system decides the control variable (e.g., heating water temperature) by considering outside temperature only. This can compromise the efficiency of the energy system since it ignores the heat accumulation in large facilities or uncertain changes in weather conditions. Despite the fact that weather-compensated control is a type of feed-forward control, like the traditional On/Off control system it also fails to contain any information about the dynamics of a building. Unlike the traditional On/Off control system, though, this system is robust and requires only simple tuning.

Braun (1990) presents a *DDC-based dynamic control* that focuses on minimizing the energy cost as well as the daily peak demand by setting the hourly room temperature. However, there is no integrated framework developed for these two objectives, and thus two separate problems are formulated and solved through heuristics. Another DDC-based control is presented by Pape et al. (1989), where the authors attempt to present electricity cost through a quadratic function of the ambient conditions and typical control variables, then solve the control problem through the use of a deterministic quadratic optimization problem. As with previous control systems, this one suffers when unpredictable and uncontrollable loads come into consideration and thus may result in an increase of the energy costs due to incorrect adjustments that cause high peak demands and high demand charges. In addition, one of the drawbacks of this system is that, for each different building and each different operating mode, the coefficients of the quadratic function need to be determined empirically.

According to Ma et al. (2012), in modern buildings with an automated control system, distinct and interconnected PID loops and switching rules are the industry standard. The control system follows basic control logic that takes into account the set-points and schedules for space heating components. Li et al. (2006) discuss the merits of PID control as a feedback control system that can deal with a facility's dynamic nature. Despite the fact that a PID controller allows for precise data tuning, it fails to integrate the impact of outside temperature. It has been pointed out that, for On/Off, rule-based, weather-compensated, and PID controllers, implementation of tuning is highly complex in the case of multiple-input multiple-output systems. For single-input, single-output systems, however, these controllers can be comparatively easy to tune (Prívara et al. 2011).

In recent years, advances have occurred in the field of control systems (Han et al. 2010). This has led to the introduction of new concepts to address two critical factors with regard to climate control—the ability to incorporate weather predictions in control logic and the efficient handling of increasingly complex HVAC systems (Oldewurtel et al. 2012). Prívara et al. (2011) address the issues above by suggesting that these requirements are satisfied by *Model Predictive Control (MPC)*, which is capable of controlling systems with multiples inputs and multiple outputs, which is typical for heating systems. Such a system is necessary, since this feedback and an advanced feedforward system can compensate for room temperature error through continuous adaptation of control parameters, inclusion of heat gains, optimal start-stop algorithms, and optimization of energy loads shifting in the control algorithm (Ghiaus and Hazyuk 2010; Underwood 1999). As Cooperman et al. (2010) state, the MPC system is becoming more “mainstream”. Sossan et al. (2014) identify that MPC strategy can effectively operate different energy resources and can reduce up to 25% of operation costs. By utilizing MPC scheme, Maasoumy et al. (2014) redesigned the HVAC control system of a commercial building to operate as a flexible provider to the smart grid. The concept of an outdoor air temperature forecasting model integrated with a predictive control strategy has been studied by many researchers (Grünenfelder and Tödtli 1985; Cho and Zaheeruddin 2003; Henze et al. 2004a, 2004b; Gwerder and Tödtli 2005; Henze et al. 2005; Bourgeois et al. 2006; Andersen et al. 2007; Ma et al. 2009; Široký et al. 2011). These studies identify that using a predictive controller can achieve energy efficiency and reduced cost compared to traditional control systems.

Despite developing and utilizing the above mentioned control models, researchers note that discrepancies can still be observed between the actual energy consumption and the estimated energy demand (Gram et al. 2011; Rose 2010; Karlsson and Moshfegh 2007; Gill et al. 2010). They also identify that occupant energy usage patterns and comfort choices significantly influence heating energy consumption (Haas et al. 1998). They thus suggest that lack of feedback in terms of occupant demand patterns may be the reason for this discrepancy (Filippin and Beascochea 2007; Piette and Kinney 2001). The following section reviews previous studies conducted with the aim of characterizing occupant patterns.

2.4 Facility User Energy Usage Pattern Model

In one of the earliest studies concerning occupancy information, Newsham et al. (1995) analyze the advantage of sensor-based lighting control. Based on survey statistics, Degelman (1999) develops an occupancy prediction model with a Monte Carlo modelling approach. For developing a lighting model, a stochastic model is proposed by Reinhart et al. (2004) that uses arrival-departure information. An artificial neural network approach is proffered by Mihalakakou et al. (2002) for analyzing energy consumption in residential buildings. In their study, several years of energy consumption data is used to train the network, and occupant influence is also assumed to be embedded in the data. Wang et al. (2005) propose a model for a single-occupant office. Two exponential distribution models representing occupancy and vacancy, respectively, are used in their study. However, they assume that all weekdays have concurrent occupancy levels and that weekends are always vacant. Bourgeois et al. (2006) use a pattern recognition algorithm to identify occupant lighting use through sensor data. A study by Brambley et al. (2005) identifies that up to 28% of energy savings (within 1 to 5 years' payback of initial investment) can be achieved through sensor-based occupant lighting control, whereas traditional control systems can save up to 15% (return within 8-10 years) (Brambley et al. 2005). Duong et al. (2006) use a hidden semi-Markov model to represent state durations, with their experiment conducted on a kitchen set-up housed in a laboratory and using a multiple-camera tracking module to detect movements.

Roy et al. (2007) develop a predictive framework for learning occupants' future paths and locations in smart homes. Andersen et al. (2007) present a study on a single room containing a single occupant in order to identify the influence of occupant behaviour on energy consumption. Page et al. (2008) develop a stochastic model for predicting individual occupancy behaviour. Brohus et al.

(2009) suggest the use of a safety factor to account for the influence of occupant behaviour on building energy consumption. Given the uncertainty associated with occupant behaviour, the safety factor coefficient is derived and multiplied by the maximum energy consumption code. To identify the most important factors affecting building energy consumption and uncertainty of occupant behaviour, Brohus et al. (2010) conduct a sensitivity analysis using Monte Carlo simulation. Zhun et al. (2010) develop a decision tree algorithm based on training data in order to generate predictive models for estimating energy demand based on categorical variables. Dong (2010) develops an integrated HVAC control model by implementing advanced machine learning methods, including adaptive Gaussian Process, Hidden Markov Model, Episode Discovery, and Semi-Markov Model. The study demonstrates the potential for the reduction of energy consumption through prediction of occupant behaviour patterns and weather conditions, though it should be noted that the occupancy model is tested in a commercial facility.

Zhao et al. (2014) develop occupant behaviour and schedule modelling through office appliance power consumption data mining, including electricity meter data of laptop computers, task lights, computer monitors, personal fans, chargers, and printers. Lam et al. (2014) develop a workday occupancy schedule and test it in an office building facilitated by office appliance energy consumption data. Dong and Lam (2014) develop a heating and cooling control model (integrated with occupant and weather prediction) for experimental test-bed setup in a single-detached home that uses solar energy, where occupant and ambient information are collected from a complex sensor network measuring acoustics, motion, lighting, RH, and indoor temperature. Shih and Rowe (2015) develop a detailed model to estimate the number of people in the room with experimental set up by using measured acoustic properties. Richardson et al. (2008) develop a method for generating stochastic occupancy time-series data indicating the number of occupants at a given time for UK households (1 person to 6 persons). Zaraket et al. (2015) develop an activity-based model for predicting household energy consumption. Energy-related occupancy behaviour in four residential low-income houses with different building envelope materials is studied by Dong et al. (2015a). Dong et al. (2015b) and Li et al. (2015) address the hour- and day-ahead energy consumption forecasts of four single-family dwellings by integrating a data-driven technique and physics-based model.

It is observed that many studies focus on controlling HVAC start/stop scheduling or indoor set-point temperature by developing personalized occupancy schedules using sensor network, measuring detailed accurate occupant information, and achieving space heating energy savings. In a study by Jazizadeh et al., a framework for personalized thermal profile is developed and integrated into the heating control strategy for an office building (2014a; 2014b). Ghahramani et al. (2014) develop an online learning approach of thermal comfort preferences for modelling zone level personalized comfort profiles to include in the heating control logic. Yang et al. (2014) utilize various sensors, such as infrared, for detecting objects as they pass through a door, door switch sensors for detecting whether a door is open or closed, as well as light sensors, sound sensors, motion sensors, CO_2 sensors, temperature sensors, and relative humidity sensors to develop occupancy modelling through machine learning techniques and establish a test-bed office building at the University of Southern California. Ghahramani et al. (2015) develop an online learning approach for developing a personalized thermal comfort model through adaptive stochastic modelling. In another study, Ghahramani et al. (2016) quantify the influence of occupancy schedule, set point, and other factors on heating energy consumption using EnergyPlus, which is an energy analysis and thermal load simulation program. The results show that, depending on the climate, significant savings can be achieved by setting different ranges of daily optimal set-point temperature.

Researchers further identify that learning the occupant energy consumption profile and its feedback can promote behavioural changes. Khashe et al. (2015) study the behavioural pattern of two groups of occupants (one group is provided information about the building being LEED certified and the other group is provided no information about the building being LEED certified) in their choices of using natural light versus artificial light. Results indicate that participants from the group with information on LEED branding are more motivated to choose natural light. Heydarian et al. (2015) investigate occupant lighting-use behaviour in a single-occupancy office space on manual and semi-automatic control systems of lighting use. The study reveals that participants' behaviours are significantly influenced by different design features such as lighting options. Most of these studies use video camera and motion sensors to measure occupant patterns (Mozer 1998; Trivedi et al. 2000; Lymberopoulos et al. 2008).

Compared to the above-mentioned models, energy simulation tools are easily deployed and time-effective methods to analyze building energy performance. Studies indicate that operational controls of facilities and their energy usage are significantly affected by such factors as number of occupants; frequency and duration of occupant presence/absence; and activity/energy usage patterns through internal heat gains from household appliances usage, moisture loads, and heating loads (Chang and Hong 2013; Papakostas and Sotiropoulos 1997). Since building energy consumption is affected by the physical parameters of a facility, the operational system, and occupant energy usage patterns, the performance of these existing energy simulation tools depends on how precisely the information is used during simulation. Existing simulation tools can use the physical parameter of a facility very precisely. However, occupant patterns are incorporated by using either a fixed or a diversity profile, which means building type (e.g., residential versus commercial), number of occupants, and duration of occupant presence are considered for use in the simulation model (Rose 2010). Moreover, existing simplistic occupancy profiles or detailed personalized behavioural profiles do not represent the nature of multi-family residential facility's energy usage patterns. This reveals deficiencies in the current systems and structures, and that a new approach is required.

As discussed above, most previous studies have focused on commercial and institutional facilities (usually with specific usage profiles: weekdays/weekends, day-time/night-time). Relatively little research has been conducted that focuses on the development of an occupant pattern model for residential facilities (Dong and Lam 2014; Shih and Rowe 2015; Richardson et al. 2008; Zaraket et al. 2015; Dong et al. 2015a; Dong et al. 2015b; Li et al. 2015). Furthermore, among the developed occupancy models mentioned above, most focus on lighting and blind control. Consideration and integration of an occupant model within the context of space heating control strategy has not yet received significant attention (especially with regard to residential facilities). The incorporation of a predictive occupant pattern model into a multi-family residential facility's space heating management strategy has not yet been thoroughly explored. The motivation underlying this study is thus to design a framework for developing multi-family residential facility occupant pattern model with the purpose of incorporating it into a space heating control strategy in order to promote sustainable building operation.

2.5 Current Needs/Problem Statement

As mentioned previously, space heating energy consumption is affected by occupant presence/absence, energy usage pattern through internal heat gain, and occupant heating choices. Researchers suggest that overlooking relevant occupant information in the development of a space heating control/operational strategy may lead to overestimation of heating demand or a discrepancy between estimated energy need and actual energy consumption. Considering these issues and in light of what has been discussed in the above literature review, the need for a comprehensive space heating control model that holistically integrates uncertainty of time-dependent occupant energy usage patterns, outdoor weather conditions, and a facility's thermodynamic performance within a control system cannot be ignored. However, some studies have integrated relevant occupancy information for a facility's space heating energy management system, and, to the author's best knowledge, available studies have been limited in scope to commercial, institutional facilities, single detached home/ apartment and lab-based facilities. Despite the fact that significant savings have been achieved (according to previous studies) by integrating occupant profiles in commercial, and institutional facilities' space heating systems, the integration of multi-family residential facility's occupant energy usage patterns in multi-family residential facility space heating operational/control systems has been largely overlooked. Recent developments in sensing and data logging make possible the collection of vast amounts of occupant energy usage data. However, in order to extract useful/relevant information from these data, there is a need for a standardized framework to assist FM with gaining useful knowledge regarding occupant energy usage patterns and their impact on heating load. This, in turn, will enable the development of a comprehensive user-centric space heating predictive control model.

Chapter 3 : METHODOLOGICAL APPROACH

Considering the stated objectives, and in light of the current needs as discussed in the previous chapter, this study seeks to develop an efficient user-centric space heating energy management strategy that addresses the inherent uncertainties with respect to multi-family residential facility occupant energy load along with weather uncertainty and thermal loss through building envelope. This section thus presents the methodological approach for developing a decision-making framework to assist facility managers with a post design user-centric space heating energy management strategy for improved energy performance while sustaining indoor environmental quality (IEQ). The approach primarily includes identifying the factors affecting space heating energy consumption of a multi-family residential facility through sensor-based monitoring strategies. Then, following the observation, it is determined what is required in order to optimize space heating energy consumption. Finally, strategies for a user-centric predictive space heating control model for a multi-family residential facility are developed.

The methodological approach is illustrated in Figure 3-1. The influencing factors (identified through sensor-based monitoring) are defined as the input parameters for the comprehensive model. These include weather information, sensor data on occupant energy usage, physical parameters of the facility (orientation, size, and material properties), as well as space heating system parameters. For simulation purposes, a mathematical model that can simulate the thermodynamic performance of the facility is developed. Physical parameters (collected from shop drawings) and the law of thermodynamics and energy conservation are used as the input for developing the facility's model representing its thermodynamic nature. To incorporate the uncertainty of occupant energy load with a predictive user-centric space heating controller, an occupant energy usage pattern prediction model is developed using sensor-based occupant energy usage data. These sensor-based data serve as the input for the development of an occupant energy usage prediction model. It is expected that the presented methodology provides optimum outputs to reduce a facility's space heating energy consumption while maintaining occupant comfort.

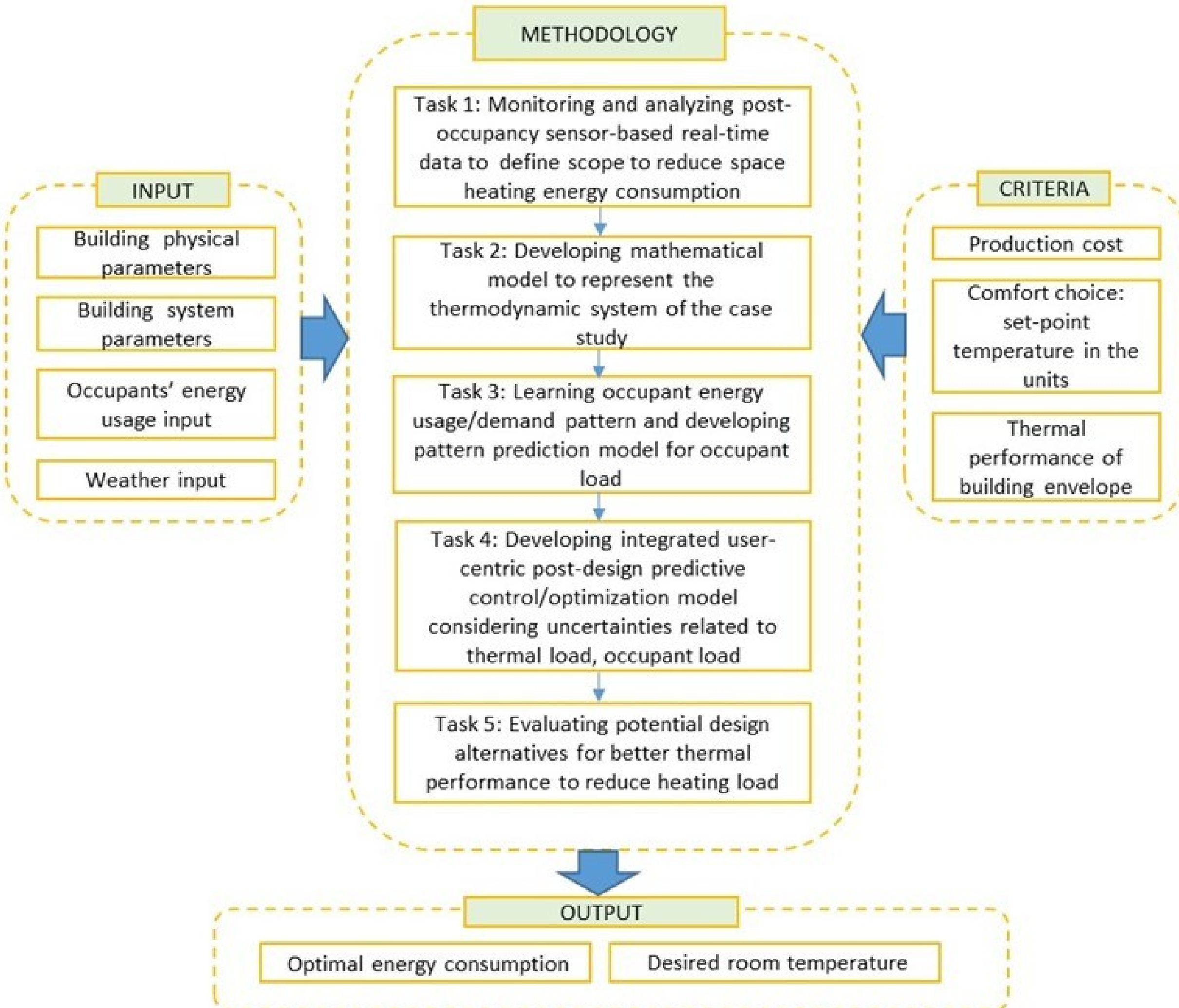


Figure 3-1: Methodology

3.1 Task 1: Developing a Post-occupancy Energy Monitoring Approach

Energy efficiency can be significantly improved by identifying problems in the system (Ahmad et al. 2016). Considering the importance of relevant information pertaining to building system performance for space heating operational improvement, this section aims to extract useful information with the purpose of integrating it within a space heating control strategy for improved energy efficiency. A number of studies (listed in Table 3-1) identify that physical parameters of a facility, operational system, occupant energy usage and behavioural patterns have significant impacts on space heating energy consumption. However, to provide better understanding of the factors affecting space heating energy consumption of a multi-family residential facility under occupancy, and for the purpose of optimizing space heating energy consumption, this study takes the approach of sensor-based monitoring of the occupancy phase, using a four-storey multi-family residential building in Fort McMurray, Alberta, as the experimental study.

The building under investigation is oriented with its longer axis facing north and south and comprises 70 affordable housing units (Sharmin et al. 2014). Because of the extreme dry-cold weather, buildings in Fort McMurray consume a large amount of energy for building space heating. To overcome this challenge, the case study building was designed to be served by an integrated heating system comprising geothermal, solar, drain water heat recovery (DWHR), and conventional electric or natural gas energy. Geothermal is used as the main heating system. The solar heating system assists in the direct transfer of energy to the geothermal field. The recovered heat from the DWHR system is also delivered to the geothermal field, which links to water-to-water heat pumps. Natural gas-burning boilers are also utilized to provide additional heat to the building. Conventional electricity is the driving power to operate the pumps in each loop. With these systems combined, the temperature of the water storage tank (for the purpose of space heating) is increased to a set-point considering only the weather load (current outdoor temperature) (Li et al. 2014; Li 2013), thus ignoring occupant load.

Table 3-1: Reference papers defining the significant influencing factors for heating energy consumption

Influencing factor for facility’s energy consumption	Literature review
Physical characteristics of facility	Sonderegger et al. 1978; Hirst and Goeltz 1985; Assimakopoulos et al. 1992; Haas et al. 1998; Petersen and Togeby 2001; Liao and Chang 2002; Pachauri et al. 2004; Sardianou 2008; NRC 2012; Zaman et al. 2012; Aqlan et al. 2014; Awad et al. 2014; Sharmin et al. 2014; Sharmin et al. 2015
Heating system	Grünenfelder and Tödtli 1985; Cho and Zaheer-Uddin 2003; Henze et al. 2004a, 2004b; Gwerder and Tödli 2005; Henze et al. 2005; Bourgeois et al. 2006; Andersen et al. 2007; Ma et al. 2009; Siroky 2011; Oldewurtel et al. 2012; Li et al. 2014; Sossan et al. 2014; Maasoumy et al. 2014; Sharmin et al. 2017
Occupants’ pattern of space heating, energy usage, water usage	Lindén et al. 2006; Andersen et al. 2007; Tommerup et al. 2007; Brohus et al. 2009; Brohus et al. 2010; Zhun et al. 2010; Zhao et al. 2014; Lam et al. 2014; Jazizadeh et al. 2014a; 2014b; Zaraket et al. 2015; Li et al. 2015; Khashe et al. 2015; Heydarian et al. 2015; Ghahramani et al. 2016; Sharmin et al. 2017
Household characteristics of facility (income, household size)	Biesiot and Noorman 1999; Schuler et al. 2000; Pachauri et al. 2004; Vringer 2005; Lenzen et al. 2006; Tso and Yau 2007; Sardianou 2008; Vassileva 2012; Vassileva et al. 2012; Albert and Rajagopal 2013

Selection of case study units:

Out of 70 units in the case study building, three units on each floor of the four-storey building (in total 12 case study units) are selected for the case study, and each of those selected have approximately the same relative floor plan. On each floor, one "one-bedroom" unit facing north, one "one-bedroom" unit facing south, and one "two-bedroom" unit facing north are selected (Figure 3-2). It should be noted that in this study the specific locations of the units in their floors are not revealed for the sake of privacy.

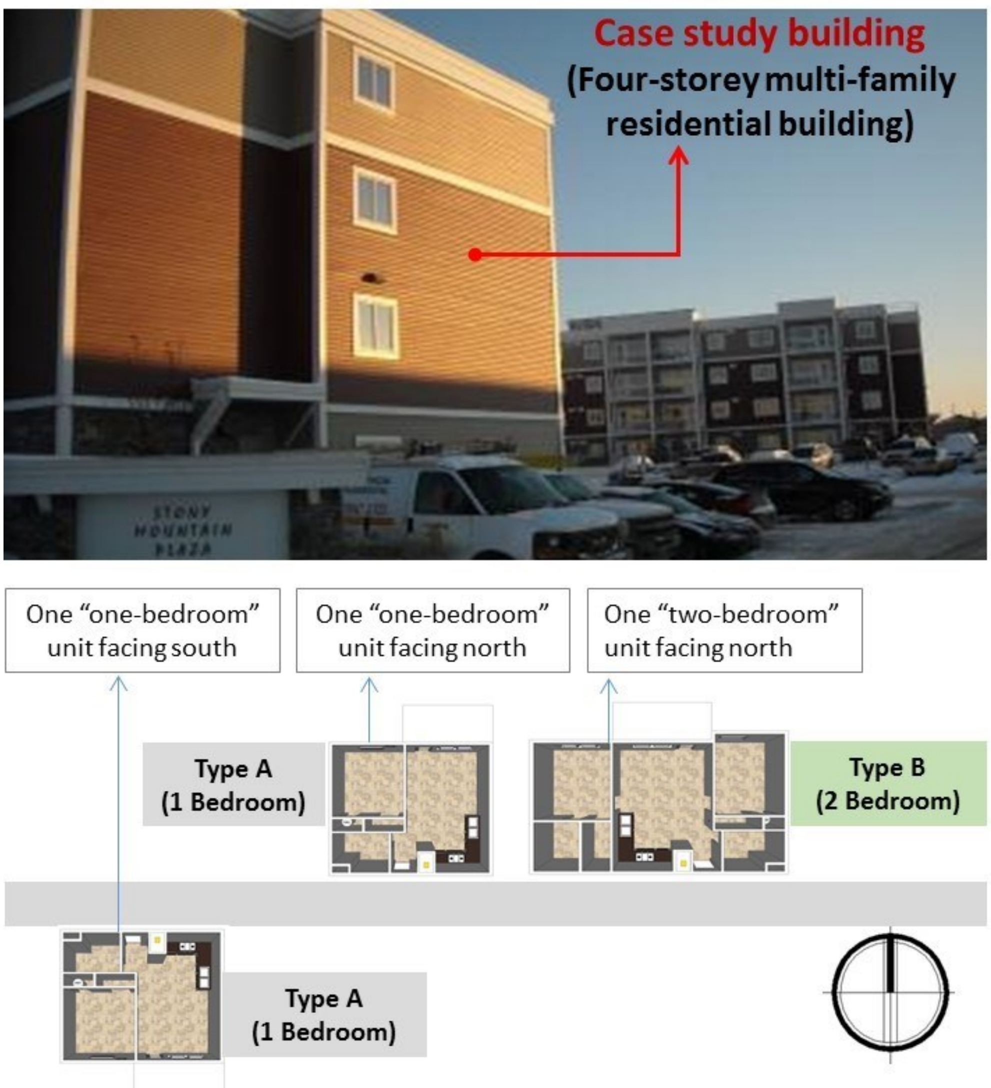


Figure 3-2: Case study building and case study units

Sensor instrumentation is installed and deployed such that real-time data of occupant heating consumption, indoor air quality (i.e., temperature, relative humidity, CO2), and electricity consumption can be measured and collected. In order to evaluate the performance of the operational strategy for water-borne heating system, sensors are also installed to measure supply-return water temperature, supply pressure, differential pressure, and variable frequency drive (VFD) in the circulation pump. Figure 3 3 shows a schemata of the system architecture for the monitoring system adopted in this study.

Installation of sensors:

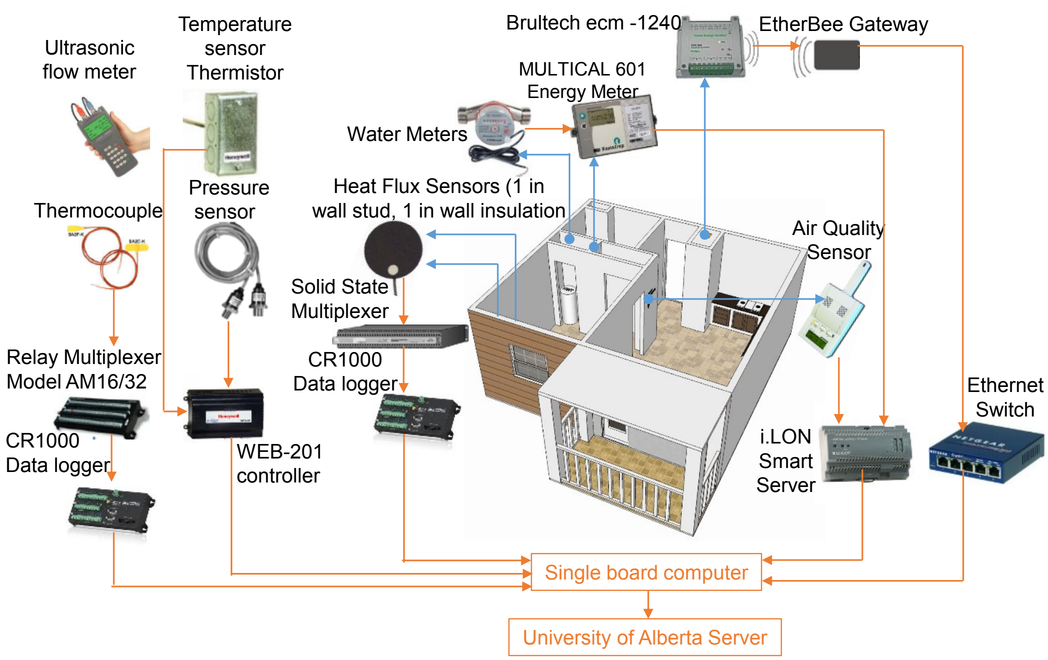


Figure 3-3: Sensor network

The following sensors are installed to collect data. (Figure 3-4 shows select screenshots from the database.)

Power consumption meters (Brultech ECM-1240): Using ZigBee, these sensors communicate with four EtherBee gateways (for each floor of the four-storey building), and are then connected to

CAT5 Ethernet cable. This in turn is connected to a single-board computer through a 5-port switch. Sensor output includes the total energy consumed thus far for each load (in Watt seconds) for each appliance/device: hot water tank (HWT), range, range hood fan, kitchen plug, bedroom plug, lighting (kitchen, bathroom, living room, and balcony), electrical duct heating (EDH), energy recovery ventilation (ERV), and refrigerator.

MULTICAL® 601 Energy Meter: Communicates with an iLONsmart server, which is then connected to a single-board computer. Sensor output includes: total energy (Wh), total volume (L), total mass (g), current flow (L/s), and current T_s and T_r (°C).

Minomess 130 Water Meter (two in each apartment): Communicates with an iLONsmart server, which is then connected to a single-board computer. Sensor output includes: total volume (in gallons) for each of the meters.

IAQ Point air monitoring device: Communicates with an iLONsmart server, which is then connected to a single-board computer. Sensor output includes: current values of CO_2 (ppm), RH (%), and temperature (°C).

Two Heat Flux Sensors (one in Stud, and one in Insulation): Connected to the CR1000 data logger (Campbell Scientific, Inc.) through a Solid State Multiplexer (Campbell Scientific, Inc.). Sensor output includes: heat flux (W/m^2).

Thermocouple: Connected to a single-board computer through AM16/32B Relay Multiplexer to increase the number of channels that are recorded with a data logger-CR1000 (Campbell Scientific Inc.). Sensor output includes: the temperature difference (°C) for supply and return pipes of each component of the integrated heating system.

Ultrasound flow rate meter: An ultrasound flow rate meter is utilized and the output includes: flow rate (L/min) measurement (one-time measurement) of the fluid.

Temperature Sensor (Thermistor): Connected to a single-board computer through "WEB-201" controller. Sensor output includes: supply water temperature (°C).

Pressure Sensor: Connected to a single-board computer through "WEB-201" controller. Sensor output includes: differential pressure (kPa), supply pressure (kPa), and variable frequency drive (VFD) (%).

Time Stamp (e.g. YYYY-MM-DD HH:MM:SS) — Apartment No: 1-12 — Phase A /B — Channel 1 — Channel 2 — Individual Plug Load

ts	apt	phase	seconds_counter (seconds)	ch1 (Ws)	ch2 (Ws)	aux1 (Ws)	aux2 (Ws)	aux3 (Ws)	aux4 (Ws)	aux5 (Ws)
2011-12-20 23:45:45	10	B	612520	201224160	1355791	18612463	291350	60775773	95820934	19861869
2011-12-20 23:45:45	12	A	538138	96052420	26184923	688960	134295	23796043	34868221	7410483
2011-12-20 23:45:45	12	B	538342	50781741	1307	389176	637583	825789	26097535	20571276

Power consumption meters (Brultech ECM-1240)

Time Stamp (e.g. YYYY-MM-DD HH:MM: SS) — Apartment No: 1-12 — Total Energy (Wh) — Total Volume (L) — Total Mass (g) — Current Flow (L/s) — Supply Temperature (° C) — Return Temperature (° C)

ts	apt	total_energy (Wh)	total_vol (L)	total_mass (g)	cur_flow (L/s)	cur_t1 (°C)	cur_t2 (°C)
2011-12-20 13:22:02	4	91944.44	58236	57890004	0.06	40.11	38.78
2011-12-20 13:22:02	9	174166.64	41610	41387000	0.07	39.89	37.93
2011-12-20 13:22:03	5	121944.45	28524	28359000	0	33.95	31.45
2011-12-20 13:22:04	1	71944.44	38334	38109000	0	18.96	18.62

MULTICAL® 601 Energy Meter

Time Stamp (e.g. YYYY-MM-DD HH:MM:SS) — Apartment No: 1-12 — CO_2 (ppm) — Relative Humidity (%) — Temperature (° C)

ts	apt	co2 (ppm)	rh (rel. humidity %)	temperature (°C)
2011-12-20 13:22:02	4	1077	40	26.5
2011-12-20 13:22:02	9	1195	32	24.7
2011-12-20 13:22:03	3	976	31	26.7
2011-12-20 13:22:03	5	386	23	22

IAQ Point air monitoring device

VFD — Supply pressure — Differential pressure

AO_P3_2_VFD_Ctrl	AI_T12_HWS_T	AI_R07_HWS_P	AI_T13_HWR_T	AI_R08_HWR_P	AV_P3_DP_SetPt	AV_P3_Diff_Pressure
60.6857757568359	41.8363876342773	247.993713378906	40.2989845275879	196.576858520508	70	51.4168548583984
68.5830917358398	41.805778503418	252.286209106445	40.3734130859375	199.878646850586	70	52.3368225097656
69.1831665039062	41.7736320495605	256.170806884766	40.4338607788086	203.207733154297	70	52.9630737304688
69.6259078979492	41.715030670166	257.755096435547	40.4946212768555	203.936050415039	70	53.8190460205078

Temperature Sensor: Thermistor

Figure 3-4: Screenshot from database

Since the purpose of installing sensors and measuring real-time data in this study is to increase the understanding of the factors relevant to space heating energy consumption, using the collected sensor data a data analysis framework is developed (Figure 3-5) to ascertain the relationships between space heating energy consumption of the facility under occupancy and factors such as physical characteristics, weather, occupant activity pattern, and operational strategy.

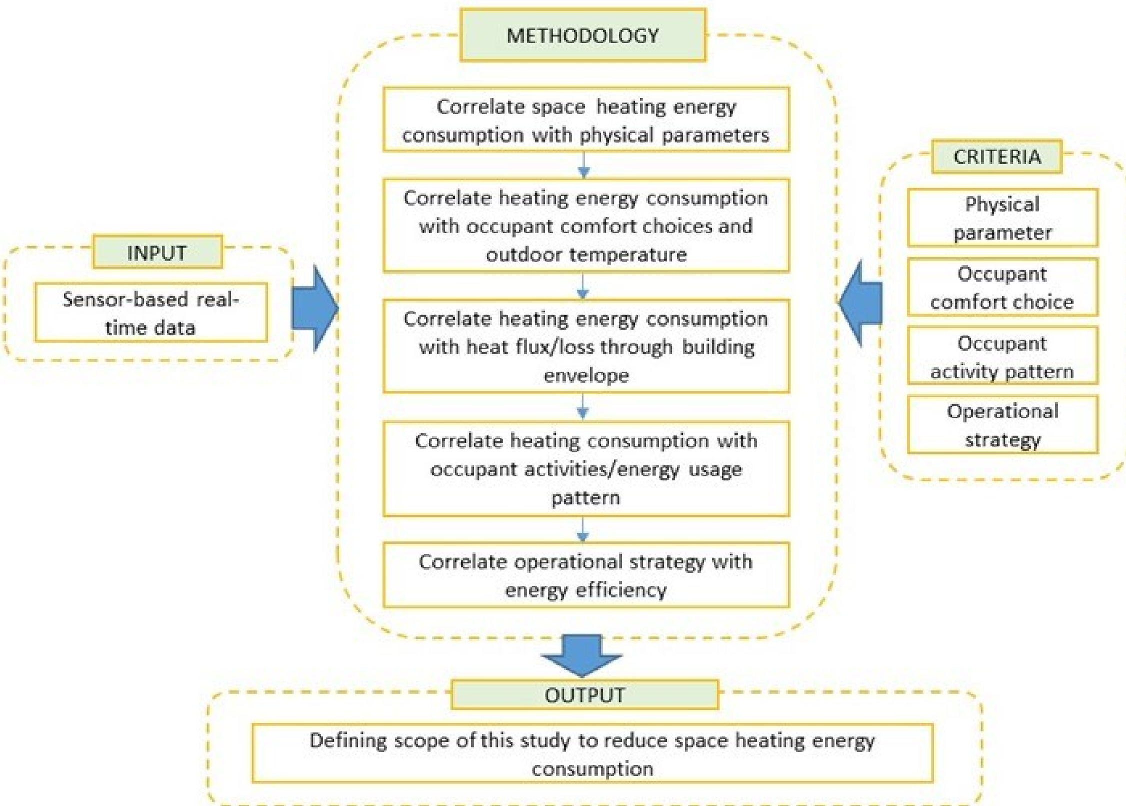


Figure 3-5: Methodological approach for sensor-based data analysis

3.2 Task 2: Modelling the Thermodynamic System and Validation

This research aims to optimize space heating energy consumption by developing an integrated user-centric space heating control strategy that holistically integrates outdoor temperature, thermodynamic performance of building envelope, and occupant information in the operation of the space heating system of a multi-family residential facility. As such a mathematical model is required that serves the following functions: (1) to incorporate thermal properties of building envelope; (2) to incorporate thermodynamic relation with disturbances such as weather load and occupant load; (3) to implement/incorporate different operational strategies for the heating system, where controllers can operate with the information from the model; (4) to implement optimization algorithm; and (5) to simulate the whole system for the required period of time. This section presents the strategy adopted for developing the mathematical model.

In consideration of the required functionalities, this research adopts the approach of developing a mathematical model to represent the thermodynamic relation between a facility's thermal mass, heat transfer, and heating system through Resistance-Capacitance (R-C) networks. Development of the thermodynamic model using electrical analogy and simulation of the model are conducted through Simscape in MATLAB. The electrical analogy and modelling of building components are briefly described below (Lin et al. 2013; Alvsvåg 2011; Bertagnolio et al. 2008; Incropera et al. 2007; Xu and Wang 2007; ASHRAE 2003; Cenegal 2002; Kreith et al. 1999; IEA 1999; Incropera and DeWitt 1996). Figure 3-6 shows the methodological approach for developing the thermodynamic model.

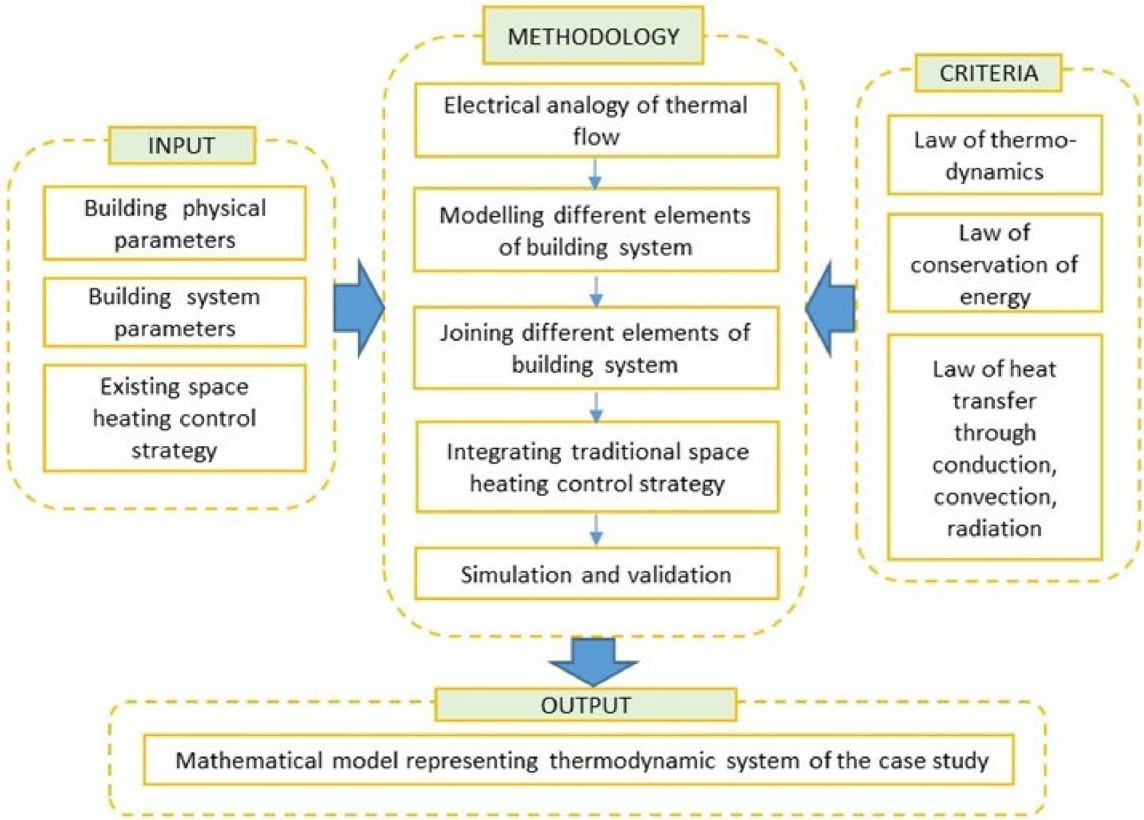
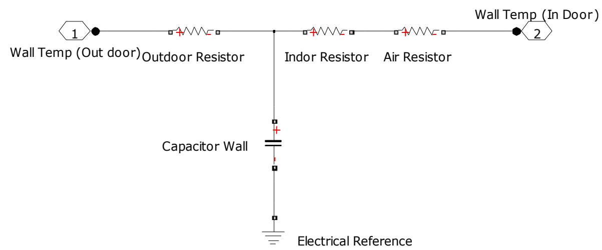
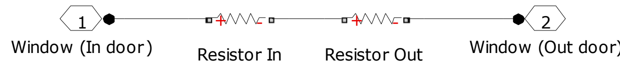


Figure 3-6: Methodological approach for developing thermodynamic model

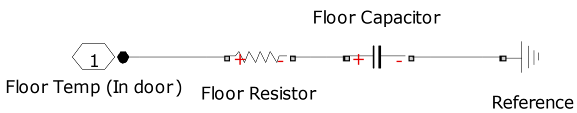
Like Fourier's law, where the flow of heat (in heat conductors) is predicted with the influence of temperature differences, in Ohm's law flow of current is predicted with the influence of voltage differences. In this study the electrical analogy for thermal flow is adopted for heat in building elements. The thermodynamic model of the case study with a traditional heating system is made up of several smaller components such as wall, ceiling, floor, and windows. According to the above concept, a circuit for a wall can be constructed using resistors and capacitors, and can be expressed as shown in Figure 3-7a (Lin et al. 2013; Alvsvåg 2011; Bertagnolio et al. 2008; Incropera et al. 2007; Xu and Wang 2007; Cenegal 2002; Kreith et al. 1999; IEA 1999; Incropera and DeWitt 1996).



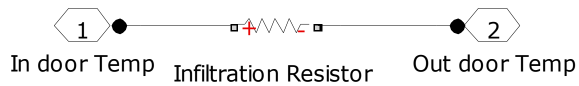
(a) Wall construction using electric circuit concepts



(b) Window construction using electric circuit concepts



(c) Floor construction using electric circuit concepts



(d) Air infiltration construction using electric circuit concepts

Figure 3-7: Room inventory construction using electric circuit concepts

In this study, a window is considered as a component that has no ability to absorb heat and which thus does not require a capacitor component. A window component is depicted in Figure 3-7b. In window circuit construction, “Resistor Out” represents the heat conduction through a window, and “Resistor In” represents heat convection between the indoor air surrounding the window and the room air (Lin et al. 2013; Alvsvåg 2011; Bertagnolio et al. 2008; Incropera et al. 2007; Xu and Wang 2007; Cenegal 2002; Kreith et al. 1999; IEA 1999; Incropera and DeWitt 1996). Ceiling and roof modelling are constructed with the same circuit methodology used for wall modelling as shown above with resistor, capacitor, and electrical ground. However, floor modelling is expressed as shown in Figure 3-7c. It should be considered that doors and windows leak air around the frames, and occupant activity increases air movement in a room. Pressure increases can also cause air infiltration due to the difference between inside and outside temperature with respect to any building component. Heat transfer and heat infiltration between adjoining rooms are also considered in this study. A heat infiltration circuit (Lin et al. 2013; Alvsvåg 2011; Bertagnolio et al. 2008; Incropera et al. 2007; Xu and Wang 2007; ASHRAE 2003; Cenegal 2002; Kreith et al.

1999; IEA 1999; Incropera and DeWitt 1996) is used as shown in Figure 3-7d. After accounting for the thermodynamic relationships for different elements of a building system, all the elements are connected in order to model the thermodynamic performance of the case study space.

3.3 Task 3: Developing Occupant Pattern Prediction Model

As mentioned above, effective functioning of the space heating system in a facility requires efficient FM coupled with well-organized relevant information. In this thesis it is expected that estimating the actual heating need of a facility by integrating (relevant) occupant information (along with heat loss associated with the thermal performance of the building envelope, and weather disturbance) may assist in optimizing space heating energy consumption during the operation phase. Therefore, this step develops an occupant pattern prediction model (comprising relevant occupant information) to integrate with a multi-family residential facility's space heating energy management strategy.

However, it should be noted that, while considering multi-family residential facilities, identifying relevant occupant information and integrating it within space heating energy management strategies poses several challenges. Unlike with commercial facilities, occupant patterns in multi-family facilities do not follow any fixed activity-demand-schedule pattern. Therefore, in view of the unique needs and nature (varying activity-schedule, privacy concerns, variation in heating demand from multiple families) of multi-family residential facilities, and considering the important role of correct and relevant information in ensuring system efficiency, the development of an effective occupant pattern model for a multi-family residential facility necessitates a comprehensive understanding of the correlation between occupant pattern and space heating energy consumption during occupancy.

This study thus proposes the approach of capturing the correlation between space heating energy consumption and occupant pattern, and thereby identifying the influencing occupant factor that defines the load during occupancy. Then, following the observations made, the scope/structure for developing an occupant pattern prediction model that can be integrated with energy management strategies for multi-family residential facilities for the purpose of reducing energy usage and cost is defined. For the purpose of learning and predicting next-hour occupant load, this study utilizes previously measured real-time occupant information. As mentioned earlier, to demonstrate the effectiveness of the sensor-based approach adopted in this study, a multi-family residential building in Fort McMurray, Alberta, is chosen as a case study.

Use of technologies such as motion detectors or infrared video camera for continuous detection of these occupant factors is not a viable choice, given occupant privacy concerns. However, different kinds of energy usage sensors can be utilized to identify relevant occupant information. Therefore, for the purpose of developing the occupant pattern model and learning occupant load pattern, this study proposes an approach that utilizes energy usage sensor-based monitoring data from a multi-family residential facility during occupancy. However, installing different kinds of energy usage sensors in each unit of the given facility may not always be possible considering the increased cost of installation and management. As such, an approach is recommended in which occupant pattern is learned from sample energy usage representative groups and the performance of the heat circulation pump as a function of holistic occupant demand state. Moreover, the objective of this study does not require the development of behavioural patterns profiles for individual building units; rather, it requires the development of a profile for the entire building occupant load/demand state holistically. In this study, the weather and time-dependent demand state profile is generated based on the frequency and duration of each activity status, and the simulation of the future demand state is triggered by the next state of outdoor temperature and time (hour of the day, day of the week, week of the month). Since the demand state profiles are learned for different groups of outdoor temperature and time, the predicted outputs are dependent on those variables; therefore, the prediction for Saturday at 19:00 with the outdoor temperature group below −20 °C may be different than for Saturday at 19:00 with the outdoor temperature group above 5 °C. The approach for developing occupant pattern model is shown in Figure 3-8 and is further described in section 4.3.

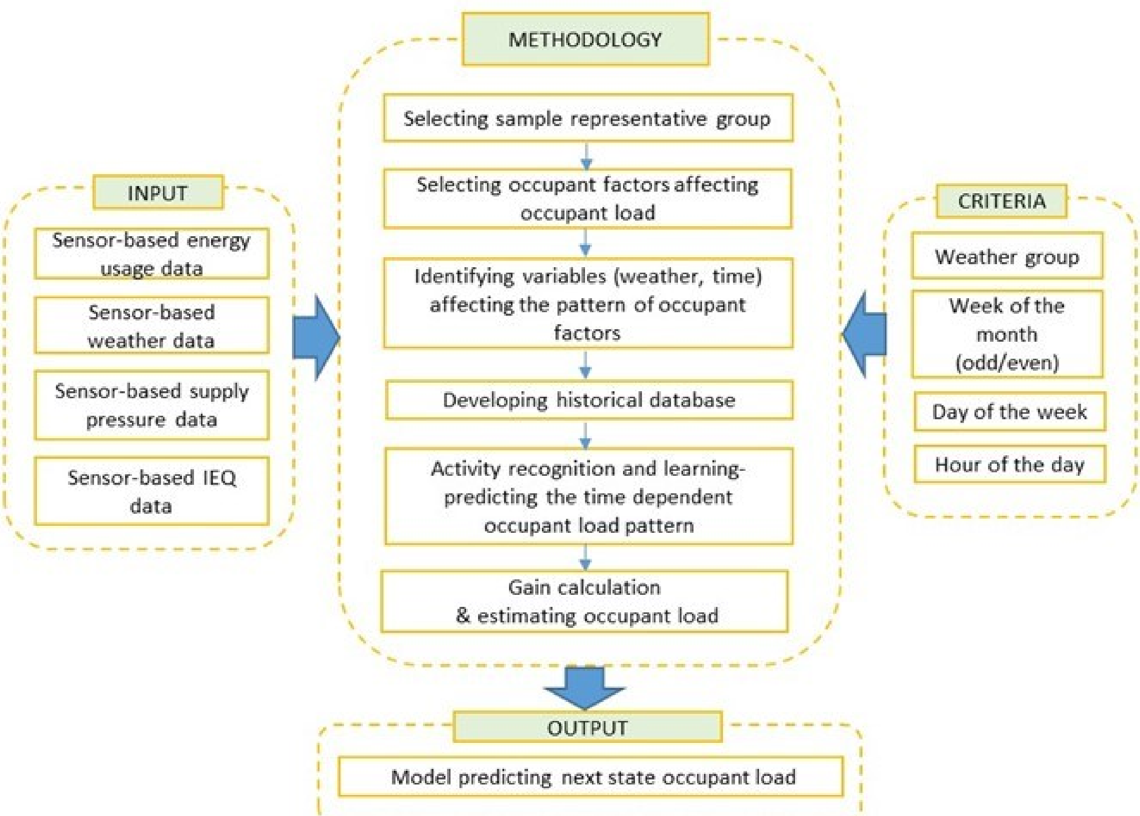


Figure 3-8: Methodological approach for developing occupant pattern prediction model

It should be noted that numerous studies have been conducted that focus on developing personalized occupant profile or case-specific user patterns based on different income/professional groups, age-sex groups, or cultural background groups (Biesiot and Noorman 1999; Schuler et al. 2000; Pachauri et al. 2004; Vringer 2005; Lenzen et al. 2006; Tso and Yau 2007; Sardianou 2008; Vassileva 2012; Vassileva et al. 2012; Albert and Rajagopal 2013). However, because of privacy concerns and cost and time constraints (rendering its actual application in multi-family residential facilities infeasible), these factors are not considered within the scope of this study.

3.4 Task 4: Integrating Occupant Prediction Model with Space Heating Control Model

The literature review identifies that, by serving approximately one-third of the nearly 67 billion ft^2 of floor spaces, building management systems (BMS) in the United States gained access to a large number of real-time data. However, as observed in current practice, often these data remain under-utilized and therefore buildings continue to be operated assuming maximum need (leading to excessive energy consumption) (Bengea 2012). By considering only current outdoor temperature (suitable for only current weather disturbance rejection) and ignoring occupant information in its space heating control strategy, the four-storey multi-family residential facility in Fort McMurray, Alberta (which has been selected as the case study for this research) also follows this practice, resulting in inefficiency.

In consideration of this, an integrated user-centric space heating control strategy is developed that accounts for the uncertainty of occupant load and the facility's thermodynamic performance within the space heating control strategy while estimating the amount of heating energy required to fulfill heating demand. This section of the research thus aims to develop an integrated model that is able to integrate predicted occupant load (along with weather disturbance) through feedforward connection/loop with a predictive controller. However, since prediction occasionally deviates from real-time activities (in cases where occupant activities do not follow any previously measured pattern), this study adopts the concept of model predictive control (MPC). MPC, along with the feedforward connection, also features a feedback loop able to correct the error (differences between prediction and real-time activities). A schematic drawing of the proposed supervisory predictive model with both feedback and feedforward connection is shown in Figure **3-9**. The figure depicts a traditional control system alongside the proposed integrated predictive control strategy that considers occupant energy usage prediction (along with weather prediction) and feedback from the current state.

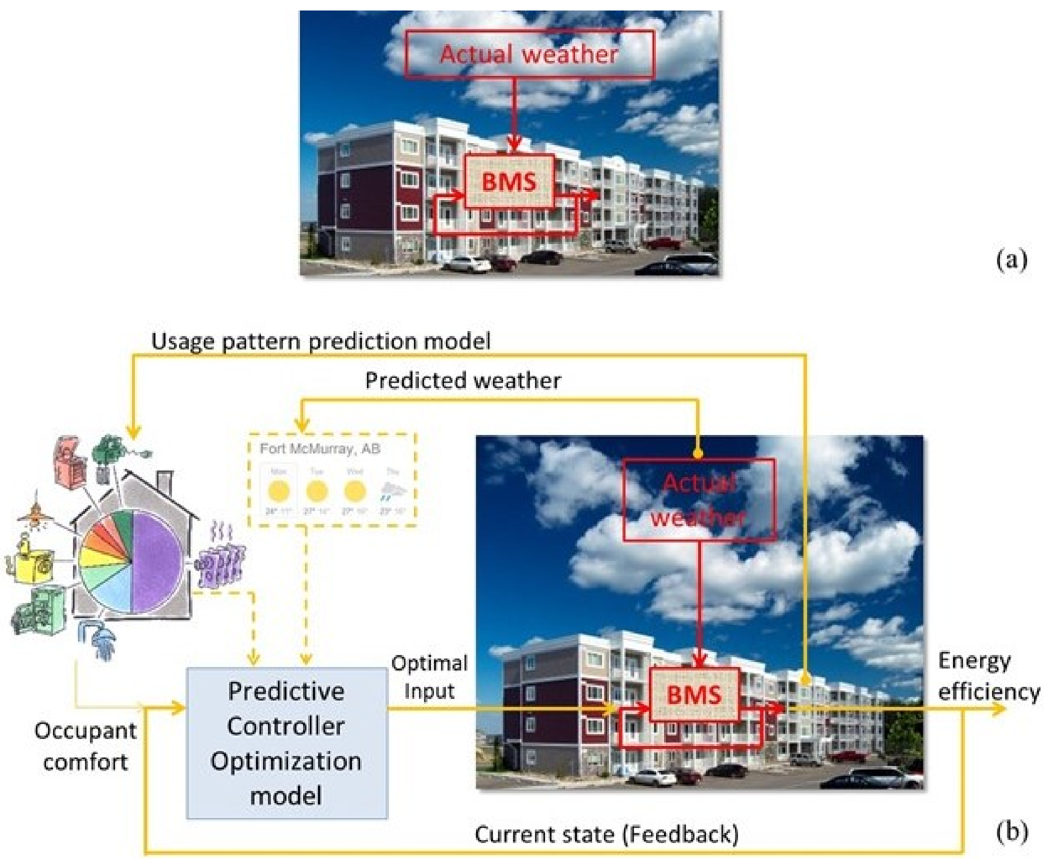


Figure 3-9: Schematic drawing of (a) traditional control system; and (b) proposed integrated predictive control strategy

It should be noted that, among the two broad control functions, local control, such as On/Off control and PID control, is the more basic control function. The supervisory control function is a high-level control system that includes modelling of the whole building system along with the low-level control (Coffey 2008). Quintana and Kummert (2015) note that updating supervisory control strategies can reduce energy consumption by 5%.

Model Predictive Control (MPC) is a supervisory optimal control strategy that follows a methodological numerical optimization process. The literature review shows that, over the years, the concept of this optimal control strategy has been invented and re-invented several times. Beginning in the 1960s, computational methods for optimal control problems were defined using the concept of "receding horizon" (without the closed-form solution) (Cannon 2016). Around the 1970s, two pioneering industrial research groups (Shell Oil and ADERSA) independently developed first-generation MPC systems—Shell Oil developed Dynamic Matrix Control (DMC) and ADERSA introduced an approach with similar capabilities (Richalet et al. 1978). Clarke et al. (1987) developed Generalized Predictive Control (GPC) (an adaptive MPC technique), which also gained recognition during the 1980s.

In various industries, predictive control is considered one of the more advanced control techniques for improving control performance in applications. During the 1980s, to improve performance, predictive control reappeared within the context of industrial process control (Cannon 2016). It is reported that, by the end of 1999, there were over 4,500 applications, mostly in oil refineries and petrochemical plants (Qin and Badgwell 2003), and MPC has been considered an effective solution for difficult multivariable control problems in these sectors (Seborg 2011). However, in the building research area MPC historically has not garnered much attention compared to the other industries. In spite of its having been historically been overlooked, MPC offers numerous advantages, such as the ability to predict the future behaviour of the system in response to predicted disturbances, the capacity to solve mathematical models of complex systems with multiple inputs/outputs, and the ability to include system constraints within the controller. Considering these advantages over other control strategies, today MPC is gathering momentum in the area of building engineering (Hazyuk 2012).

MPC utilizes a system model to simulate the future control input sequence and predictive behaviour of the given process/plant. The predicted sequence of the output signal is generated through the system model based on each future control input sequence. The system model utilizes the previous sequences of the input and output signals to simulate the future behaviour of the process. Analyzing the predicted output sequences, the control signal is optimized at regular intervals with respect to a performance index (Balan 2009). As stated by Hazuk (2012), by predicting the impact of controlled input, MPC can make decisions efficiently to achieve the desired performance (Hazuk 2012). It should be noted that the model and current measurements can be used to simulate the predicted output value if the system model is a reasonably accurate dynamic model of the process. In this regard, as Seborg (2011) mentions, "*the success of MPC (or any other model-based approach) depends on the accuracy of the process model. Inaccurate predictions can make matters worse, instead of better*".

Therefore, this step of the study aims to develop a reasonably accurate dynamic model of the thermodynamic process of the case study facility. This section first develops a system model of the facility, and then integrates the predictive controller-optimization model. The methodology/framework (Figure 3-10) followed to develop the process model and optimization predictive controller is presented below:

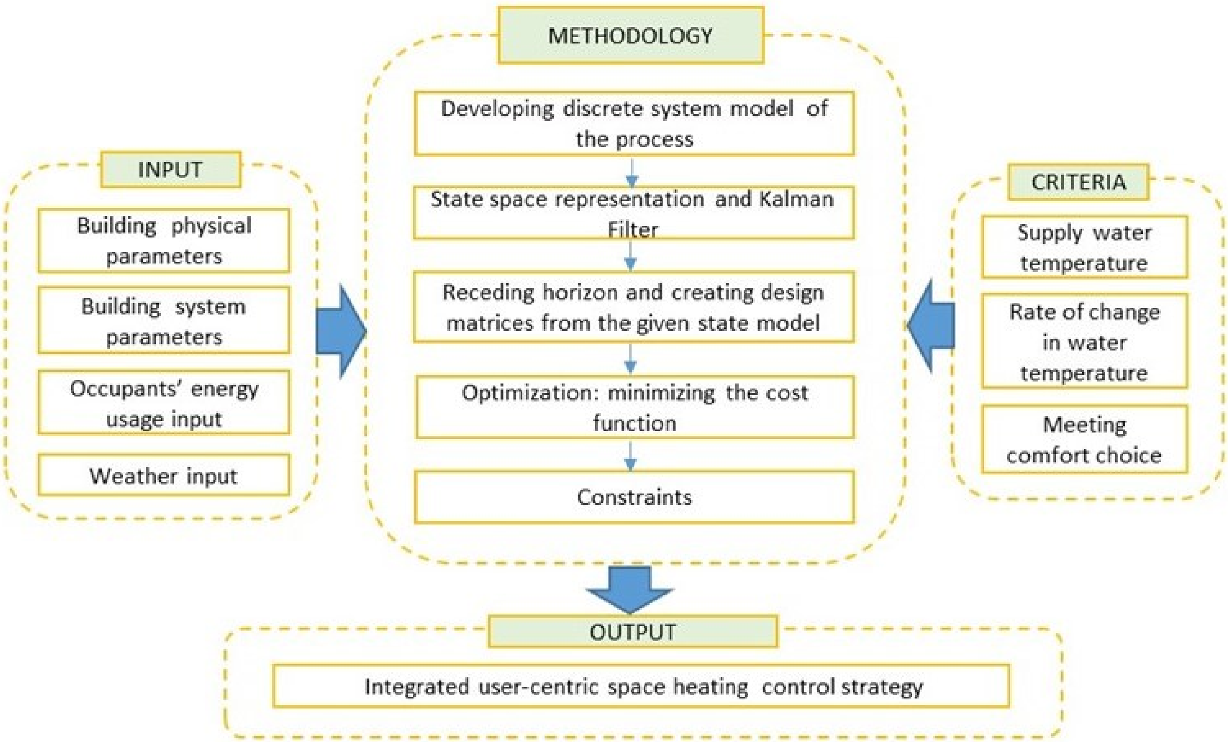


Figure 3-10: Methodological approach for developing integrated space heating control strategy

Developing a system model in Simulink:

In order to use MPC for developing the integrated predictive user-centric space heating control model, a process/ system model is required. Therefore, this section describes use of the heat-balance approach to develop the system model using MATLAB Simulink. It should be noted that the state space representation is derived from the developed heat-balance Simulink model of the process.

State space representation and state estimation using Kalman Filter:

In this step, state space representation of the thermodynamic heat balance model is derived. The state space model estimates the states and the Kalman filter estimates the filtered current-state vector. The estimated current-state vector is then sent to the predictive controller, which predicts the estimated output of the process.

Receding horizon and creating design matrices from the given state model:

Once the state space representation of the system model (representing the real process) has been developed, design matrices are estimated from the state space model. At any current state, the predictive controller estimates the future response of the model starting from current time until prediction horizon with the purpose of reaching the goal (meeting the reference point or set-point) within the predefined length of time, i.e., prediction horizon). The model finds different options of input control sequence that lead to the set-point, and, by considering the objectives and constraints, further identifies the optimized input trajectory. Once the correct optimized input trajectory is selected by the model, it only applies the first input (from the selected input trajectory) to the system, thus completing the first step. This process is repeated in the next step starting from the current time until the same length of prediction horizon is reached. The process described here, called “receding horizon”, is the core concept on which MPC is based (Seborg 2011; Koch 2013; Kwon and Han 2005).

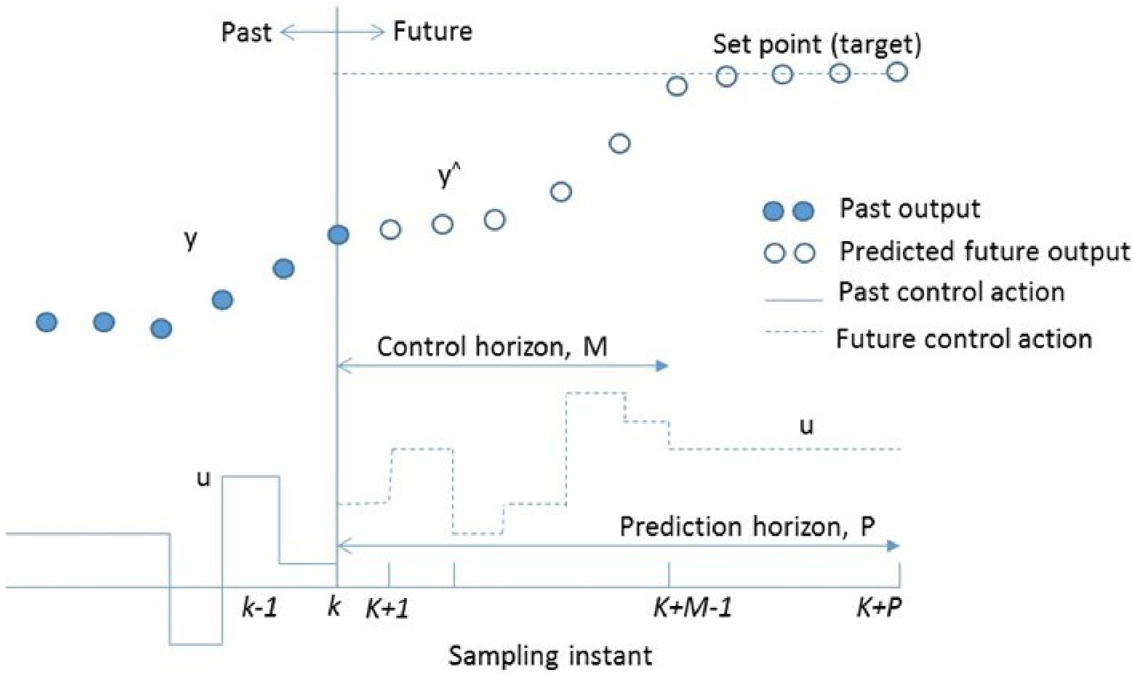


Figure 3-11: Concept of receding horizon (Source: Seborg 2011)

Optimization Algorithm:

When estimating the control sequence toward the future predicted horizon for a fixed number of steps (*P*), MPC works to minimize the objective function. During the process, only the first control output of the control sequence is taken, and the optimization is then recalculated for the next step (Kouvaritakis and Cannon 2016; Seborg 2011; Kwon and Han 2005). This task focuses on reduction of cost function. During the process, the primary objective of the heating system is to provide the required room temperature to all the users of a multi-family facility. In other words, the room temperature should always meet the reference set-point with negligible error. In this study, another two objectives are included which involve increasing the efficiency of the heating system—(1) to reduce the rate of change of temperature of input water supply, and (2) to reduce the temperature of the water supply itself—so that the energy loss is minimized while maintaining the heating demand of the facility.

Constraints:

After defining the reduced cost function, this task defines the constraints for the integrated model. There are three variables that need to be controlled in this study: (1) the output of the MPC controller should be able to meet the reference set-point with negligible error; (2) the temperature of the water supply should be optimized; and (3) the rate of change of supply water temperature should be minimal.

3.5 Task 5: Evaluating Design-alternatives for Improved Thermal Performance of Building Envelope

Following the observation from sensor-based data analysis, it is identified that, along with the occupant activity pattern and the operational strategy during occupancy, physical parameters (orientation) significantly affect indoor temperature profile, which in turn affects the heating load. Therefore, in order to reduce space heating energy consumption from the facility holistically while optimizing space heating energy consumption through operational strategies during occupancy, the evaluation of different design alternatives during the design phase to reduce space heating energy consumption should also be included within the space heating energy management framework.

It is observed (by analyzing real-time measured sensor data) that north-facing units have higher heating energy consumption than south-facing units, and it is inferred that higher temperature difference between the outer and inner surface of the north-facing external walls through north-facing building envelope (compared to south-facing units) may be the cause of higher heating consumption in north-facing units. However, multiple factors, such as occupant activity pattern and comfort choices, may combine to influence the measured value (energy usage sensor data).

Therefore, to further investigate the isolated impact of orientation on thermal performance of building envelope, an established *mathematical model* (CIBSE method) is used in this study to analyze the impact of directional orientation on indoor temperature profile.

It is noted based on both the sensor-based data and the mathematical model that north-facing units have a different thermal performance profile than the other units, a fact which eventually causes higher heating load in north-facing units (compared to south-facing units). This observation points to the need for a different configuration for north-facing building envelope for better thermal performance, and for performance analysis of various design alternatives for north-facing units.

Performance analysis of design alternatives by assessing the environmental and energy impacts of design decisions is considered an integral part of the design process for energy-efficient high-performance buildings (Augenbroe et al. 2004; Wetter 2011). It is expected that the overall building performance can thus be improved through quantifiable predictions by selecting the best design alternative in terms of energy efficiency (Jalaei and Jrade 2014; Aksamija 2012). This study adopts the simulation approach for performance analysis of different potential design alternatives (for future design reference). By adopting a *simulation-based approach*, this study evaluates one factor at a time, thereby promoting better understanding of potential design alternatives.

A Literature review is conducted to identify the design standards and IEQ standards which are to provide the basis for detailed evaluation criteria for different potential design alternatives. Accordingly, two performance evaluation criteria are identified: (1) maintaining indoor temperature profile with reduced heating load; and (2) evaluating daylighting performance of the changing parameters (parameters that have been changed for better thermal performance), as there is a possibility that the changing parameters may affect the indoor daylight level by influencing IEQ and dependence on artificial lighting. For the purpose of reducing the energy load on mechanical means while sustaining standard IEQ, this research proposes the framework depicted in Figure 3-12.

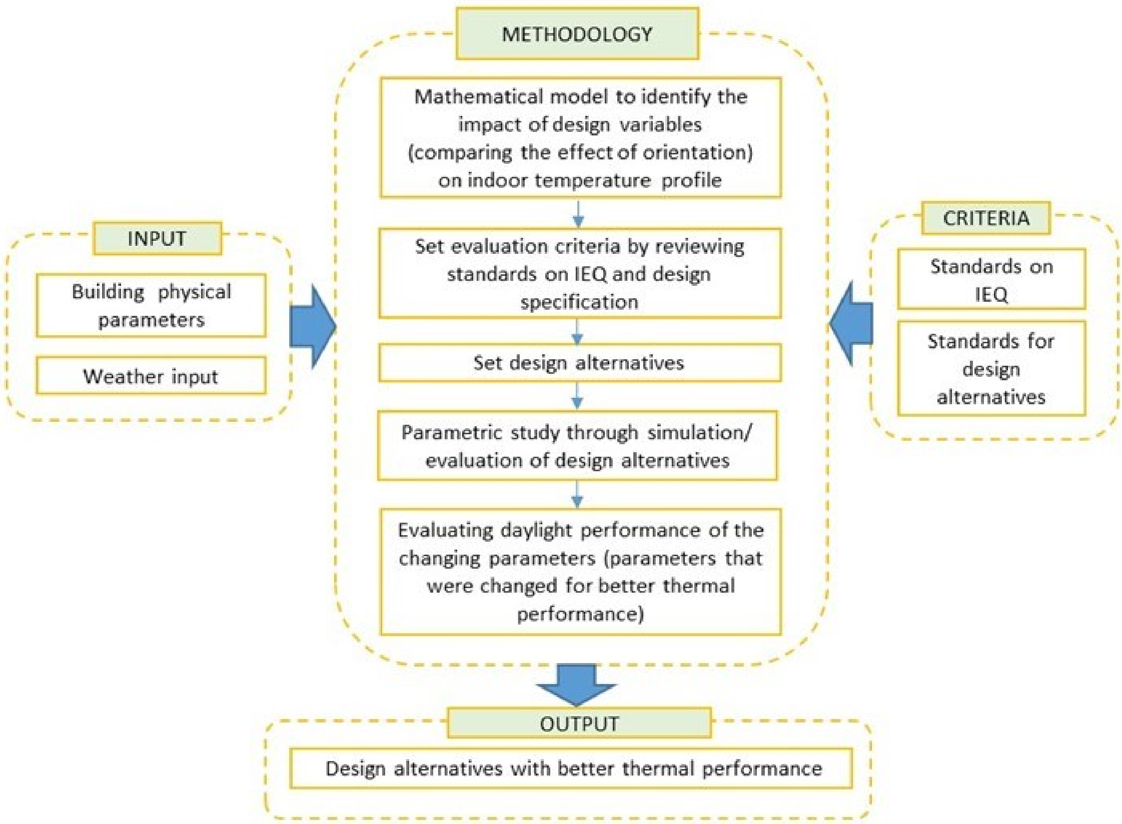


Figure 3-12: Methodological approach for performance evaluation of design alternatives

The approach presented in this chapter includes the study and analysis of building energy performance, space heating system performance, and IEQ under occupancy. This entails extracting useful information related to space heating energy consumption to assist facility managers with a holistic user-centric approach to optimizing the space heating energy consumption and comfort level for multi-family residential facilities in cold regions.

Chapter 4 : METHODOLOGY IMPLEMENTATION

This chapter focuses on implementation of the methodology described in Chapter 3 to achieve the desired goal of developing a user-centric predictive control model for improved space heating energy efficiency of a multi-family residential facility. The proposed methodology comprises five tasks, described in detail in sections 4.1 to 4.5.

4.1 Developing a Post-occupancy Energy Monitoring Approach

As mentioned above, the first task towards optimizing space heating energy consumption of a multi-family residential facility is to identify the variables affecting it during occupancy (through a sensor-based monitoring approach). This section focuses on analyzing the measured sensor-based data to extract information pertaining to space heating energy consumption by following the data analysis framework shown in section 3.1, Figure 3-5.

4.1.1 Real-time sensor-based data analysis

As shown in Figure 3-5, the measured data is first analyzed to determine whether occupant heating energy usage load varies based on the physical characteristics of a given unit, i.e., to find the correlation between space heating energy consumption and physical parameters. Correlations among the varying heating energy loads with different factors such as occupant comfort choices/maintained indoor temperature, building thermal performance, and occupant appliance usage patterns are then investigated. To investigate whether operational strategy influences the heating energy consumption, the study further investigates the performance of the space heating system in terms of energy consumption. Following the observations described in this section, this study defines what measures are required in order to improve the efficiency of space heating energy consumption and addresses the identified issues by developing a holistic methodological approach.

Investigation of the correlations between space heating energy consumption and different user groups:

The literature review identifies that thermal performance of the physical parameters of the building plays a significant role in the variations observed in energy consumption in different households (Branco et al. 2004). To investigate whether different physical parameters of the case study facility have an impact on a unit's heating load/energy consumption, heating energy consumption load for three different groups of units (A: north-facing "one-bedroom" units, B: south-facing "one-bedroom" units, and C: north-facing "two-bedroom" units) is investigated.

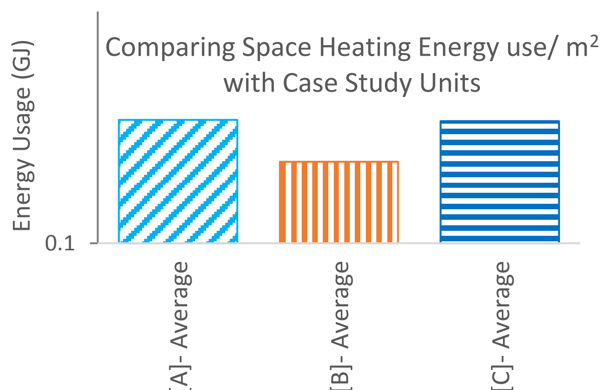


Figure 4-1: Heating energy consumption for different unit types

The results indicate that, in some cases, space heating energy consumption varies for different user groups (based on physical characteristics) of the case study building. When comparing space heating energy consumption for north-facing and south-facing units, it is observed (Figure 4-1) that south-facing units have lower heating consumption (0.13 GJ/m^2) than north-facing units (around 0.15 GJ/m^2); solar heat may be the reason for lower heating demand in the south-facing units. However, when comparing heating load for different unit sizes, it is observed that the heating energy consumptions in “two-bedroom” units and in “one-bedroom” units do not show any variation, presumably due to the fact that the number of occupants and the heating load do not necessarily increase with the size of the units. Based on the finding that north-facing units have higher heating load than south-facing units, it is investigated whether the discrepancies are caused by factors (other than directional orientation) such as occupant comfort choice and heat loss through the building envelope.

Investigation of the correlation between heating energy consumption and maintained indoor temperature and outdoor temperature:

To evaluate whether indoor temperature (as maintained by occupant) is contributing to the heating energy consumption level in the case study units, indoor temperature readings in the north- and south-facing units are compared. The sensor data shows that the maintained indoor temperature in north-facing units is lower than in south-facing units, even though heating energy consumption is higher in north-facing units (Figure 4-2). In addition to indoor temperature, it is expected that heating energy consumption is significantly affected by outdoor temperature. It is observed that the measured data (Figure 4-3) also follows that pattern: the lower the outdoor temperature, the higher the consumption of heating energy will be. It is for this reason that many researchers have proposed the integration of outdoor temperature within the control strategy.

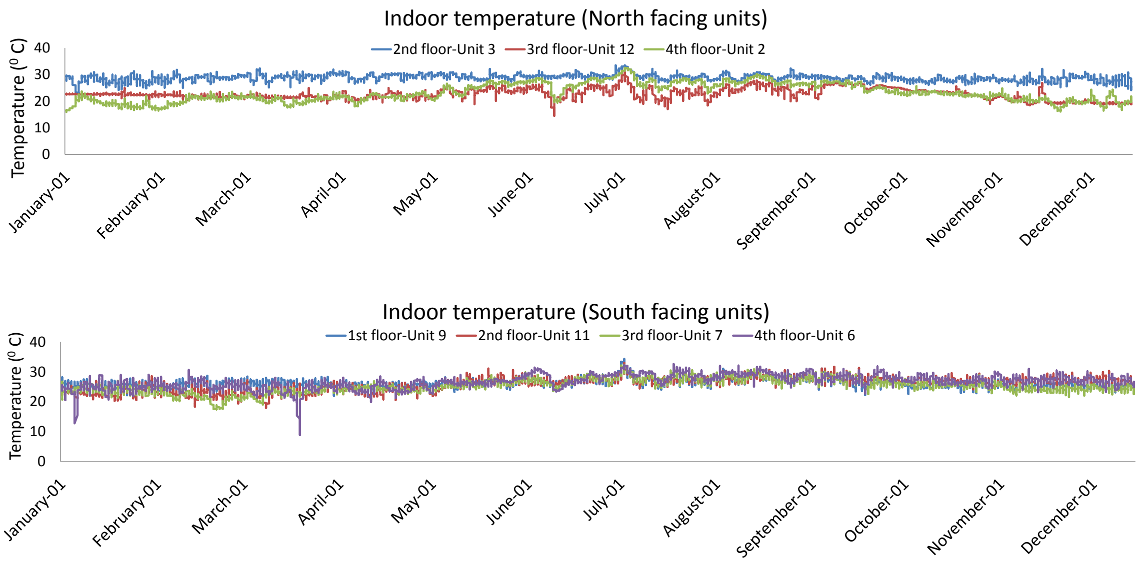


Figure 4-2: Indoor temperature in north- and south-facing units

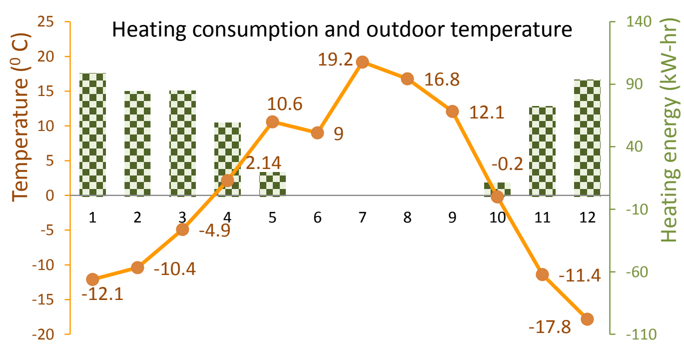


Figure 4-3: Heating consumption and outdoor temperature

Investigation of the correlation between heating energy consumption and heat flux/loss through building envelope:

To identify whether thermal performance is affecting the lower indoor temperature and higher heating consumption in north-facing units, heat flux readings through north-facing and south-facing units are compared. As expected, north-facing units have greater heat loss than south-facing units, and this may be the cause of the higher heating consumption in the north-facing units (Figure 4-4).

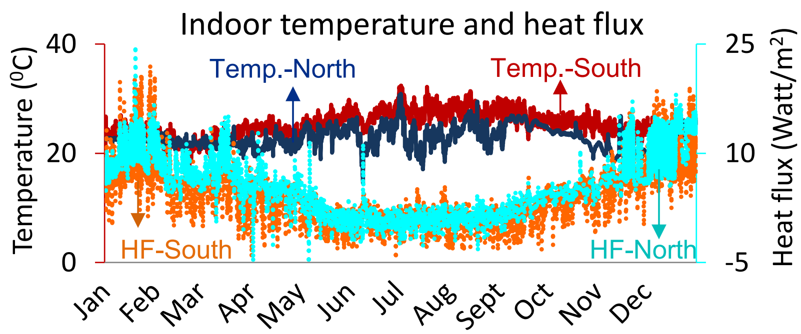


Figure 4-4: Heat flux and maintained indoor temperature in north and south-facing units

Investigation of the correlation between heating consumption and occupant activity pattern:

In the existing space heating control system (water heating system) of the selected case study facility, radiators are used to provide heating to each unit of the building. Hot water is sent through a radiator to heat it; the radiator gains heat, and then dissipates heat into the room. The heating energy consumption in the units can be represented by the heat that the radiator dissipates in order to reach and maintain the room temperature desired by the occupant. Once the desired indoor temperature has been reached in any unit, the valve in that unit gets closed, meaning the flow of supply water stops. This points to the possibility of situations where a room reaches its desired temperature through internally generated heat from operation of different appliances, triggering the closing of the valve in the unit and ultimately a decrease in actual heating energy consumption.

To identify whether occupant activity pattern has any impact on the actual heating energy consumption in the units, the sensor-based occupant energy usage data is correlated with the case study unit's space heating energy consumption. Interestingly, it is observed that some of the occupant activities (usage of lighting, hot water tank, stove, etc.) affect indoor temperature (Figure 4-5), which in turn affects heating energy consumption. It is postulated that radiators may not exploit all the available energy in the supplied hot water (in a case where occupant load is not considered while estimating heating load and there is extra available energy in the supplied hot water), a situation which is likely to lead to substantial heat loss to the ambient surroundings.

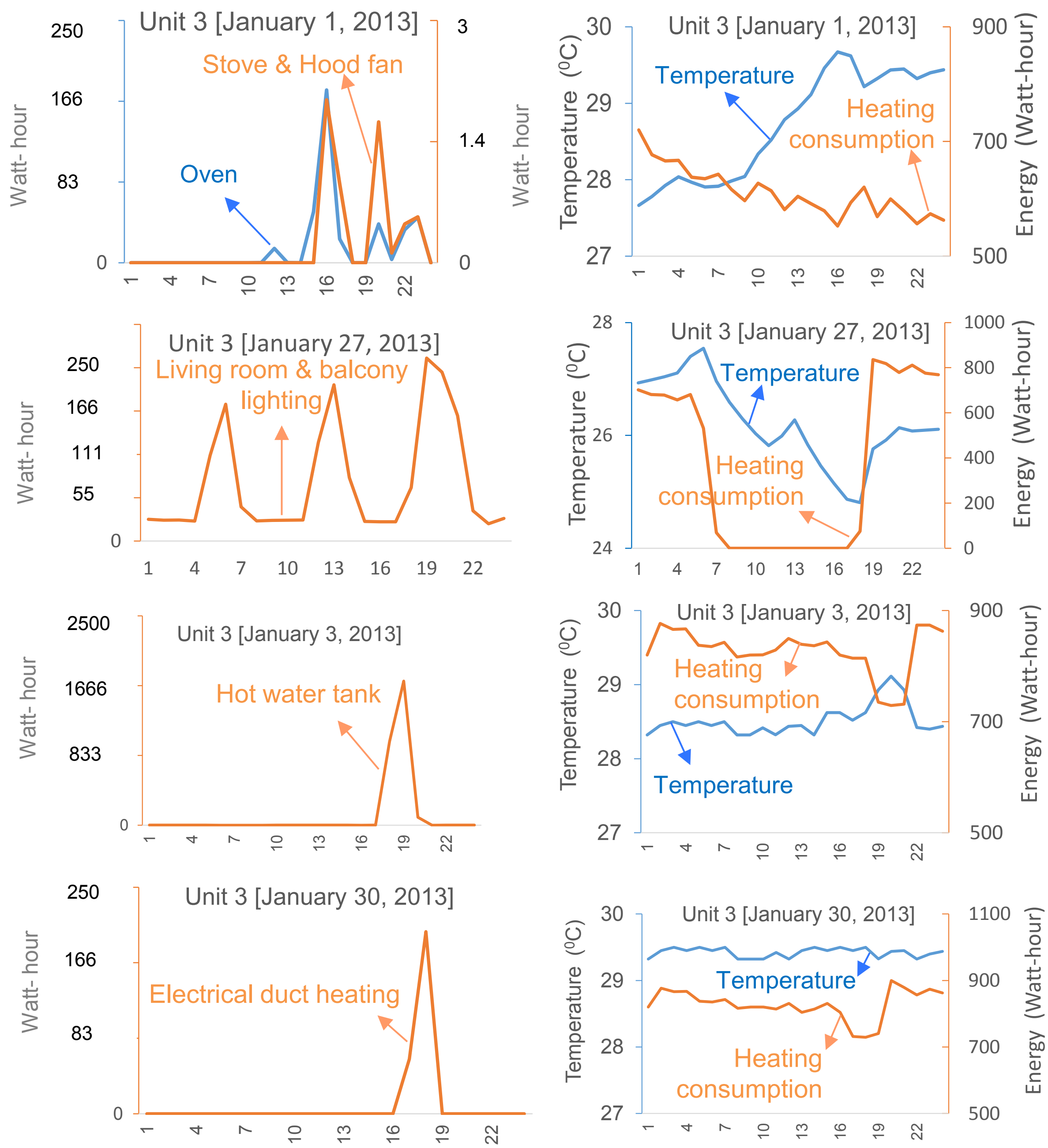


Figure 4-5: Impact of appliance usage on heating consumption

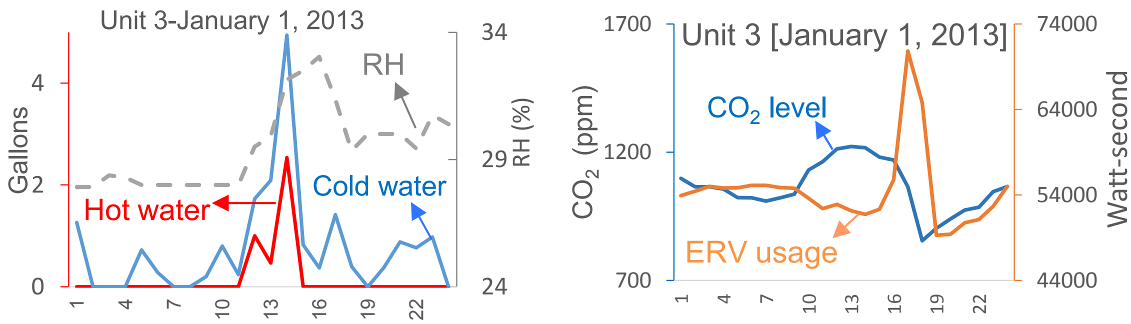


Figure 4-6: Impact of water usage on indoor RH level

In addition to the fact that occupant activity pattern affects indoor temperature and thus heating energy consumption, it is identified that there are other parameters of indoor environmental quality (IEQ), such as indoor CO_2 level and relative humidity (RH), that are significantly affected by occupant activities, including energy recovery ventilation (ERV) usage patterns and water consumption patterns (Figure 4-6). The above observations clearly indicate the influence of occupant activity patterns on heating energy consumption, and therefore should be included in energy management strategies.

Investigation of the correlation between operational strategy and energy efficiency:

Based on the observation that occupant energy usage pattern affects heating consumption, this study investigates how the efficiency of the existing operational strategy (Figure 4-7) is affected its overlooking of the above-mentioned occupant information. As shown in Figure 4-7, the case study building currently considers only outside temperature when determining when the heating mode should be turned on as well as the set-point temperature of the water storage tank.

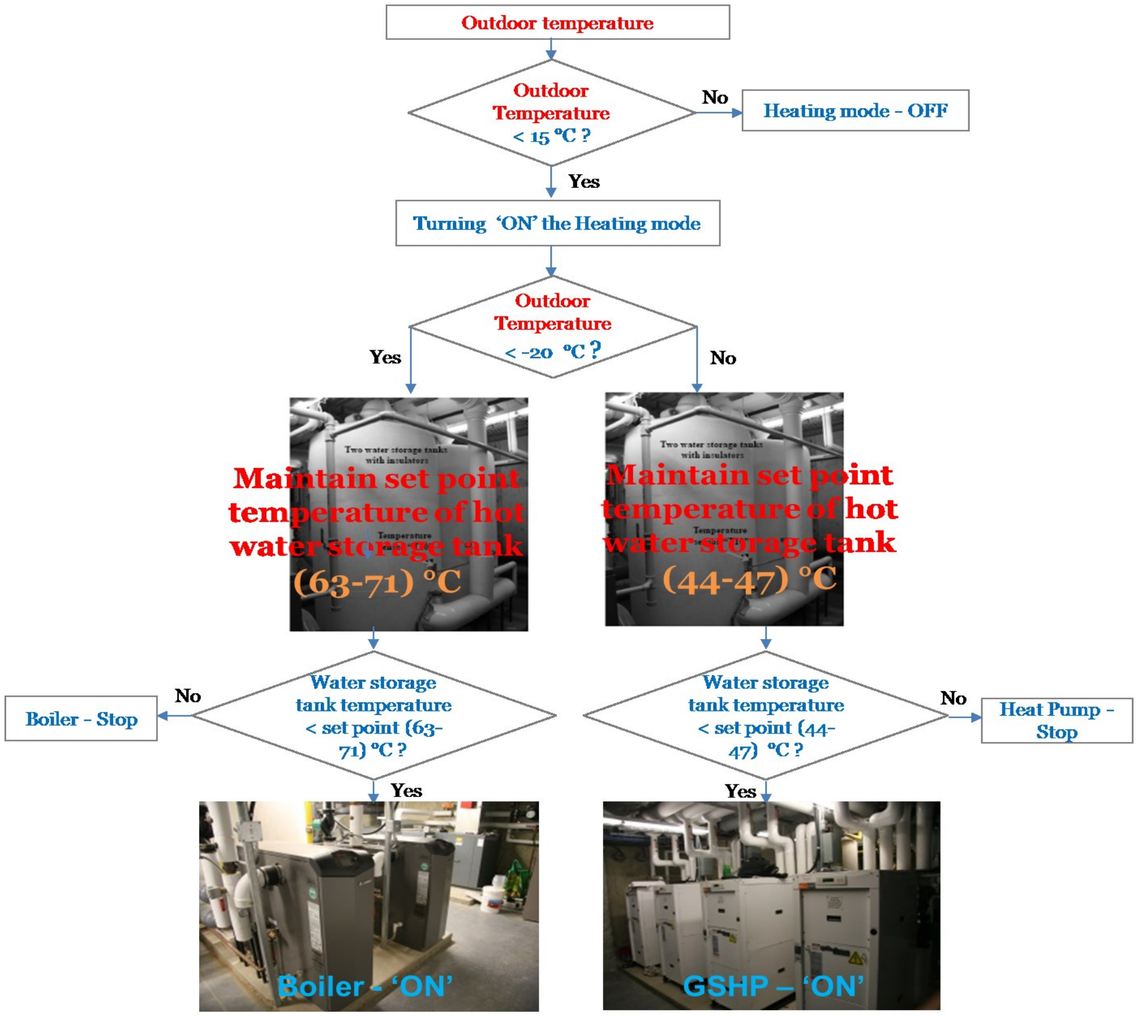


Figure 4-7: Schematic drawing of existing control strategy

As stated in Li et al. (2013), the current outside temperature controls the heating mode of the case study building. When the outside temperature decreases below 15 °C, the GSHP system heating mode turns ON. When the outside temperature falls below −20 °C, the GSHPs switch OFF while two natural gas burning boilers turn ON. Heat pumps 1, 2, 3, and 4, and boilers 1 and 2 begin to heat water and transfer it to the water tank when the temperature of the water tank falls below the specific set-point ranges of [44 °C to 47 °C] and [63 °C to 71 °C], respectively (Li et al. 2013; Li 2013).

Efficiency in energy production:

Since occupant demand and internal heat gain are not considered in the current control strategy, this study investigates whether the estimated energy need by the building management system (BMS) is in balance with the actual heating energy consumption by occupants. Therefore, the heating energy production by the BMS and the consumption in the case study units are compare. The energy generated by an integrated heating system (geothermal, solar panel, drain water heat recovery, and boiler) of the case study building has been estimated in a previous study (Li et al. 2013) based on the temperature difference, fluid specific heat, and circulated fluid mass using the following Equations 4-1, 4-2, and 4-3. The energy consumption in the residential units is collected from sensor-based measured data, and it is observed that, when total heat production is compared with actual heating consumption, a gap exists between the produced heating energy and actual energy consumption (Figure 4-8). As a result, the lower the outdoor temperature, the greater the amount of energy is produced, and the larger the gap between energy supply and energy demand. It is possible that the omission of occupant information in the control system may have led to an overestimation of the energy need and may have caused the gap.

$$Q = C * M * T \quad [4\text{-}1]$$

$$M = \rho * V \quad [4\text{-}2]$$

$$\sum_{i=1}^{n} Q = C_i * M_i * T_i = \sum_{i=1}^{n} C_i * R_{\mathrm{m}_i} * t_i * \left(T_{\mathrm{Supply}_i} - T_{\mathrm{Return}_i}\right) \quad [4\text{-}3]$$

where

$Q =$ Thermal Energy (kJ)

$C =$ Specific heat (kJ/kg°C)

$M =$ Mass of fluid within a period of time (kg)

ΔT = Temperature differences (°C)

ρ = Density of fluid (kg/m^3)

V = Volume of fluid (m^3)

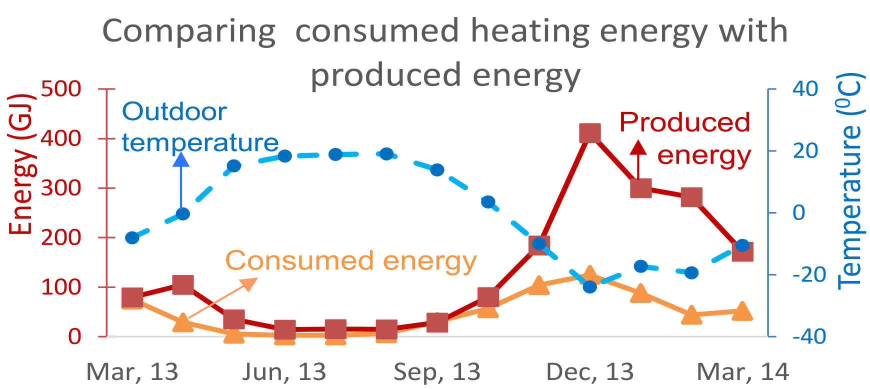
R_m = Mass flow rate of fluid (Kg/hr)

R_v = Volume flow rate of fluid (m^3/hr)

T_{Supply} = Temperature of supply pipe (°C)

T_{Return} = Temperature of return pipe (°C)

t = Serving time or operation time (hr)



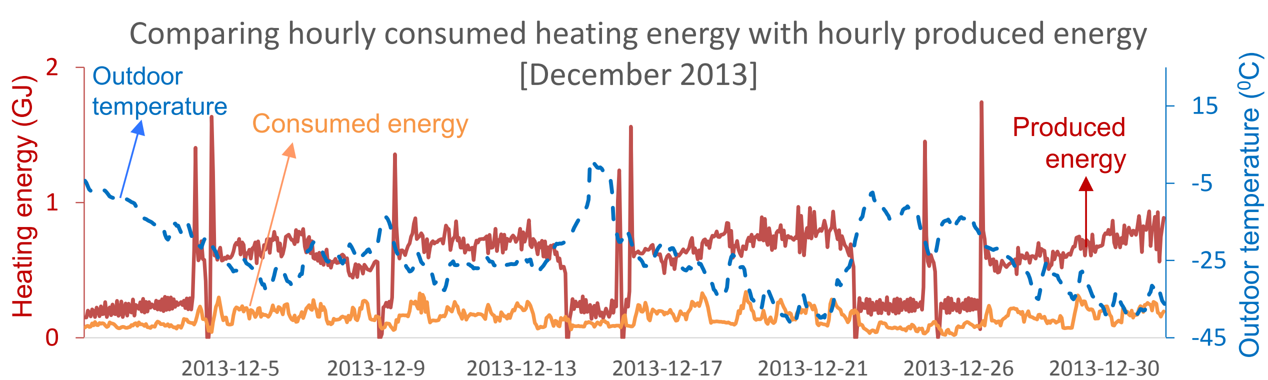
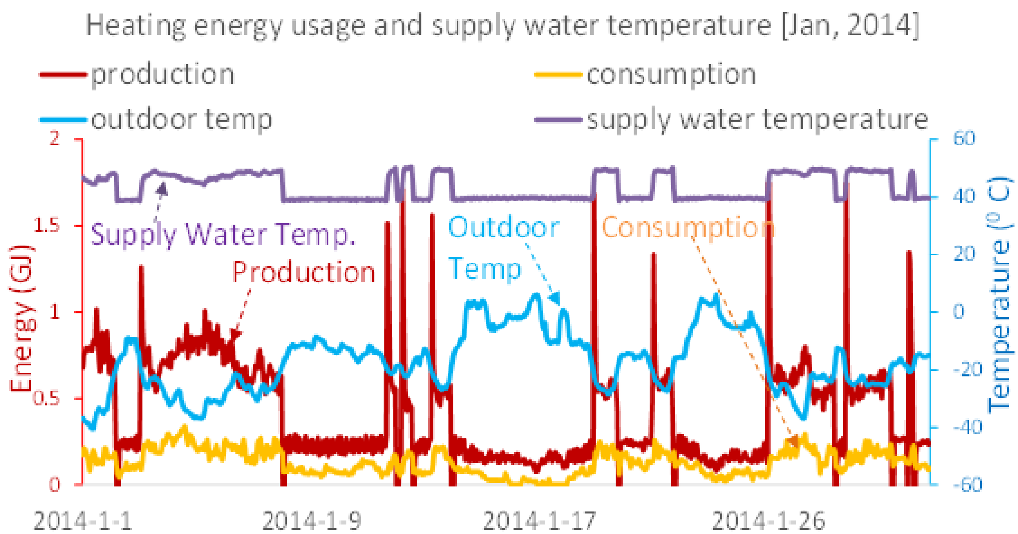


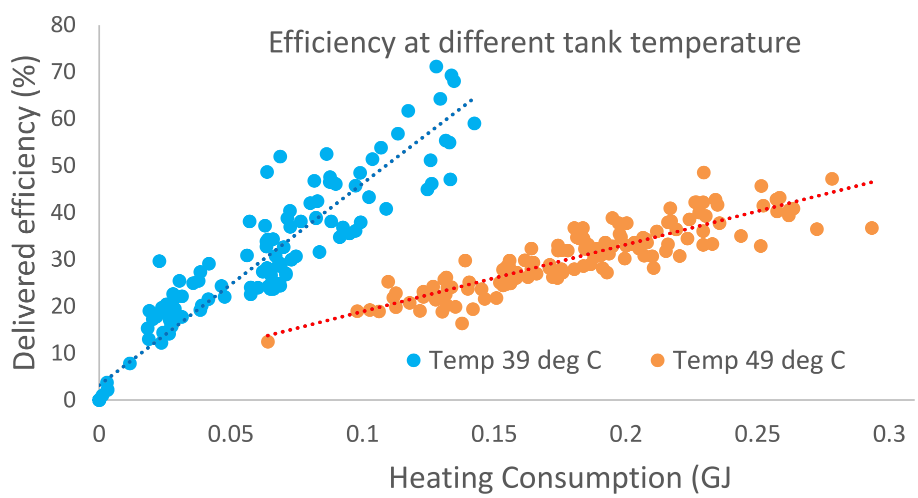
Figure 4-8: Comparison of actual heating energy consumption with produced heating energy

With the existing operational strategy of the case study building, the set-point temperature of the supply water tank currently depends on only outside temperature, and thus causes inefficiency in the system. This phenomenon can be clearly observed from the data analysis (Figure 4-9a), when the space heating supply water temperature is adjusted to 39 °C and 49 °C based on the outside temperature during the month of January. The results confirm that a lower outdoor temperature results in a higher maintained temperature of the hot water.

Additionally, it is identified that, during the times when the actual heating load/consumption of the case study units is within 0.15 GJ, the BMS system, irrespective of actual heating load, adjusts the supply water temperature to either 39 °C or 49 °C depending on the lower and higher outdoor temperature, respectively (Figure 4-9a). However, it should be noted that (Figure 4-9b), at a demand point of 0.15 GJ, maintaining the supply water temperature at 39 °C can lead to approximately 70% delivered efficiency, whereas, at the same demand point, maintaining the supply water temperature at 49 °C will decrease the efficiency of the system to 25%. Thus, a gap is created between demand and supply energy, thereby reducing the efficiency of the system. It is found that system efficiency is lower when demand is lower, indicating that the BMS system is producing more energy than necessary.



[a]

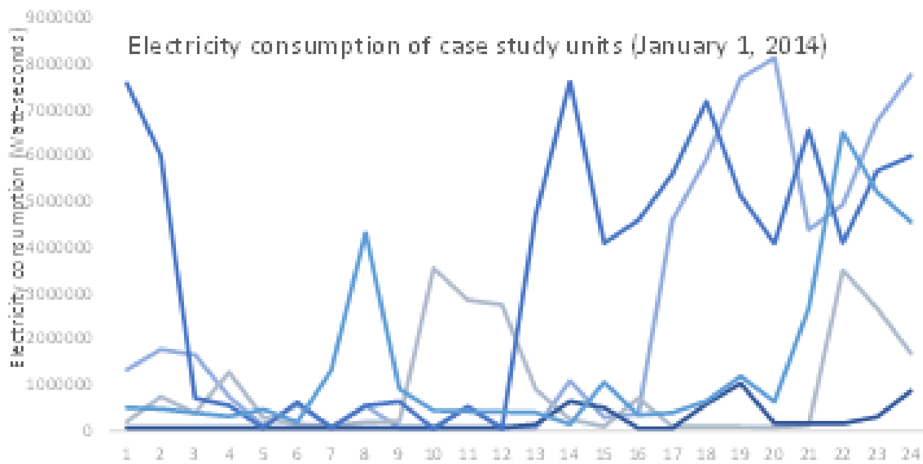


[b]

Figure 4-9: Heating energy usage, supply water temperature, and delivered efficiency

Efficiency of heat pump:

It should be noted that if the BMS produces more energy than needed, meaning that the hot water sent through the radiator has a higher temperature than what is demanded/needed, then the valves in the units will begin to close frequently and the supply pressure in the loop will increase. On the other hand, if the hot water sent through the radiator has a lower temperature than what is demanded/needed, then most of the unit valves will be open, thus decreasing the pressure in the loop. In this situation, in response to the varying occupant demand, the circulation pump will be continuously changing its speed, which will reduce the efficiency.



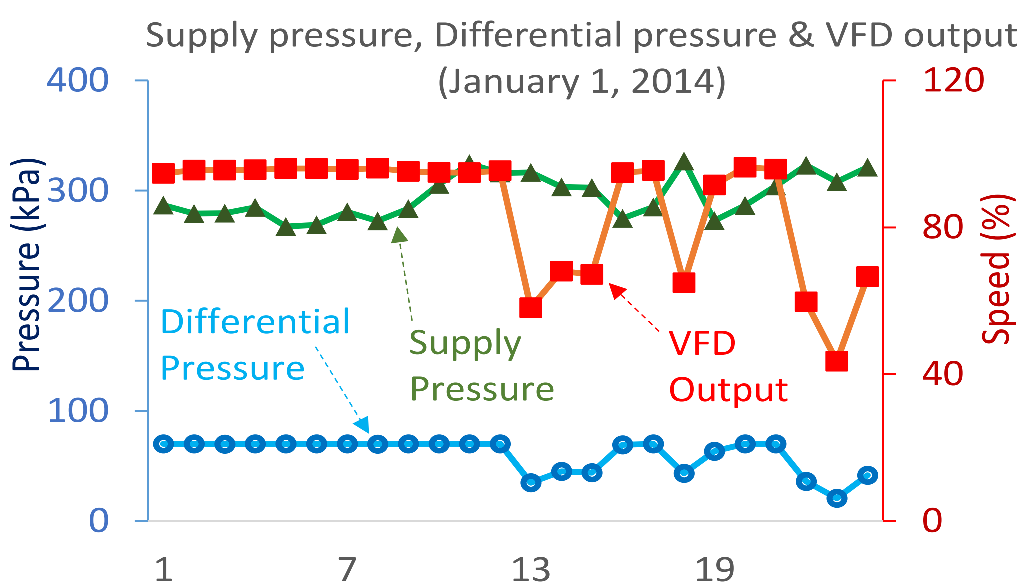


Figure 4-10: Supply pressure, differential pressure, and VFD output

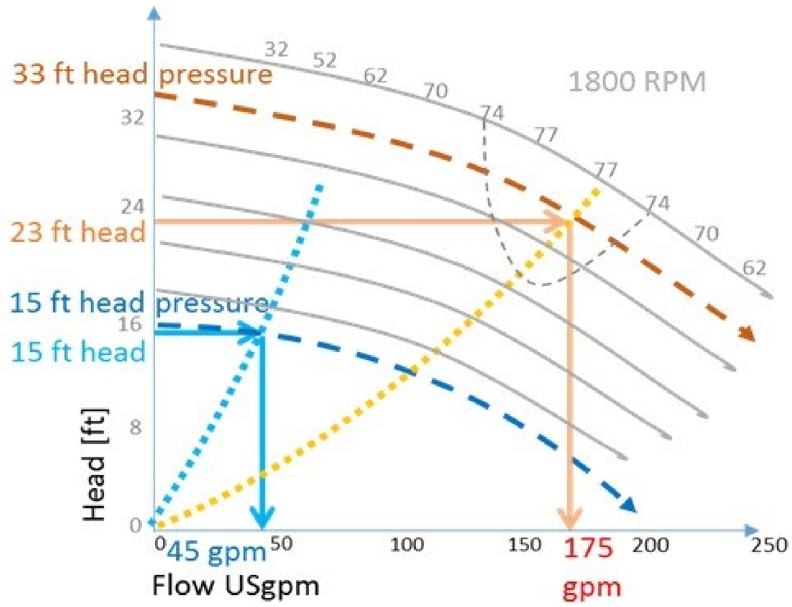


Figure 4-11: Efficiency of heat pump

For example, as observed from the supply pressure data (Figure 4-10), during the morning (at 08:00) the supply pressure in the system is lower, which indicates that most of the valves in the units are open because of high heat demand. It is possible that lower internal heat gain from occupant appliance usage (Figure 4-10) has caused lower room temperature in the units, therefore causing increased demand on the space heating system. In this situation the 2 HP (1,800 RPM) heat pump is running with 95% speed (1,710 RPM), which entails (based on the affinity law: Equation 4-4) around 33 ft of head pressure. As seen from the data analysis, the differential pressure during that time is 70 kPa (23 ft), which indicates that the flow rate (FR) of hot water is 175 gallons per minute (gpm) (Figure 4-11). This shows that the system is running at nearly full efficiency.

$$\frac{d_{p1}}{d_{p2}} = \left(\frac{n_1}{n_2}\right)^2 \qquad [4\text{-}4]$$

where

d_p = head or pressure (ft)

n = wheel velocity in revolutions per minute (RPM)

On the other hand, as can be seen from the supply pressure data in Figure 4-10, during the evening (at 18:00) the supply pressure in the system is higher, which indicates that most of the valves in the units are closing because of low demand. It is possible that higher internal heat gain from occupant appliance usage (Figure 4-10) has caused desired room temperature to be reached in the units, therefore causing reduced demand from the space heating system. In this situation the 2 HP (1,800 RPM) heat pump is running with 65% speed (1,170 RPM), which entails (based on the affinity law: Equation 4) around 15 ft of head pressure. As seen from the data analysis the differential pressure during that time is 45 kPa (15 ft), which indicates that the flow rate of hot water is around 50 gpm. Therefore, the system is failing to run at full efficiency. Based on the above examples it can be observed that, with the current control strategy, the heat pump cannot always run at full efficiency (Figure 4-11).

4.1.2 Identifying the scope of this study to reduce space heating energy consumption

The above data analysis reveals that space heating energy consumption is affected primarily by three factors: (1) thermal performance of building envelope, (2) occupant energy usage pattern, and (3) operational strategy. Accordingly, it should be further investigated whether these factors define the scope for an effective energy management strategy.

Discussion on physical parameters:

Data analysis shows the relationship between heat flux and heating energy consumption such that units with higher heat flux in general have higher heating energy consumption, (though with some exceptions). As mentioned above, the results identify that north-facing units have comparatively higher heat flux, pointing to the need for different physical parameters (opening size, insulation) for the north-facing orientation. Since in the case study units around 30% of the surface area comprises openings while 70% of the surface area comprises insulated wall area, the design evaluation considers both opening and wall design alternatives. It is expected that evaluating different design alternatives (for future design reference) for north-facing units that have better thermal performance compared to the existing ones will reduce heat flux through north-facing units and eventually will reduce space heating energy consumption.

Discussion on integrating occupant energy usage pattern in space heating control strategy:

Since the data analysis identifies that the actual heating load of the building and operational efficiency are significantly affected by occupant demand/energy usage pattern, occupant energy usage pattern should be considered in the space heating control strategy.

Discussion on estimating optimal set-point temperature of hot water storage tank:

As mentioned above, with the existing operational strategy of the case study building, the set-point temperature of the supply water tank in the current state depends on only outside temperature, and this causes inefficiency in the system. Since the set-point temperature of the supply water tank affect the delivered efficiency, overall heating energy consumption, and operational cost, the set-point temperature of the supply water needs to be optimized by estimating occupant energy load pattern. Rather than continually changing the heat pump speed based on varying occupant demand load, maintaining the heat pump operating speed within the range of 90% to 95% efficiency while adjusting the supply water temperature considering occupant heating load/demand would significantly increase the efficiency of the space heating system. As described in later sections, incorporating occupant actual demand information (along with weather prediction and facility's thermodynamic relation) within the control/operational strategy serves to reduce energy consumption (by producing optimum heating energy).

4.2 Modelling the Thermodynamic System of the Case Study with Traditional Heating System

Simulation of any process or quantifiable predictions of a system model by addressing the impacts of different variables is considered an integral aspect of the design of energy-efficient high-performance buildings (Augenbroe et al. 2004; Wetter 2011). The most accurate results can be achieved through hourly simulation (Zhai and McNeill 2014). Therefore, this study adopts a simulation approach for performance analysis of the thermodynamic relationships among the facility's thermal mass, heat transfer, and heating system.

4.2.1 Developing the model

For the purpose of simulation, a simulation model is developed of the case study room with existing thermal parameters using MATLAB Simscape. First, the physical features and the thermal properties of the case study room are defined in the model. Within the model, the thermal transmittance of outer and inner surface of external-internal walls, ceilings, floors, windows; convective resistance between wall to air, window-air, air-infiltration, radiator-air; the radiation resistance between radiator-wall, and the capacitance of room air, wall, and ceiling are implemented using Equations 4-5 to 4-18 (Incropera et al. 2007; Cenegal 2002; Magnussen 2011; Kreith et al. 1999). As shown in Figure 4-12, the circuits for the walls are constructed using resistors and capacitors, implementing outer and inner thermal transmittance of external and internal walls. Windows are considered as components that have no ability to absorb heat, and therefore no capacitor component is included for window modelling. In the window circuit construction, "Resistor Out" represents the heat conduction through a window, and "Resistor In" represents heat convection between the indoor air surrounding the window and the room air. Ceiling and roof modelling are constructed with the same circuit methodology used for wall modelling, with resistor, capacitor, and electrical ground.

$R_{Convective\_Thermal\_Resistance} = 1/(U_{ExternalWall} * Area_{Wall})$ [4-5]

where

$R_{Convective\_Thermal\_Resistance}$ = Convective thermal resistance from the outside air through the outer part of the wall (K/W)

$U_{ExternalWall}$ = Overall heat transfer coefficient (W/m^2 K)

$1/U_{ExternalWall}$ = Reciprocal of $R_{ExternalWall}$

$R_{ExternalWall} = R_1 + R_2 + R_3 \ldots\ldots\ldots = L_1/K_1 + L_2/K_2 + L_3/K_3$ [4-6]

where

$R_{ExternalWall}$ = Outer thermal transmittance

$K_1, K_2, K_2 \ldots\ldots\ldots$ = Heat transfer coefficient of the element (W/m^2 K)

$L_1, L_2, L_3 \ldots\ldots\ldots$ = Thickness of the element (m)

$R_{InternalWall} = 1/(2 * U_{InternalWall} * Area_{Wall})$ [4-7]

where

$R_{InternalWall}$ = Thermal transmittance of entire internal wall (K/W)

$U_{InternalWall}$ = Heat transfer coefficient (W/m^2 K)

$$R_{ConvectiveWallAir} = 1/(h_{WallAir} * Area_{Wall}) \quad [4\text{-}8]$$

where

$R_{ConvectiveWallAir}$ = Convective thermal resistance (between interior wall surface and indoor air) (K/W)

$h_{WallAir}$ = Convective heat transfer coefficient between interior wall surface and indoor air (W/m^2 K)

$$R_{ConvectiveWindowAir} = 1/(h_{WindowAir} * Area_{Window}) \quad [4\text{-}9]$$

where

$R_{ConvectiveWindowAir}$ = Convective thermal resistance (between interior window surface and indoor air) (K/W)

$h_{WindowAir}$ = Convective heat transfer coefficient between interior window surface and indoor air (W/m^2 K)

$$R_{RadiationWindowWall} = 1/(h_{WindowWall} * Area_{Window}) \quad [4\text{-}10]$$

where

$R_{RadiationWindowWall}$ = Thermal radiation resistance (between window and walls)

$h_{WindowWall}$ = Radiative heat transfer coefficient between interior window surface and walls

$$R_{TransmittanceWindow} = 1/(U_{window} * Area_{Window}) - 1/(1/R_{ConvectiveWindowAir} + 1/R_{RadiationWindowWall}) \quad [4\text{-}11]$$

where

$R_{TransmittanceWindow}$ = Thermal Transmittance (Window)

$R_{ConvectiveWindowAir}$ = from Equation 4-9

$R_{RadiationWindowWall}$= from Equation 4-10

$Mass_{Infiltration} = (Volume_{room} * Density_{air} * Change_{Air})/hour$ [4-12]

where

$Mass_{Infiltration}$= Mass of infiltrated air (kg/sec)

$Change_{Air}$= Number of air changes per hour

$Density_{air}$= density of air (kg/m^3)

$R_{ConvectiveInfiltration} = 1/(Mass_{Infiltration} * cp_{Air})$ [4-13]

where

$R_{ConvectiveInfiltration}$ =Convective Resistance (between Indoor air and infiltration)

cp_{Air} = Specific heat capacity of air (J/Kg-k)

$R_{RadiationRadiatorWall} = 1/(h_{radiator} * Area_{radiator} * Number_{radiators})$ [4-14]

where

$R_{RadiationRadiatorWall}$= Thermal radiation resistance (between radiator and wall surface)

$h_{radiator}$ = heat transfer coefficient

$R_p = (Temperature_{Radiator} - Temperature_{Room})/(HeatEffect_{Radiator} * Number_{radiators})$ [4-15]

$R_{ConvectiveRadiatorAir} = R_p - R_{RadiationRadiatorWall}$ [4-16]

where

$R_{ConvectiveRadiatorAir}$ = Convective resistance (between radiator and indoor air)

$C_{air} = Volume_{Room} * Density_{air} * cp_{Air}$ [4-17]

where

C_{air} = Heat capacity of the air in the room

$C_{Wall/Floor} = Volume_{Wall/Floor} * Density_{Wall/Floor} * cp_{Wall/Floor}$ [4-18]

where

$C_{Wall/Floor}$= Heat capacity of wall or floor

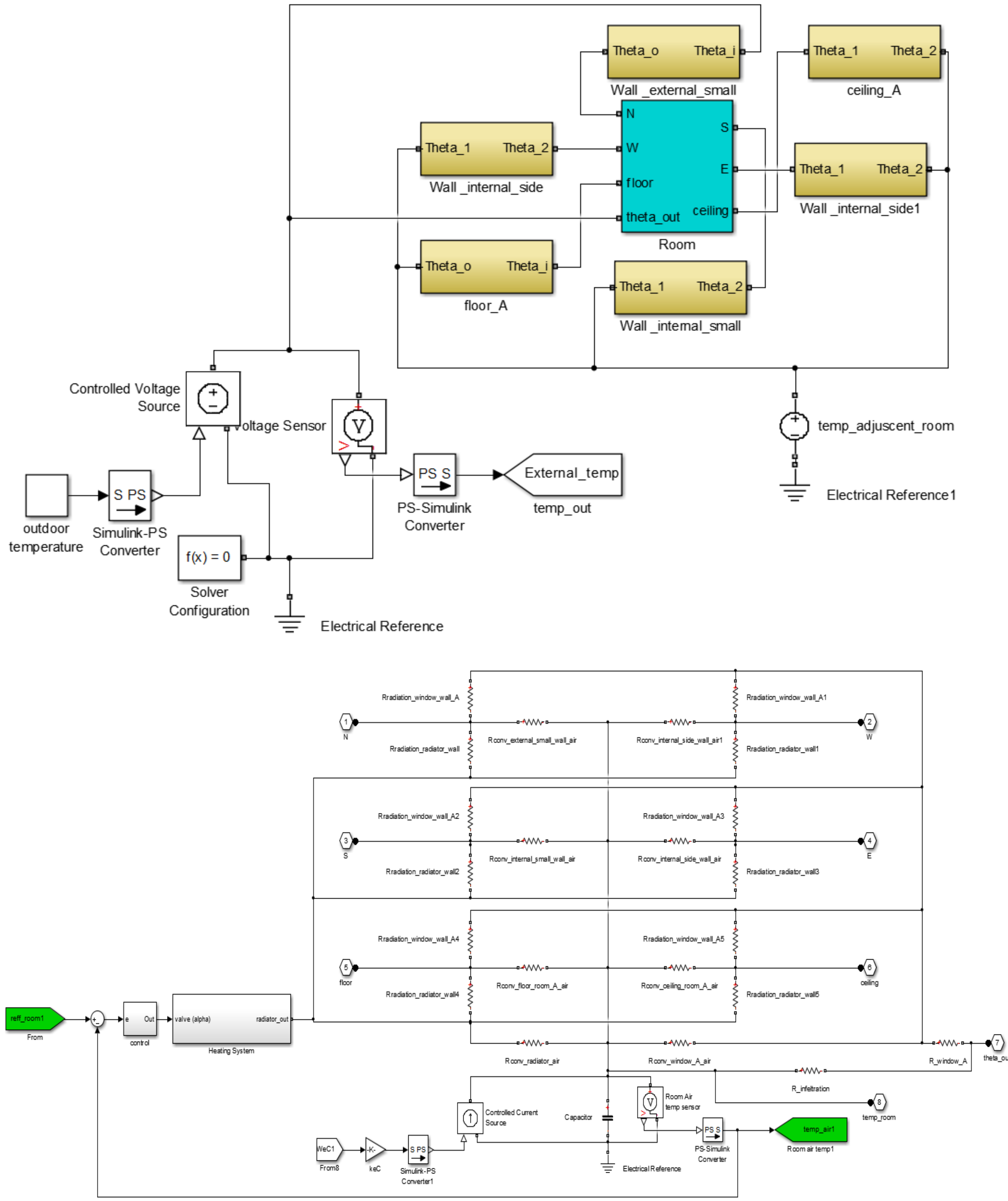


Figure 4-12: R-C network model of room with traditional control system

As mentioned above, the selected case study facility has a water heating system where hot water is sent through the radiator. Then the hot water heats up the radiator metal, dissipates some heat in order to reach the desired set-point temperature in the units, and, once the room reaches its desired temperature, the valve closes and the water returns to the loop. To implement the thermodynamic relation of this existing traditional heating control system, the following equations (Equations 4-19, 4-20, and 4-21) are used (IEA 1999; Magnussen 2011).

$$\frac{d}{dt}(C_r X_r) = \alpha \rho_w c_w \left(X_{supply} - X_r\right) - \theta_r \qquad [4\text{-}19]$$

$$\theta_r = \frac{1}{R_{ConvectiveRadiatorAir}}(X_r - X_a) + \frac{1}{R_{RadiationRadiatorWall}}(X_r - X_{w1}) + \frac{1}{R_{RadiationRadiatorWall}}(X_r - X_{w2}) \qquad [4\text{-}20]$$

$$X_{return} = (1-\alpha) \; X_{supply} + \alpha X_{r,} \qquad [4\text{-}21]$$

where

X_r = Radiator metal temperature

X_{supply} = Supply water temperature

X_{return} = Return water temperature

X_{w1} , X_{w2}= Wall surface temperature

X_a = Indoor air temperature

θ_r = Heat dissipation from the radiator

ρ_w = Density of water

$c_w = Specific\ heat\ capacity\ of\ water$

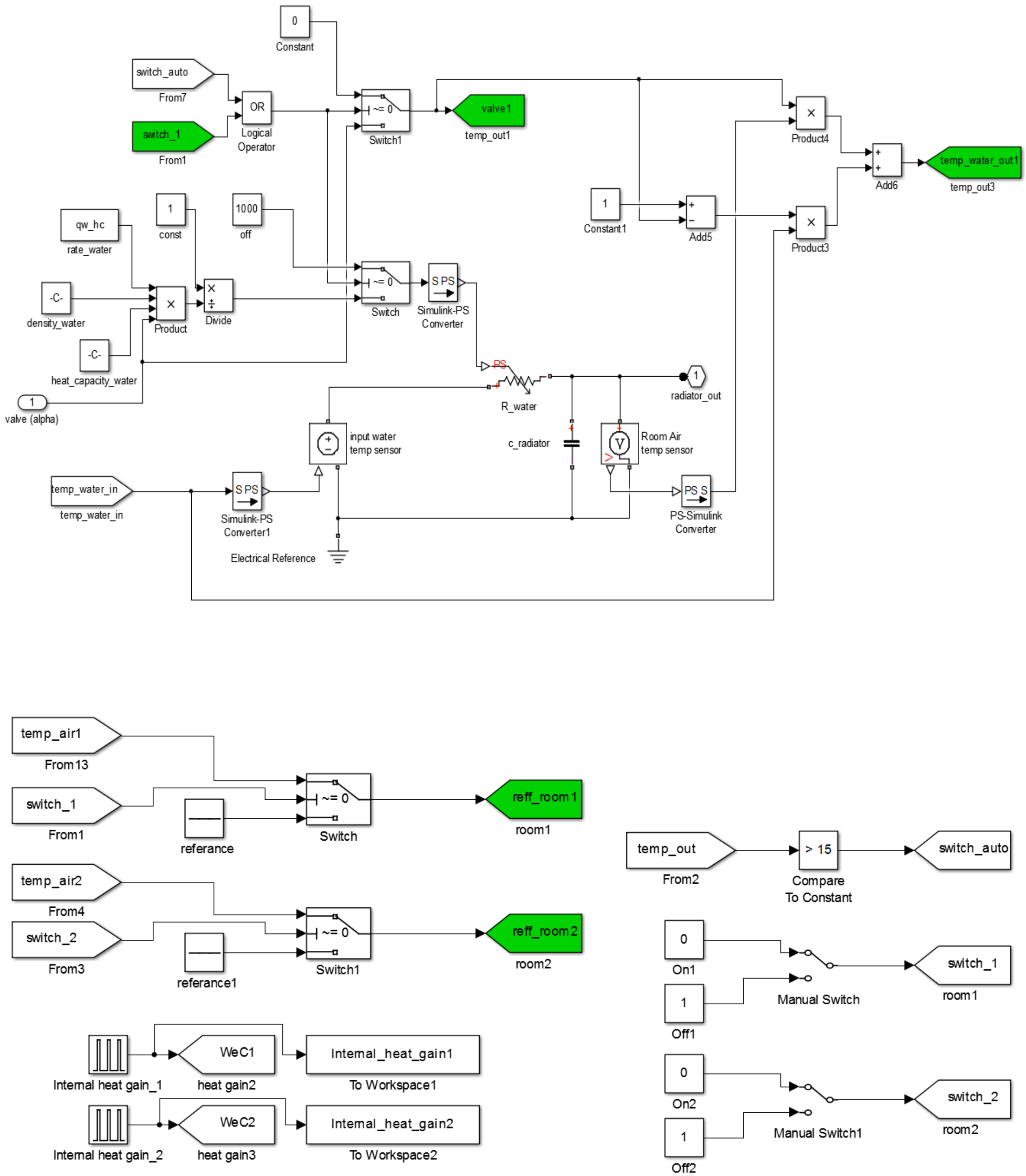


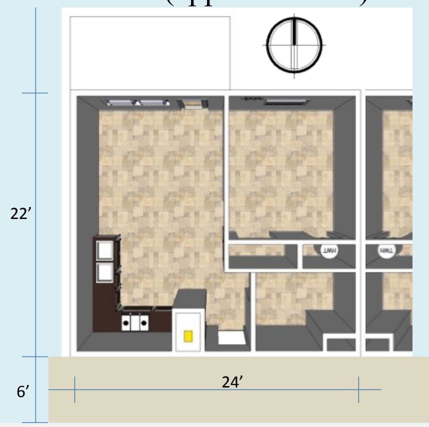
Figure 4-13: R-C model of the existing traditional space heating control system

Figure 4-13 shows the developed Resistance-Capacitance (R-C) network model of the existing traditional space heating control system for simulating the thermodynamic relationships among the case study facility's thermal mass, heat transfer, and existing traditional heating system. As shown in Figure 4-13, the rate of change in radiator metal temperature is modelled by considering supply water temperature, percentage of valve opening, flow rate-density-specific heat capacity of water, and the heat dissipation rate from the indoor radiator. Heat dissipation from the radiator is further modelled by considering the temperature differences between wall/floor/ceiling surface temperatures and indoor room air temperature, radiator metal temperature, and indoor room air temperature. Modelling of the return water temperature includes the temperature of supply water, amount of hot water flow through the radiator (α), and the amount of water bypassing the radiator $(1 - \alpha)$.

4.2.2 Validation of the thermodynamic model

Before developing the proposed user-centric predictive control strategy and evaluating the performance of different design alternatives and operational strategies through the simulation model, the model is validated with the measured real-time sensor data. A one-bedroom unit on the second floor of the four-storey residential building is chosen as the example space. The example space is initially created with the original configuration (47 m^2) of the case study room. The model is created with surrounding obstructions (buildings, trees) removed, as this obstructs a major part of penetrated daylight. Table 4-1 shows the parameters of the model of the example space.

Table 4-1: Parameters (as found in the mechanical drawing and specification) for constructing the initial simulation model

Total floor area	528 ft^2 (approx. 49 m^2) 
Height	3 m
Wall	7′ × 16′ exterior OSB R 20 BATT insulation 6 mm poly vapour 7′ × 16′ OSB 5′ × 8′ gypsum board (indoor)
Floor	200 mm thick
Ceiling	Reflectance: 0.7
Glazing	(transmittance: 0.92, U value: 6 W/m^2K) living room (SA) 6′ × 4′ bedroom (SB) 4′ × 4′

For the first part of the validation of the developed model (with heating system turned OFF), the interior space is considered vacant. The simulation model is set up with the real-time measured sensor data of the case study unit 3 on January 4, 2013, where no heating system was operated during that period and indoor temperature dropped from 26 °C to 23 °C in 24 hours without the presence of the occupant. As such, no internal heat gain is considered for the simulation time. However, it is considered that the case study unit was affected by heat flow from surrounding units. The sensor-based measured outdoor temperature on that day was −8 °C with a daily temperature variation of 2 °C, following a Sine wave temperature fluctuation. The model is simulated for 24 hours using these considerations. The simulated result (Figure 4-14) shows an indoor temperature drop from approximately 26 °C (80 °F) to 22 °C (70 °F) during the simulation time.

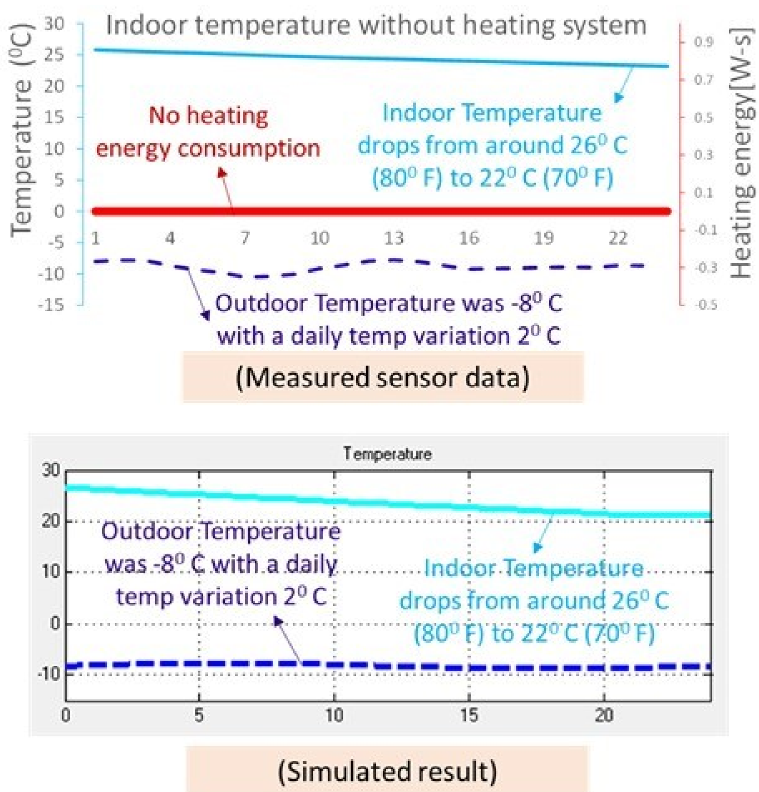


Figure 4-14: Validation of the model (without heating system turned ON)

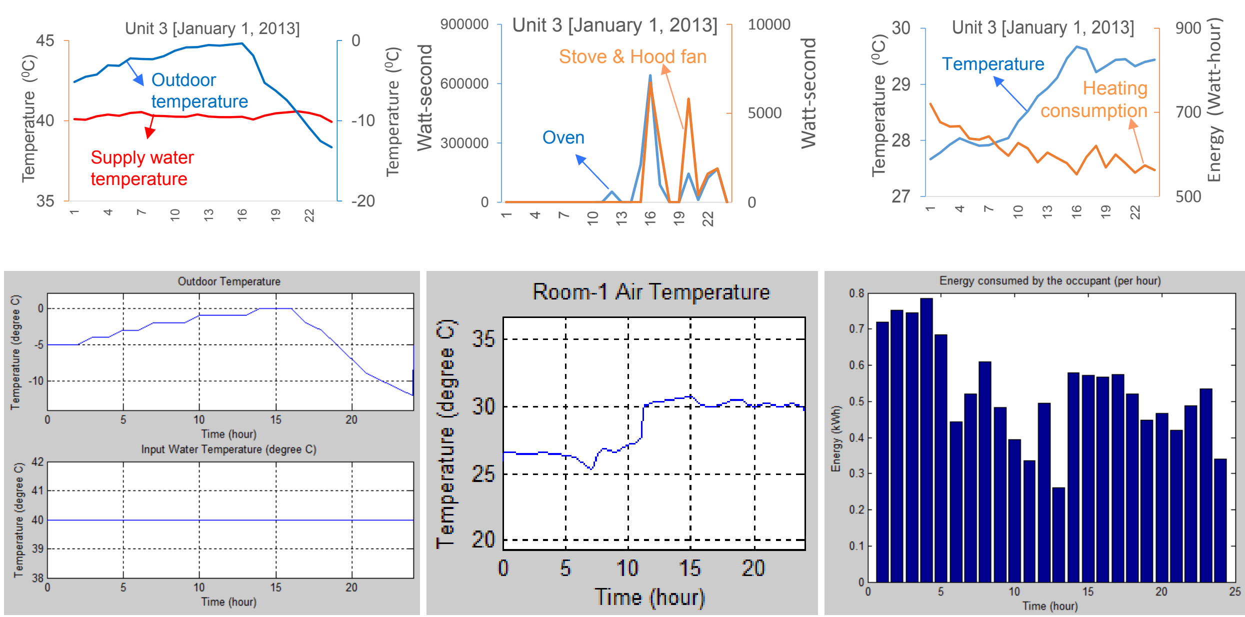


Figure 4-15: Validation of the model (with heating system turned ON)

For the second part of the validation (with heating system turned ON), the simulation model is set up with the same apartment (case study unit 3), except when occupants are present and the measured sensor-based energy usage data indicates the incidence of different activities such as cooking, hot water tank usage, lighting energy consumption, implying generation of a high level of internal gain. Figure 4-15 shows the outdoor temperature profile of the day. As observed from the measured sensor data, the supply water temperature is 40 °C and the heating energy consumption is decreasing, even though the indoor temperature continually increases in the case study unit. Once the developed model is simulated for 24 hours using these considerations, the simulation results show a similar pattern of increased indoor temperature but decreased heating consumption. Here, it should be noted that an exact match between the numbers from measured data and simulation results should not be expected, given that, within the scope of this study, it is not possible to identify which other occupant factors (e.g., the opening of windows) may have influenced the indoor temperature profile of the case study unit.

4.3 Developing Occupant Pattern Prediction Model

As mentioned in Chapter 3 and earlier in this section, for the purpose of developing the occupant pattern model, this study proposes an approach (Figure 3-8) that utilizes sensor data from energy usage monitoring of a multi-family residential facility during occupancy. The methodological approach is described in the following section.

4.3.1 Selecting sample representative group

As mentioned above, this study utilizes previously measured sensor-based data to learn the occupant load pattern. However, it is recognized that installing different kinds of energy usage sensors in each unit of multi-family residential facilities may not always be possible considering the increased cost of installation and management. Moreover, the scope/objective of this study does not require learning or predicting the personalized behavioural patterns of occupants of individual units; but rather aims for understanding the occupant load of the entire building holistically. Based on these considerations, this study suggests an approach of monitoring and learning the occupant patterns by installing energy usage sensors in sample case study units (rather than installing sensors in all the units) during the occupancy phase. For this purpose, this step first selects sample case study units (based on physical characteristics) and later groups them (based on energy usage pattern) as sample energy usage representative groups representing the energy usage pattern of a multi-family residential facility.

It is observed that not all the units of a building possess the same characteristics (directional orientation, unit size, etc.). As such, this study proposes an approach to selecting sample units that represent all the physical characteristics associated with different types of units available in a multi-family residential facility. For better categorization, this study selects 12 case study units with approximately the same relative floor plans (Figure 3-2) which are representative of all the units available in the building. After selecting the sample case study units (based on the representation of different physical characteristics of units in the case study building), this step further categorizes the case study units into sample energy usage representative groups (that have similar types of activity pattern and energy usage load) by analyzing and identifying whether the sample case study units with different physical characteristics show different occupant energy usage pattern. By analyzing sensor-based energy usage data (for 2 years), it is observed (Figure 4-16) that the sample north- and south-facing case study units show different energy usage patterns (whereas, sample one-bedroom and two-bedroom case study units do not show any notable difference in energy usage patterns). Accordingly, the units are further grouped into two sample energy usage representative groups.

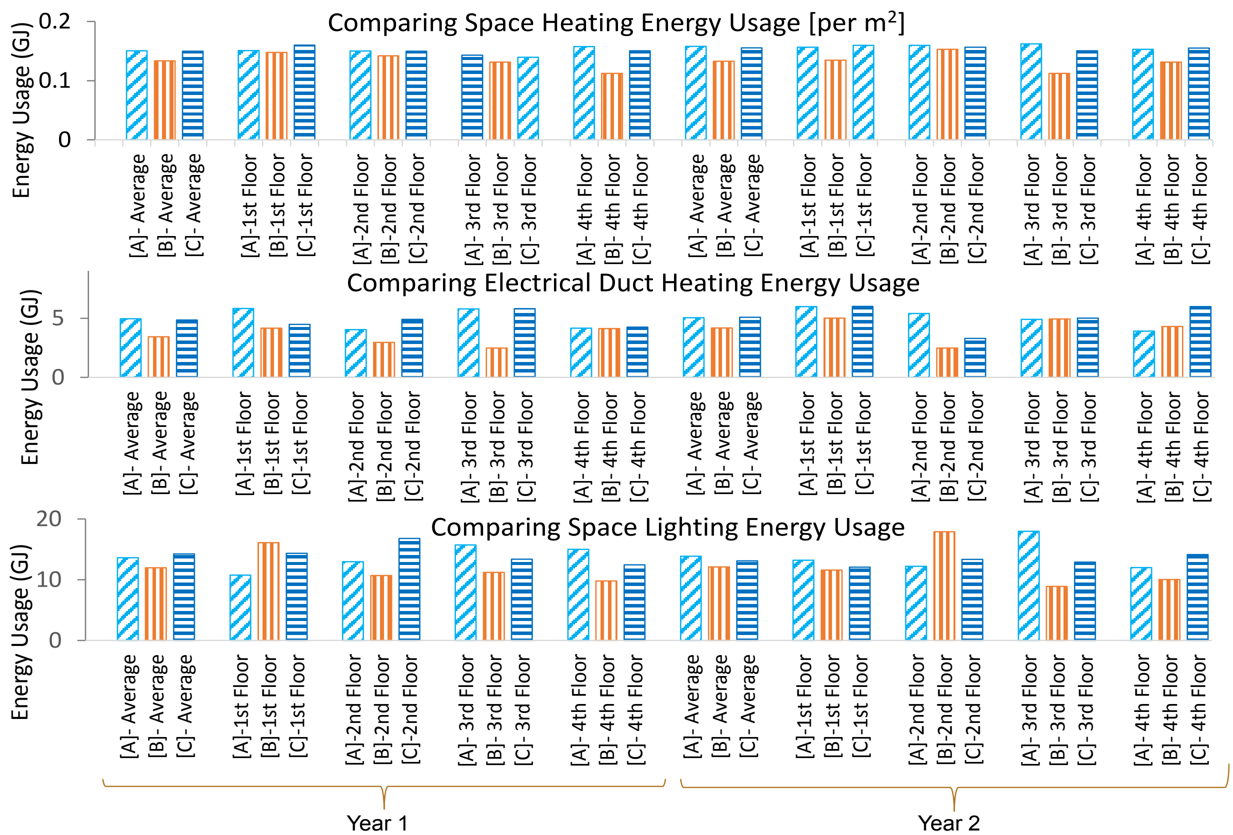


Figure 4-16: Energy usage load for different unit types

4.3.2 Identifying influencing occupant factors affecting occupant load

Given that occupant load has significant effects (similar to those of weather load) on actual heating demand, it is important to estimate occupant load (with the purpose of integrating within space heating control strategy to optimize space heating energy consumption) by first identifying occupant factors that are affecting occupant load (heating demand).

Analysis of the sensor energy usage data shows that (as discussed in section 4.1) internally generated heat (associated with occupant activities, Figure 4-5) affects indoor temperature, and ultimately affects occupant load and space heating energy consumption. Therefore, for the purpose of estimating occupant load, internally generated heat is identified as one of the occupant factors, and sensor-based energy usage data is utilized to learn occupant activity patterns. However, it is recognized that, in addition to the internally generated heat associated with occupant activities in the individual units, there are other occupant factors that affect the occupant load and thus heating energy consumption. For example, the state of desired set-point temperatures in the building's units directly affects the heating load, and the window opening pattern of occupants affects building energy consumption (Shi and Zhao 2016). It should be noted that, due to privacy concerns and time constraints, learning the pattern of these occupant factors remains beyond the scope of this study, since it may require motion sensor or survey. It is also acknowledged that measuring indoor temperature using IAQ sensors cannot be an option for identifying occupant comfort choice since the measured indoor temperature is usually the combined effect of a number of factors (internally generated heat, window opening pattern, etc.) rather than an isolated impact of occupant comfort choice or thermostat control.

However, through the analysis of sensor-based data (as discussed in section 4.1 and illustrated in Figure 4-10 and Figure 4-11), a significant correlation is identified between these occupant factors and the performance of the heat pump (flow rate, pressure state). This is due to the fact that the heating system (heat pump) continuously varies its supply hot water flowrate (FR) and supply pressure (SP) state in order to deal with the varying occupant load of the facility throughout the day, which also ultimately affects the space heating energy consumption. Therefore, in order to estimate occupant load, along with considering internally generated heat as an occupant factor, this study utilizes the measured sensor-based data of the performance of the heat circulation pump (flow rate, pressure state) to learn the pattern of occupant load of the facility.

It should be noted that, like outdoor temperature and thermal resistance of the building envelope, both of the above-mentioned influencing occupant factors (internally generated heat associated with occupant activities, and supply pressure state of the system) act as positive incentives while estimating the hourly heating demand (supply water temperature). In other words, an increase of these occupant factors indicates reduced heating demand from the BMS. Therefore, it is expected that developing a pattern prediction model that addresses the uncertainties related to these occupant influencing factors and integrating it within the control strategy can assist with estimating the optimum energy need of a multi-family residential facility in order to supply accordingly.

4.3.3 Identify factors (weather, time) affecting the pattern of those activities

Based on the understanding that occupant activities have a significant impact on space heating energy consumption by affecting IEQ, this step further investigates, for the purpose of developing the occupant pattern prediction model with the relevant variables, how these occupant activities are affected by different variables. As observed in Figure 4-17, outdoor temperature, hours of a day, different days of a week, and different weeks of a month show notable impact on energy usage patterns. Figure 4-17a and Figure 4-17b indicate that occupant energy usage pattern is affected by varying outdoor temperature. It is further observed (Figure 4-17c) that, in one unit, stove usage is higher on Tuesdays, and in the south-facing case study units stove usage is comparatively higher on Saturdays and Sundays (Figure 4-17d). Studying average hourly energy usage (for a month) of case study units shows (Figure 4-17e) an increase in lighting energy consumption in the early and late hours of the day. It can be expected that learning weather dependent, time-ordered occupant energy usage patterns will assist the BMS in estimating internal heat gain from occupant presence and activities. This is important for calculating optimum heating energy need, and therefore these components are included as variables in predicting future-state occupant load.

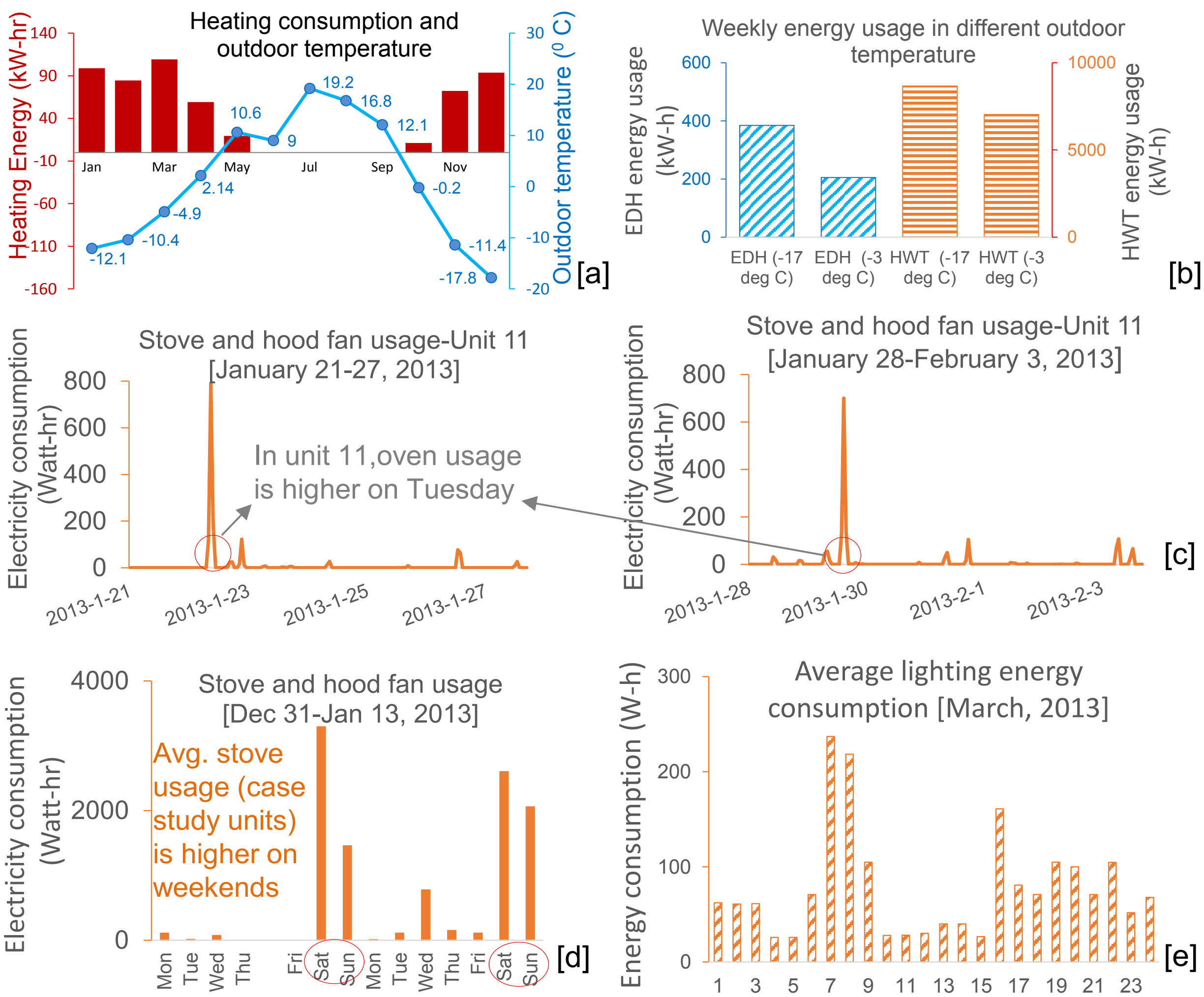


Figure 4-17: Identifying variables affecting occupant activity (energy usage) pattern

4.3.4 Developing an historical database

The historical database includes all the factors and variables (findings observed from the above sensor-based data analysis) relevant to space heating energy consumption. Since it is observed that some activities (such as lighting, hot water tank, plug load, stove, and electrical duct heating) and state of heat pump (such as supply pressure and flow rate) have been shown to have an impact on heating load, the historical database in this study is designed to include previously measured data for those selective factors. Because some IEQ metrics (such as CO_2, RH) can indicate the presence or absence state of occupants, which also has an impact on indoor temperature (by adding internally generated heat) and ultimately on heating load, previously measured data are included for those selective factors. Because occupant factors are affected by different variables such as outdoor temperature, hours of a day, days of a week, weeks of a month, all the previously measured data are organized according to the different weather groups, hours of a day, days of a week, and weeks of a month. Historical data is organized for both the sample energy usage representative groups representing north-facing units and those representing south-facing units. Considering that occupant energy usage pattern may change after a certain period of time, the developed model assists the BMS in updating the previously measured data with the above-mentioned format as necessary.

4.3.5 Activity recognition-learning—predicting the time dependent occupant load pattern

This study involves identifying and learning occupant energy usage patterns (from sample energy usage representative groups) by defining the varying statuses of occupant activities in terms of several conditions. Occupant activity status is defined based on the extent of usage of installed power, (e.g., lighting: ceiling fixture—five lamps: 60 W each; hot water tank: 3,500 W, stove:

5,000 W, electrical duct heating: 3,200 W), and the conditions are defined based on the extent of internally generated heat associated with different states of the activities (based on the literature review). Lighting states are divided into three categories: (1) lights ‘OFF’ (0 to 29 Wh of lighting energy usage), (2) low lighting energy usage (30 to below 100 Wh of lighting energy usage), and (3) high lighting energy usage (above 100 Wh of lighting energy usage). Hot water tank (HWT) states are divided into two categories: (1) ‘OFF’ and standby state (0 to 70 Wh of HWT energy usage); and (2) running state (above 70 Wh of HWT energy usage). Plug states are divided into four categories: (1) ‘OFF’ or 0 Wh of energy usage); (2) low plug load energy usage (above 0 to 500 Wh of energy usage); (3) medium plug load energy usage (above 500 to 1,000 Wh of energy usage); and (4) high plug load energy usage (above 1,000 Wh of energy usage). Stove states are divided into three categories: (1) stove ‘OFF’ (0 Wh of energy usage); (2) low stove energy usage (below 2,000 Wh of energy usage); and (3) high stove energy usage (above 2,000 Wh of energy usage). Electrical duct heating (EDH) states are divided into two categories: (1) ‘OFF’ state (0 Wh of EDH energy usage); and (2) running state (above 0 Wh of energy usage). CO_2 states are divided into three categories: (1) absence state (below 400 ppm of CO_2 level); (2) standard level occupancy state (400 to below 1,000 ppm of CO_2 level); (3) non-standard state (1,000 ppm and above of CO_2 level). RH states are divided into two categories: (1) absence state (below 30% of RH level); and (2) occupancy state (above 30% of RH level). This study, along with learning the occupant energy usage pattern, aims to uncover the state of flow rate and supply pressure for different weather groups, hours of a day, days of a week, and weeks of a month. Supply pressure states are divided into two categories: (1) high state of supply pressure (above 200 kPa), associated with low state of flow rate (below 90%); and (2) low state of supply pressure (below 200 kPa), associated with high state of flow rate (above 90%).

It should be considered that, while learning the occupant pattern for the purpose of estimating next-hour occupant load, this study aims to identify what states of activities frequently occur (with high probability) for any specific hour, day, week, or outdoor temperature. However, it is recognized that, while predicting next state activity status, choosing high probability activity states in every case does not necessarily capture the uncertainties of real life. Therefore, we use random variables from the uniform distribution $U(0,1)$ to simulate the activity status with a given probability (Yang 2014). For example, at any specific outdoor temperature and time group, if the probability of the running state of EDH usage (based on the frequency profile generated from the historical database) is 0.25 (meaning, 0.75 probability that EDH will be in the 'OFF' state) and the random number $u\sim U(0,1)$ drawn in the simulation falls to the range above 0.25 to 1, the model will choose the high probability option (EDH will be in the 'OFF' state). On the other hand, if the random number $u\sim U(0,1)$ drawn in the simulation falls to the range 0 to 0.25, the model will choose the low probability option (EDH will be in the running state). Following the approach discussed above, this study predicts: (a) future states of internally generated heat associated with average energy loads of occupant activities; and (b) next-state supply pressure, indicating the state of the facility's heating demand.

4.3.6 Estimating occupant load (gain factor)

Using the predicted information of (1) future state internally generated heat associated with different states of occupant activities, and (2) future state flow rate-supply pressure associated with facility heating demand state, this step finally estimates the future state occupant load factor for the purpose of integrating it into the user-centric control strategy. It should be noted that in this study both of the influencing occupant factors (internally generated heat, and flow rate-supply pressure state of the system) are considered as positive incentives while estimating occupant load factor. This means that the predicted increased value of the internally generated heat state (compared to the average state value) indicates reduced future state occupant load or lower heating demand (supply water temperature) from the BMS, and that a predicted increased value of supply pressure state of the system (compared to the average state value) indicates reduced next-state occupant load or lower heating demand/need from the BMS.

Since there are many factors, both known and unknown (in addition to internally generated heat associated with occupant activities), that have an impact on the predicted supply pressure state associated with the facility's heating demand state, it is recognized there can be situations when indications of occupant load (while estimating next-hour supply water temperature) may vary for the two predicted occupant factors—predicted internally generated heat and predicted flow rate-supply pressure state. In such situations, the value of occupant load factor is modified to follow the instruction with higher heating demand state. In order to validate the results of the developed occupant pattern prediction model, predicted occupant activities for hours 02:00, 07:00, 20:00 (randomly selected) (Figure 4-18) are compared with the sensor data (Figure 4-19) from that time period. As observed, the predicted results match the sensor data.

```
predicting hour 2 in Temperature -12
Light_low status in the next hour. : off
Light_high status in the next hour. : off
HWT  status in the next hour. : off
Plug_low  status in the next hour. : on
Plug_medium  status in the next hour. : off
Plug_high  status in the next hour. : off
Stove_low  status in the next hour. : off
Stove_high  status in the next hour. : off
EDH  status in the next hour. : off
Indoor_Humidity  status in the next hour. : low
Indoor_CO2 status in the next hour. : Standard level_OccupantPresent
SP  status in the next hour. : low
Total gain:  300
```

```
predicting hour 7 in Temperature -11
Light_low status in the next hour. : on
Light_high status in the next hour. : off
HWT  status in the next hour. : on
Plug_low  status in the next hour. : on
Plug_medium  status in the next hour. : off
Plug_high  status in the next hour. : off
Stove_low  status in the next hour. : off
Stove_high  status in the next hour. : off
EDH  status in the next hour. : off
Indoor_Humidity  status in the next hour. : high
Indoor_CO2 status in the next hour. : Standard level_OccupantPresent
SP  status in the next hour. : high
Total gain:  992
```

```
predicting hour 20 in Temperature -10
Light_low status in the next hour. : off
Light_high status in the next hour. : on
HWT  status in the next hour. : on
Plug_low  status in the next hour. : off
Plug_medium  status in the next hour. : off
Plug_high  status in the next hour. : on
Stove_low  status in the next hour. : off
Stove_high  status in the next hour. : on
EDH  status in the next hour. : off
Indoor_Humidity  status in the next hour. : high
Indoor_CO2 status in the next hour. : Non-standard level
SP  status in the next hour. : high
Total gain:  2964
```

Figure 4-18: Predicted occupant activities from occupant pattern prediction model

Hour	Lighting	HWT	Plug	Stove	EDH	Humidity	CO_2	SP
1	0.03	0.05	0.32	0.00	0.00	29.10	794.28	199.99
2	0.02	0.05	0.36	0.00	0.00	27.56	691.21	194.72
3	0.00	0.05	0.32	0.00	0.00	27.33	488.79	191.11
4	0.00	0.05	0.35	0.00	0.00	27.35	487.01	195.12
5	0.01	0.06	0.25	0.00	0.00	27.19	485.96	196.83
6	0.03	0.05	0.24	0.00	0.00	26.88	484.81	194.28
7	0.03	0.77	0.12	0.00	0.00	31.58	785.03	204.94
8	0.04	0.06	0.80	0.00	0.00	36.40	784.98	203.40
9	0.04	0.65	0.83	0.00	0.00	26.38	283.94	201.04
10	0.03	0.02	0.32	0.00	0.00	20.34	283.69	198.98
11	0.04	0.04	0.43	0.00	0.00	21.40	282.95	198.62
12	0.04	0.03	0.32	0.00	0.00	21.23	286.03	198.90
13	0.04	0.02	0.44	0.00	0.00	19.33	286.98	194.71
14	0.03	0.01	0.43	0.00	0.00	19.62	285.33	195.24
15	0.01	0.01	0.35	0.00	0.00	20.90	284.25	197.77
16	0.02	0.02	0.34	0.00	0.00	28.05	284.24	190.28
17	0.01	0.04	0.42	0.00	0.00	31.37	984.58	195.69
18	0.07	0.80	0.92	0.00	1.67	30.47	1187.81	207.66
19	0.09	0.76	3.49	1.80	1.06	31.55	1188.28	201.89
20	0.07	0.76	8.86	3.28	0.00	33.59	1079.32	201.97
21	0.10	0.01	5.35	0.00	0.00	32.67	989.85	298.79
22	0.08	0.04	0.35	0.00	0.00	30.67	827.51	194.33
23	0.03	0.06	0.35	0.00	0.00	30.83	789.68	195.14
0	0.04	0.07	0.38	0.00	0.00	30.69	796.13	197.96

Figure 4-19: Sensor-based testing data

In order to validate the results of the developed occupant pattern prediction model, occupant activities are predicted for two months (not consecutive months). The first testing/prediction is carried out based on the first month following the end of the training months. In order to evaluate the performance of the model when training data are not frequently (monthly) updated, the second testing/prediction is done with the fourth month following the end of training (with a time gap of three months from the end of training months). The results are compared in terms of number of matches between the prediction and sensor-based testing data.

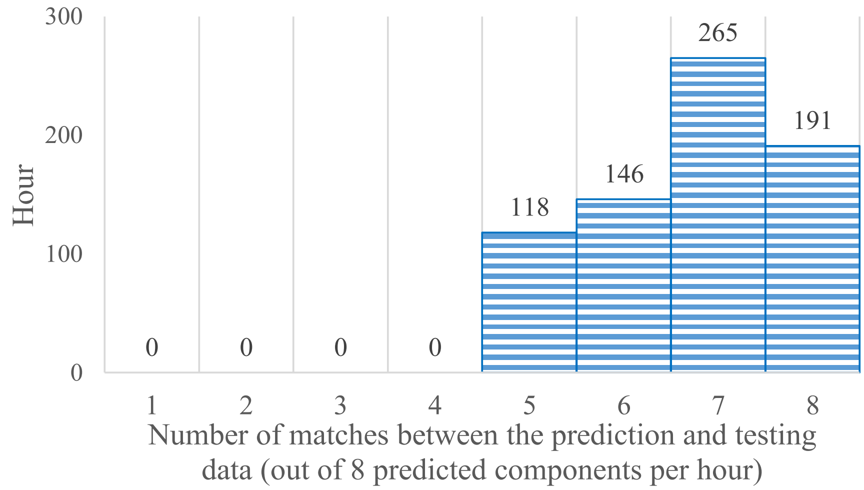


Figure 4-20: Histogram showing accuracy rate in first month following end of training months

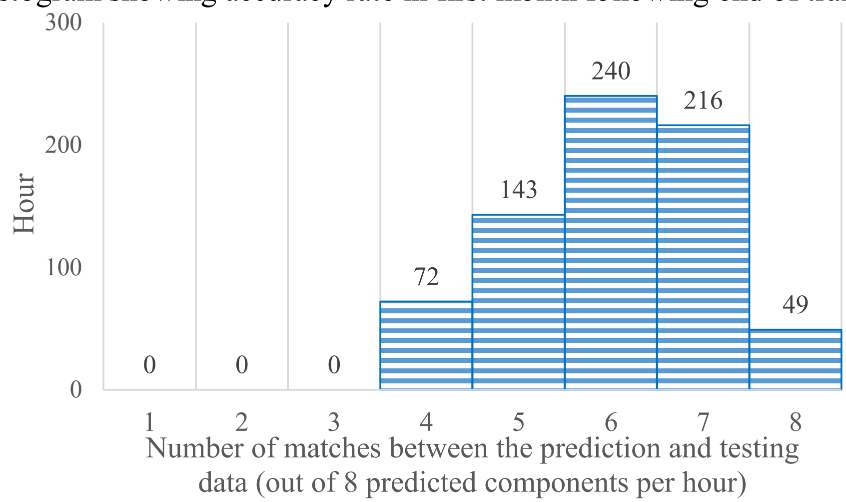


Figure 4-21: Histogram showing accuracy rate in the 4th month following the end of training months

It can be seen from Figure 4-20 and Figure 4-21 that the performance of the load prediction is successful. For the first testing (first month), the number of matches per hour (out of eight predicted components per hour) and their frequency are plotted in the histogram presented in Figure 4-20, and for the second testing (fourth month) the number of matches per hour (out of eight predicted components per hour) and their frequency are plotted in the histogram presented in Figure 4-21. As expected, the first testing month shows better performance with an overall 84% accuracy rate, and with a comparatively large number of hours for 87% (7 out of 8 prediction match for 265 times) and 100% (8 out of 8 prediction match for 191 times) accuracy rate. The fourth month has an overall 75% accuracy rate with comparatively less number of hours for 87% (7 out of 8 prediction match for 216 times) and 100% (8 out of 8 prediction match for 49 times) accuracy rate. It is possible that some changes in occupant energy usage pattern may have occurred within the three-month gap (prior to the testing in the fourth month), thereby causing a reduction in the overall accuracy rate (by 9%). It should be noted that, for ease of comparison, 720 hours (30 days) from each month are predicted (even though one of the testing month has 31 days). Considering that occupant energy usage pattern changes after a certain period of time, the developed model assists in updating the historical data (learning data) at a high (monthly) frequency.

4.4 Developing Integrated User-centric Space Heating Control Model

Since model predictive control (MPC) utilizes state space representation of a system model in order to estimate future control input sequence and predictive behaviour of the process and optimize control signal at regular intervals, the accuracy of the process/system model plays a significant role in the effective functioning of the controller. This section of the study focuses on implementation of the framework (discussed in section 3.4) for developing a reasonably accurate process model of the system for an integrated user-centric predictive control model.

4.4.1 Developing a process model in Simulink

The concept underlying the heat balance formula (Goyal and Barooah 2012; Xu and Wang 2008; Incropera et al. 2007; Wang and Xu 2006; Cenegal 2002; Mendes et al. 2001; Incropera 1996; Kreith et al. 1999; Hudson and Underwood 1999; IEA 1983) as expressed in Equations 4-22 to 4-24 is used to develop the process model for the proposed predictive controller. Screenshots of the modelling of the process models are presented in Figure 4-22, Figure 4-23, Figure 4-24, and Figure

4-25. Figure 4-22 shows the discrete heat balance model of an individual unit which comprises modelling of different building components—walls, floor, ceiling, indoor radiator, and indoor air temperature. For example, Figure 4-23 shows the heat balance model of the external wall of the unit which is modelled by considering rate of change in outdoor temperature, wall surface temperature, and thermal (resistance and capacitance) properties of the wall. Figure 4-24 shows the heat balance model of the indoor room air temperature. The rate of change in indoor room air temperature is modelled considering the temperature differences among all the surface temperature of walls, floor, ceiling and indoor room air temperature, outdoor air temperature, and thermal properties of indoor air (capacitance value of indoor air). Figure 4-25 shows the discrete heat balance model of the indoor heating system, modelling the rate of change in radiator metal temperature, heat dissipation from the radiator, and return water temperature.

$$\frac{d}{dt}(C_a X_a) = \frac{1}{R_{wa}}(X_w - X_a) + \frac{1}{R_{ra}}(X_r - X_a)$$

$$C_a \frac{dx_a}{dt} = \frac{1}{R_{wa}}(X_w - X_a) + \frac{1}{R_{ra}}(X_r - X_a) \quad [4\text{-}22]$$

where

C_a = Capacitance value for indoor air

X_w = External wall temperature

R_{wa} = Thermal resistance value for external wall

X_a = Indoor air temperature

R_{ra} = Convective resistance between the radiator and the air

X_r = *Radiator surface temperature*

For the wall, a differential equation is written as:

$$C_w \frac{dx_w}{dt} = \frac{1}{R_{wa}}(X_a - X_w) + \frac{1}{R_{rw}}(X_r - X_w) + \frac{1}{R_{ow}}(X_{out} - X_w) \quad [4\text{-}23]$$

$$\frac{dx_w}{dt} = \frac{1}{C_w R_{wa}} X_a + \left(-\frac{1}{C_w R_{wa}} - \frac{1}{C_w R_{rw}} - \frac{1}{C_w R_{ow}}\right) X_w + \frac{1}{C_w R_{rw}} X_r + \frac{1}{C_w R_{ow}} X_{out}$$

where

C_w = Capacitance value for external wall

X_{out} = Outdoor air temperature

R_{ow} = Convective thermal resistance from the outside air through the outer part of the wall (K/W)

R_{rw} =Thermal radiation resistance (between radiator and wall surface)

For the radiator, the differential equation is given as:

$$C_r \frac{dx_r}{dt} = \frac{1}{R_{ra}}(X_a - X_r) + \frac{1}{R_{rw}}(X_w - X_r) + \frac{1}{R_r}(X - X_r) \quad [4\text{-}24]$$

$$\frac{dx_r}{dt} = \frac{1}{C_r R_{ra}} X_a + \frac{1}{C_r R_{rw}} X_w + \left(-\frac{1}{C_r R_{ra}} - \frac{1}{C_r R_{rw}} - \frac{1}{C_r R_r}\right) X_r + \frac{1}{C_r R_r} X$$

where

$C_r = Capacitance\ value\ of\ radiator$

X = Supply water temperature

R_r =Thermal resistance (between radiator and supply water temperature)

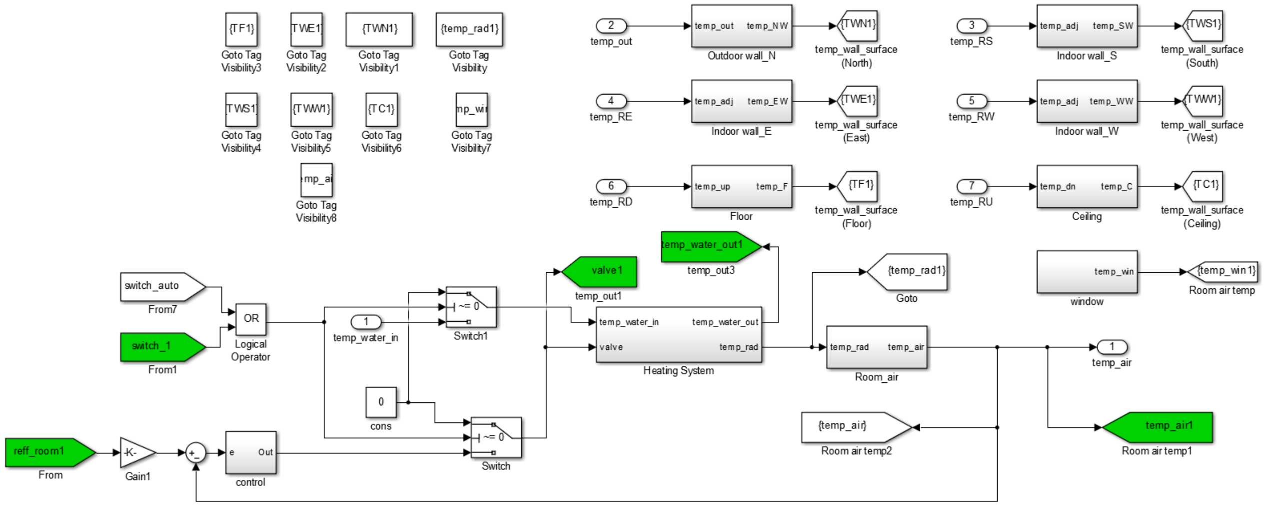


Figure 4-22: Top view of heat balance modelling of the case study

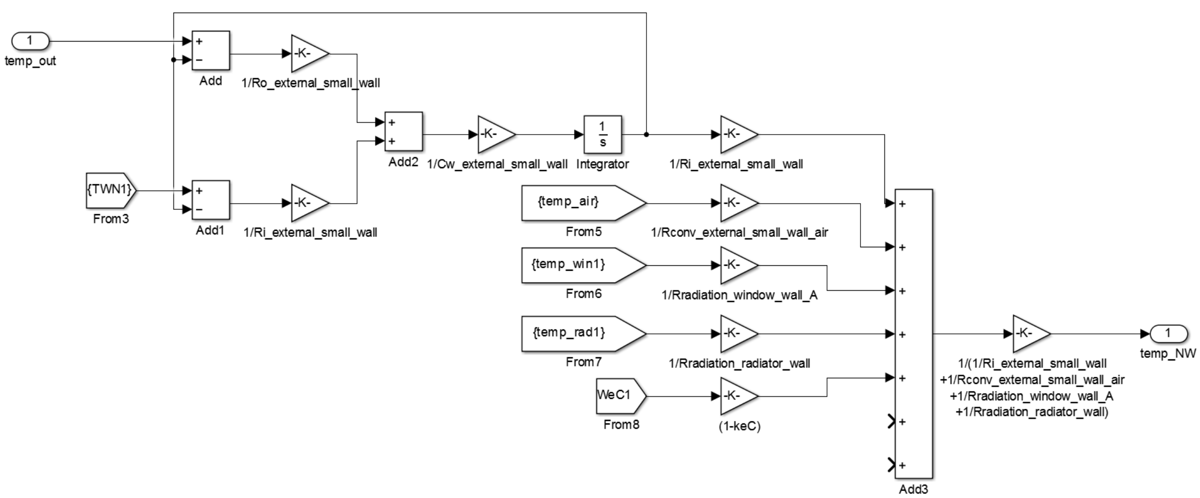


Figure 4-23: Heat balance modelling of the outdoor wall

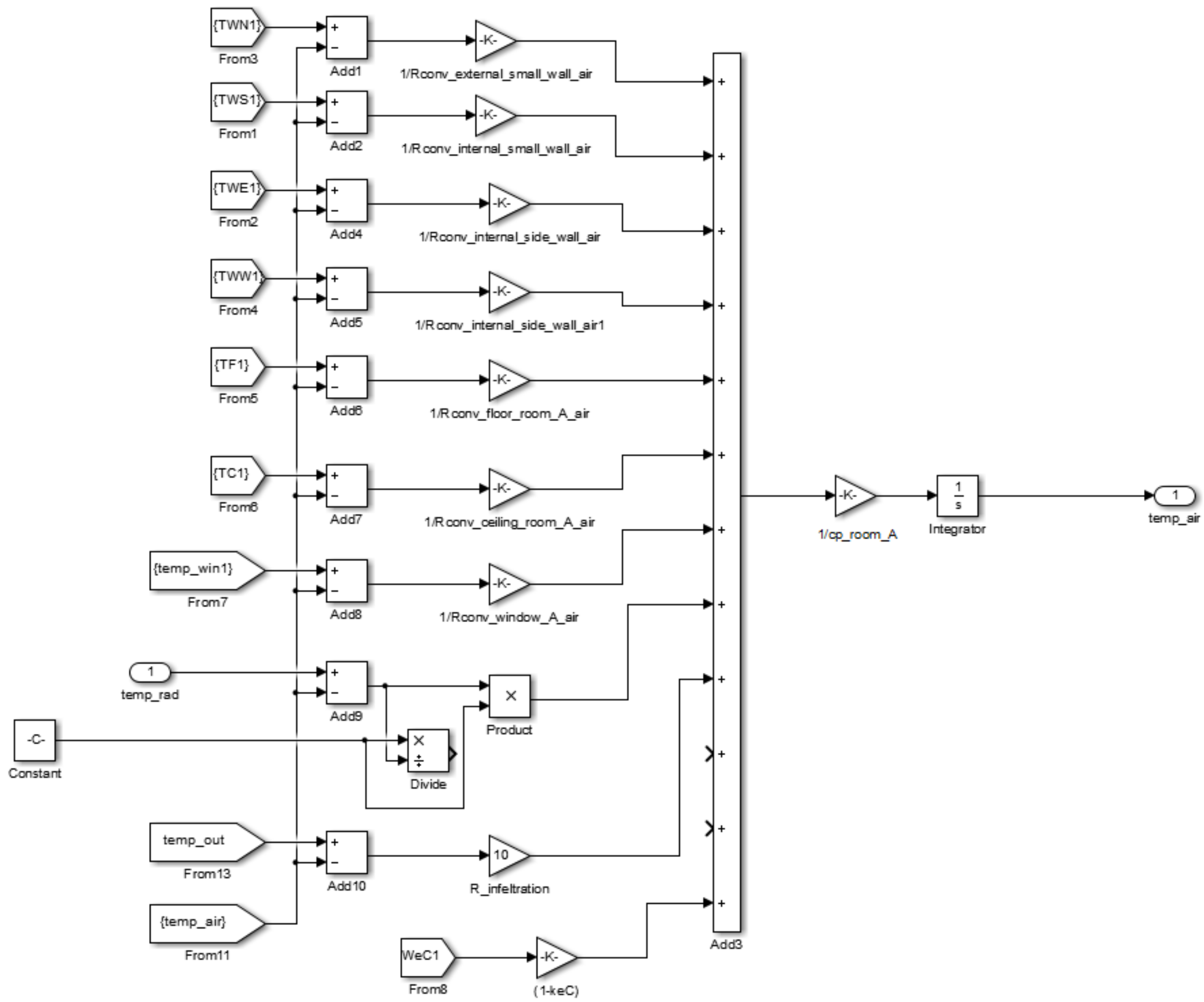


Figure 4-24: Heat balance modelling of room air temperature

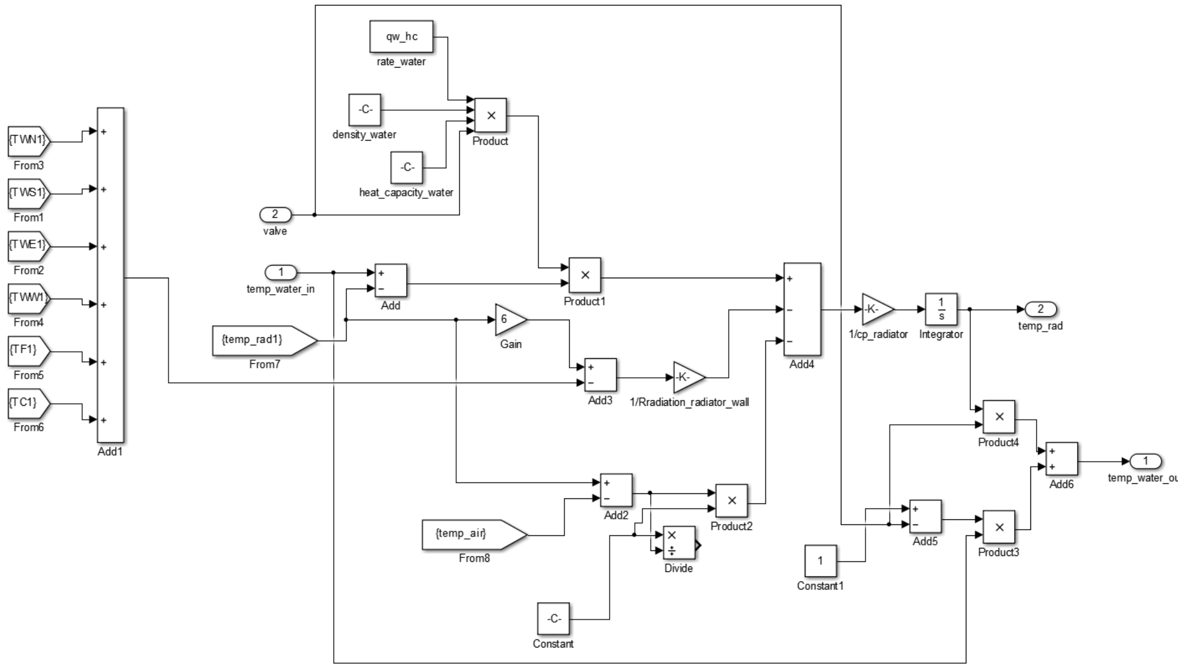


Figure 4-25: Heat balance modelling of existing traditional heating system

4.4.2 State space representation and state estimation using Kalman filter

This step derives the state space representation of the developed heat balance model from the previous step. The mathematical concept underlying the derivation of the state-space model (Kouvaritakis and Cannon 2016; Control Systems/State-Space Equations 2006; Kwon and Han 2005; Lundh and Molander 2002; Polderman and Willems 1998) from a partial section of the developed heat-balance model is presented in Figure 4-26, which shows the mathematical relationships among a single wall, a radiator, room air, and input supply water temperature.

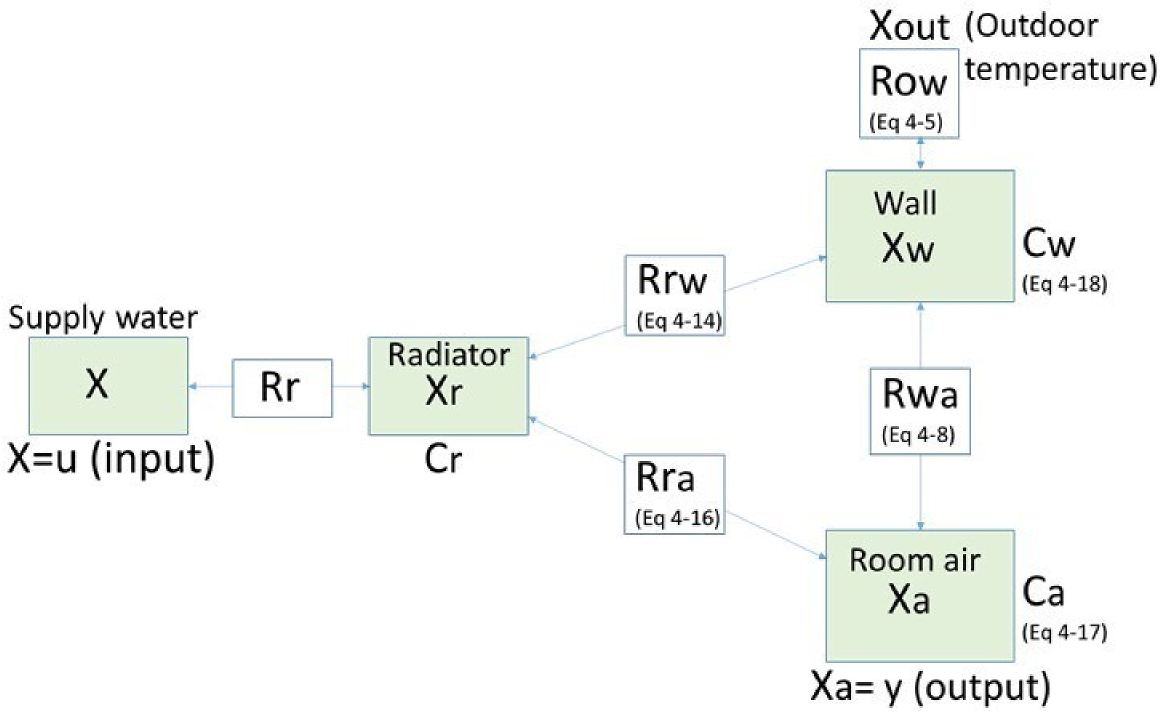


Figure 4-26: Representation of thermal relationships among input supply water, radiator, wall, and room air

The differential equations (Equations 4-22, 4-23, and 4-24) representing the thermal relationships among the room air, wall, and radiator can be expressed as Equations 4-25, 4-26 and 4-27 at the current k^{th} step (k):

$$\left(\frac{dx_a}{dt}\right)_k = \left[\frac{1}{C_a R_{wa}}\right] X_w(k) + \left[\frac{1}{C_a R_{ra}}\right] X_r(k) + \left[-\frac{1}{C_a R_{wa}} - \frac{1}{C_a R_{ra}}\right] X_a(k) \quad [4\text{-}25]$$

$$\left(\frac{dx_w}{dt}\right)_k = \left[\frac{1}{C_w R_{wa}}\right] X_a(k) + \left[\frac{1}{C_w R_{rw}}\right] X_r(k) + \left[\frac{1}{C_w R_{ow}}\right] X_{out}(k) + \left[-\frac{1}{C_w R_{wa}} - \frac{1}{C_w R_{rw}} - \frac{1}{C_w R_{ow}}\right] X_a(k) \quad [4\text{-}26]$$

$$\left(\frac{dx_r}{dt}\right)_k = \left[\frac{1}{C_r R_{ra}}\right] X_a(k) + \left[\frac{1}{C_r R_{rw}}\right] X_w(k) + \left[\frac{1}{C_r R_r}\right] X(k) + \left[-\frac{1}{C_r R_{ra}} - \frac{1}{C_r R_{rw}} - \frac{1}{C_r R_r}\right] X_a(k) \quad [4\text{-}27]$$

It should be considered that at the current k^{th} step (k),

$$\frac{dx_a(k)}{dt} = \frac{\Delta x_a(k)}{\Delta t} = \frac{X_a(k+1)-X_a(k)}{\Delta t} \qquad [4\text{-}28]$$

Therefore, the general formula for X_a , X_w and X_r at the $(k+1)$th step is as expressed in Equations 4-29, 4-30, and 4-31:

$$X_a(k+1) = \frac{\Delta t}{R_{wa}C_a}X_w(k) + \frac{\Delta t}{R_{ra}C_a}X_r(k) + \left[1 - \frac{\Delta t}{C_a R_{wa}} - \frac{\Delta t}{C_a R_{ra}}\right]X_a(k)$$

$$X_a(k+1) = A_{11}X_a(k) + A_{12}X_w(k) + A_{13}X_r(k) \qquad [4\text{-}29]$$

$$X_w(k+1) = A_{21}X_a(k) + A_{22}X_w(k) + A_{23}X_r(k) + D_2X_{out}(k) \qquad [4\text{-}30]$$

$$X_r(k+1) = A_{31}X_a(k) + A_{32}X_w(k) + A_{33}X_r(k) + B_3X(k) \qquad [4\text{-}31]$$

Therefore, the state-space representation of the system can be expressed as Equation 4-32 and 4-33:

$$\begin{vmatrix} X_a(k+1) \\ X_w(k+1) \\ X_r(k+1) \end{vmatrix} = \begin{vmatrix} A_{11} & A_{12} & A_{13} \\ A_{21} & A_{22} & A_{23} \\ A_{31} & A_{32} & A_{33} \end{vmatrix} \begin{vmatrix} X_a(k) \\ X_w(k) \\ X_r(k) \end{vmatrix} + \begin{vmatrix} 0 \\ 0 \\ B_3 \end{vmatrix} X(k) + \begin{vmatrix} 0 \\ D_2 \\ 0 \end{vmatrix} X_{out}(k) \qquad [4\text{-}32]$$

$$y(k) = \begin{vmatrix} 1 & 0 & 0 \end{vmatrix} \begin{vmatrix} X_a(k) \\ X_w(k) \\ X_r(k) \end{vmatrix} \qquad [4\text{-}33]$$

The above two equations are similar to the state space representation (Equation 4-34 and 4-35) of any process model:

$$\bar{X}(k+1) = A\bar{X}(k) + BU(k) + Dd(k) \quad [4\text{-}34]$$

$$y(k) = CX(k) \quad [4\text{-}35]$$

where $\bar{X}(k)$ is state vector, $U(k)$ is input vector, and $y(k)$ is vector of outputs which are to be controlled.

In this step, a Kalman filter is used to estimate unknown states of the system and to filter out the disturbances. The theoretical knowledge of the system (state space representation) and the feedback measurements $y(k)$ (room temperatures of the units) from the thermodynamic model (representing the real building, which is subject to actual occupancy and weather disturbance) are used to estimate the state vector $\bar{X}(k)$ of the eight states (surface temperature of four walls, floor, ceiling, radiator metal temperature and the indoor air temperature). There are two parts, $\hat{x}_k^+$ and $\hat{x}_k^-$, referred to as *a posteriori* and *a priori*, respectively. The difference between *a posteriori* and *a priori* is that *a posteriori* includes the current time feedback while *a priori* does not. The following equations (Equations 4-36 to 4-40) are used to model the above concept (Simon 2006; Pentenrieder 2005; Ribeiro 2004; Welch and Bishop 1995). Figure 4-27 shows the modelling of the above concept.

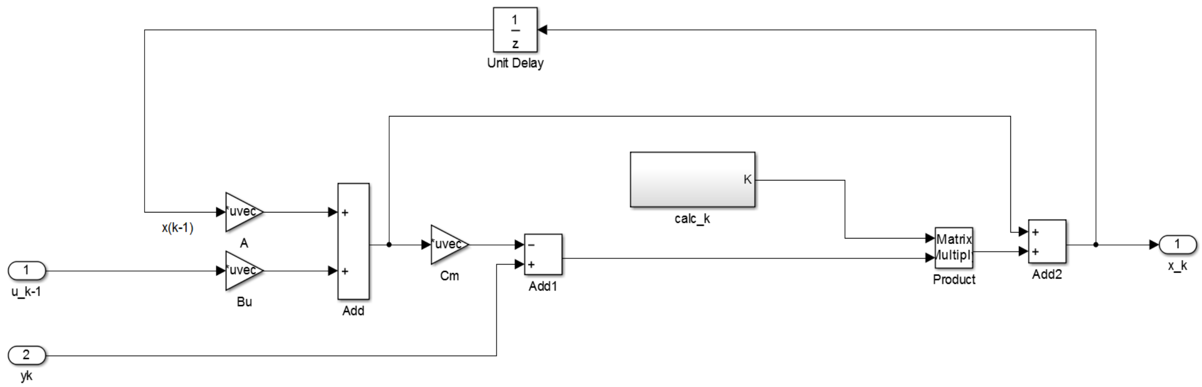
$$P_k^- = A_{k-1} P_{k-1}^+ A_{k-1}^T + Q_{k-1} \quad [4\text{-}36]$$

$$K_k = \frac{P_k^- C_k^T}{C_k P_k^- C_k^T + R_k} \quad [4\text{-}37]$$

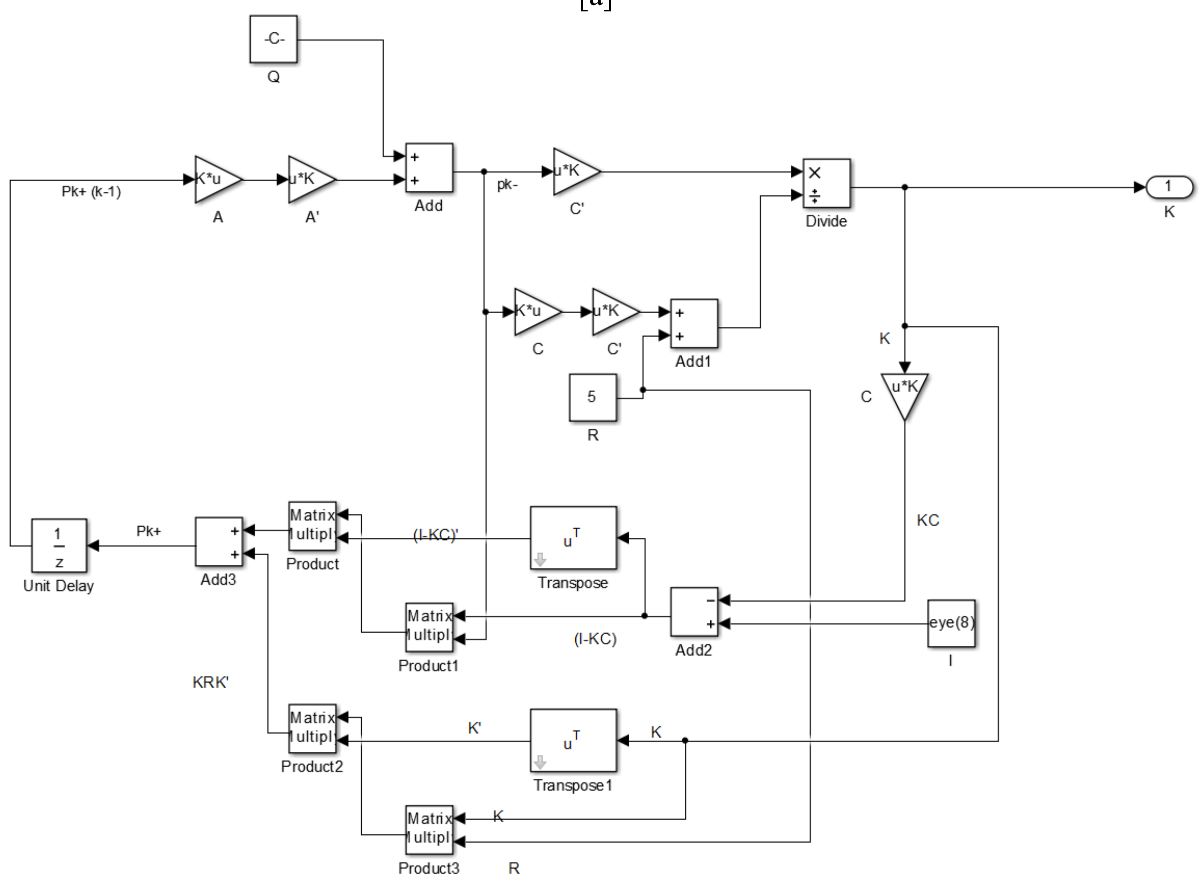
$$\hat{x}_k^- = A_{k-1}\hat{x}_{k-1}^- + B_{k-1}u_{k-1} \quad [4\text{-}38]$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k(y_k - C_k\hat{x}_k^-) \quad [4\text{-}39]$$

$$P_k^+ = (1 - K_kC_k)P_k^-(1 - K_kC_k)^T + K_kR_kK_k^T \quad [4\text{-}40]$$



[a]



[b]

Figure 4-27: Kalman filter

As shown in Figure 4-27a, a Kalman filter estimates (using Equation 4-38) the theoretical state vector ($\hat{x}_k^-$) from the previous state input (supply water temperature) and the previous posteriori state estimate. Using Equation 4-39, the filtered state vector ($\hat{x}_k^+$) is finally estimated by finding the difference between the current-state feedback temperature and the theoretically estimated temperature, which is then multiplied with the optimal gain (K_k) and added to the theoretical state vector to get better approximation of the real system. Figure 4-27b shows how the optimal gain (K_k) is calculated with *a posteriori* (P_k^+) and *a priori* (P_k^-) of covariance of the estimation error. Based on the reliability of the model and the feedback measurements, Q_k and R_k are tuned.

4.4.3 Receding horizon and creating design matrices from the given state model

As mentioned earlier, the predictive controller uses the concept of receding horizon and works by estimating the output (room temperature) for different input values (supply water temperature) (Seborg 2011; Koch 2013; Kwon and Han 2005; Lundh and Molander 2002). This step demonstrates how the outputs (room temperature) of future steps [$(k+1), (k+2) \ldots$ *to* $(k+H_p)$] are calculated and design matrices are created from a given state space model from the current step, *k*.

As expressed in Equations 4-41, 4-42 and 4-43, the discretized state space model predicts the future responses of the system by using the current-state vector (temperature estimated from Kalman filter), current-state input of supply water temperature (expressed as the change in supply water temperature at current state with addition/subtraction to the previous state input of supply water temperature) and the predicted disturbances; thus, the design matrices are derived as expressed in Equation 4-44.

$$y(k+1) = CAX(k) + CB_u u(k-1) + CB_u \Delta u(k) + CB_v d(k) \qquad [4\text{-}41]$$

$$y(k+2) = CA^2 X(k) + [C\{AB_u + B_u\}]u(k-1) + [C\{AB_u + B_u\}]\Delta u(k) + CB_u \Delta u(k+1) +$$
$$CAB_v d(k) + CB_v d(k+1) \qquad [4\text{-}42]$$

$$y(k+3) = CA^3 X(k) + [C\{A^2 B_u + AB_u + B_u\}]u(k-1) + [C\{A^2 B_u + AB_u + B_u\}]\Delta u(k) +$$
$$[C\{AB_u + B_u\}]\Delta u(k+1) + CB_u \Delta(k+2) + CA^2 B_v d(k) + CAB_v d(k+1) + CB_v d(k+2)$$

[4-43]

$$\begin{vmatrix} y(k+1) \\ y(k+2) \\ y(k+3) \end{vmatrix} = \begin{vmatrix} CA \\ CA^2 \\ CA^3 \end{vmatrix} X(k) + \begin{vmatrix} CB_u \\ C\{AB_u + B_u\} \\ C\{A^2 B_u + AB_u + B_u\} \end{vmatrix} u(k-1) +$$

$$\begin{vmatrix} CB_u & 0 & 0 \\ C\{AB_u + B_u\} & CB_u & 0 \\ C\{A^2 B_u + AB_u + B_u\} & C\{AB_u + B_u\} & CB_u \end{vmatrix} \begin{vmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \Delta u(k+2) \end{vmatrix}$$

$$+ \begin{vmatrix} CB_v & 0 & 0 \\ C\{AB_v + B_v\} & CB_v & 0 \\ C\{A^2 B_v + AB_v + B_v\} & C\{AB_v + B_v\} & CB_v \end{vmatrix} \begin{vmatrix} du(k) \\ du(k+1) \\ du(k+2) \end{vmatrix} \qquad [4\text{-}44]$$

The above Equation 4-44 can be expressed in general form as Equation 4-45:

$$\bar{y}(k) = \Psi_1 \bar{X}(k) + \Psi_2 u(k-1) + \Psi_3 \overline{\Delta u}(k) + \Psi_4 \bar{d}(\mathrm{k}) \qquad [4\text{-}45]$$

where

$$\bar{y}(k) = \begin{vmatrix} y(k+1) \\ y(k+2) \\ y(k+3) \\ \vdots \\ y(k+H_p) \end{vmatrix}, \ \overline{\Delta u}(k) = \begin{vmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \Delta u(k+2) \\ \vdots \\ \Delta u(k+H_p-1) \end{vmatrix}, \ \bar{d}(\mathrm{k}) = \begin{vmatrix} du(k) \\ du(k+1) \\ du(k+2) \\ \vdots \\ du(k+H_p-1) \end{vmatrix}$$

$$\Psi_1 = \begin{vmatrix} C & 0 & 0 & \dots & 0 \\ 0 & C & 0 & \dots & 0 \\ 0 & 0 & C & \dots & 0 \\ \vdots & & \ddots & \dots & \vdots \\ 0 & 0 & 0 & \dots & C \end{vmatrix} \begin{vmatrix} A \\ A^2 \\ A^3 \\ \vdots \\ A^{H_p} \end{vmatrix}$$

$$\Psi_2 = \begin{vmatrix} C & 0 & 0 & \dots & 0 \\ 0 & C & 0 & \dots & 0 \\ 0 & 0 & C & \dots & 0 \\ \vdots & & \ddots & \dots & \vdots \\ 0 & 0 & 0 & \dots & C \end{vmatrix} \begin{vmatrix} B_u \\ \sum_{i=0}^{1} (A^i B_u) \\ \sum_{i=0}^{2} (A^i B_u) \\ \vdots \\ \sum_{i=0}^{H_p-1} (A^i B_u) \end{vmatrix}$$

$$\Psi_3 = \begin{vmatrix} C & 0 & 0 & \dots & 0 \\ 0 & C & 0 & \dots & 0 \\ 0 & 0 & C & \dots & 0 \\ \vdots & & \ddots & \dots & \vdots \\ 0 & 0 & 0 & \dots & C \end{vmatrix} \begin{vmatrix} B_u & 0 & 0 & & \dots & 0 \\ \sum_{i=0}^{1} (A^i B_u) & B_u & 0 & & \dots & 0 \\ \sum_{i=0}^{2} (A^i B_u) & \sum_{i=0}^{1} (A^i B_u) & B_u & & \dots & 0 \\ & & & & \dots & \vdots \\ \vdots & & \ddots & & & \sum_{i=0}^{H_p-H_c} (A^i B_u) \\ \sum_{i=0}^{H_p-1} (A^i B_u) & \sum_{i=0}^{H_p-2} (A^i B_u) & \sum_{i=0}^{H_p-3} (A^i B_u) & \dots & & \end{vmatrix}$$

In this step, by creating the design matrices, the predictive controller estimates the indoor room temperatures in response to potential input trajectories (supply water temperature that may lead to the desired reference point room temperature) for future steps until reaching the prediction horizon. Then, following the estimation of future outputs, the optimization model finally finds the one input trajectory that ensures the efficient behaviour of the model considering the constraints established for this study, and then only the first element of the optimal input trajectory is implemented in the current state. Since MPC utilizes the concept of receding horizon, the entire process is repeated in the next steps.

4.4.4 Optimization algorithm

It should be noted that this study aims to ensure the optimal amount of energy production (reducing the supply water temperature) to reduce the potential heat loss through the surroundings without compromising occupant comfort (by controlling the set-point temperature of the units). This study thus adopts the approach of estimating the error (difference between the desired room temperature and the current-state room temperature of individual units of the multi-family residential building) through a feedback loop. Iterations of this estimation continue until the error becomes close to zero over the prediction horizon window. Prediction horizon (H_p), it should be noted, is the number of discrete time steps until the time the behaviour of the system is predicted in response to predicted knowledge of disturbances (weather and occupancy pattern) through a feedforward connection (Kouvaritakis and Cannon 2016; Seborg 2011; Kwon and Han 2005). While optimizing the input/manipulated variables (supply water temperature) over the period of control horizon (H_e), this study aims to ensure that the rate of changes in input variable stays within an efficient range. Control horizon (H_e), it should be noted, is the number of discrete time steps until the time the predictive controller works on optimizing the input/ manipulated variable (Kouvaritakis and Cannon 2016; Seborg 2011; Kwon and Han 2005). The feedforward loop used in this study allows the optimizer to proceed rather than wait until the disturbances appear. In addition, considering the fact that the predicted knowledge of the disturbance can deviate from the actual state, the feedback loop of the developed controller allows the predictive controller to be fed with the current state and forced to change the input signal to reduce the error. By addressing the above discussed objectives as expressed in Equations 4-46, 4-47, and 4-48 the predictive controller optimization works by minimizing a cost function (Kouvaritakis and Cannon 2016; Seborg 2011; Kwon and Han 2005)

1. To reduce the error between the reference set-point and room temperature, and therefore:

$$\sum_{i=1}^{H_p} \|y(k+i) - \Upsilon(k+i)\|^2 \quad [4\text{-}46]$$

2. To reduce the rate of change of input supply water temperature, and therefore:

$$\sum_{i=0}^{H_e} \|\Delta u(k+i|k)\|^2 \quad [4\text{-}47]$$

3. To reduce the required supply water temperature, and therefore:

$$\sum_{i=0}^{H_e} \|u(k+i|k)\|^2 \quad [4\text{-}48]$$

It should be considered that not all the above-mentioned objectives are of equal importance, so a tuning or weighting parameter is added with each objective. Thus, the objective function or cost function can be expressed as Equation 4-49:

$$J(k) = \sum_{i=1}^{H_p} \|y(k+i|k) - \Upsilon(k+i|k)\|^2 \; Q(i) + \sum_{i=0}^{H_e} \|\Delta u(k+i|k)\|^2 \, R(i) +$$
$$\sum_{i=0}^{H_e} \|u(k+i|k)\|^2 \mathrm{S(i)} \quad [4\text{-}49]$$

Equation 4-49 can be written in matrix form as Equation 4-50:

$$J(k) = [\bar{y}(k) - \bar{r}(k)]^T Q[y(k) - \bar{r}(k)] + \overline{\Delta v}(u)^T x \, R \, x \, \overline{\Delta u}(u) + \bar{u}(u)^T \, x \, S \, x \, \bar{u}(u) \qquad [4\text{-}50]$$

It should be noted that, in this thesis, the first objective is considered during constraint setting; thus, the cost function reduces to Equation 4-51 (by setting Q = 0):

$$J(k) = \overline{\Delta u}(k)^T x \, R \, x \, \overline{\Delta u}(k) + u(k)^T \, x \, S \, x \, \bar{u}(k) \qquad [4\text{-}51]$$

There are two unknown variables in Equation 4-51: (a) the rate of change of input (water temperature), $\overline{\Delta u}(k)$, and the input (water temperature) itself, $\bar{u}(k)$. For ease of minimizing the cost function (4-51), the number of variables is reduced from two to one by considering the fact that current-state (at step k) input $\bar{u}(k)$ can be described as the addition of the previous state input $u(k-1)$ and current-state change in input $\Delta u(k)$ as expressed in Equation 4-52:

$$u(k) = u(k-1) + \Delta u(k) \qquad [4\text{-}52]$$

Based on Equation 4-52, the input of the system can be estimated for future steps (until reaching the control horizon), as expressed in Equation 4-53, 4-54 and 4-55, and can be expressed in matrix form as shown in Equation 4-56.

The above equations can be written as follows:

$$u(k+1) = u(k-1) + \Delta u(k) + \Delta u(k+1) + 0.\, \Delta u(k+2) + \ldots\ldots .0.\Delta u(k+H_e) \qquad [4\text{-}53]$$

$$u(k+2) = u(k-1) + \Delta u(k) + \Delta u(k+1) + \Delta u(k+2) + \ldots\ldots .0.\Delta u(k+H_e) \qquad [4\text{-}54]$$

$$u(k+H_e) = u(k) + \Delta u + (k) + \Delta u(k+1) + \Delta u(k+2) + \cdots \ldots + \Delta u(k+H_e) \qquad [4\text{-}55]$$

The above equations can be written in matrix form as Equation 4-56:

$$\begin{vmatrix} u(k) \\ u(k+1) \\ u(k+2) \\ \vdots \\ u(k+H_e) \end{vmatrix} = \begin{vmatrix} 1 \\ 1 \\ 1 \\ \vdots \\ 1 \end{vmatrix} u(k-1) + \begin{vmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ \vdots & & \ddots & \dots & \vdots \\ 1 & 1 & 1 & \dots & 1 \end{vmatrix} \begin{vmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \Delta u(k+2) \\ \vdots \\ \Delta u(k+H_e) \end{vmatrix} \qquad [4\text{-}56]$$

Equation 4-56 can be expressed in general form as Equation 4-57:

$$\bar{u}(k) = Xu(k-1) + V\overline{\Delta u}(k) \qquad [4\text{-}57]$$

where $X = \begin{vmatrix} 1 \\ 1 \\ 1 \\ \vdots \\ 1 \end{vmatrix}, V = \begin{vmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ \vdots & & \ddots & \dots & \vdots \\ 1 & 1 & 1 & \dots & 1 \end{vmatrix}$

Considering Equation 4-57, the cost function (Equation 4-51) can be expressed as Equation 4-58:

$$J(k) = [u(k-1)^T X^T S\, Xu(k-1)] + \overline{\Delta u}(k)^T \times [2V^T S\, Xu(k-1)]\overline{\Delta u}(k)^T \times [R + V^T S V^T]\, \overline{\Delta u}(k) \qquad [4\text{-}58]$$

Here, it should be noted that in Equation 4-58, $[u(k-1)^T X^T S\, Xu(k-1)]$ is constant and does not affect the minimization problem. Accordingly, the reduced cost function can be expressed as Equation 4-59:

$$[J(k)]_{min} = \overline{\Delta u}(k)^T . G + \overline{\Delta u}(k)^T H . \overline{\Delta u}(k) \qquad [4\text{-}59]$$

4.4.5 Constraints

The reduced cost function that is to be minimized is:

$$\overline{\tfrac{1}{2}\Delta u}(k)^T H . \overline{\Delta u}(k) + \overline{\Delta u}(k)^T . G \qquad [4\text{-}60]$$

where $H = 2[R + V^T S\theta]$ and $G = 2G^T SXu(k-1)$, and both are known values.

It can be seen that there is only one variable in the cost function: $\overline{\Delta u}(k)$. For a certain set of values of the vectors $\overline{\Delta u}(k)$, the value of the cost function will be minimum and that set of values are to be determined using quadratic optimization (Kouvaritakis and Cannon 2016), which can be done using the quadprog solver from the optimization toolbox in MATLAB.

In this thesis, quadratic optimization determines the value of variable $\overline{\Delta u}(k)$, which in turn minimizes the objective function as expressed in Equation 4-60. But while solving the QP problem, the constraint should be provided for $\overline{\Delta u}(k)$ in the form of Equation 4-61 (Kwon and Han 2005):

$$A\overline{\Delta u}(k) \leq b \qquad [4\text{-}61]$$

where "*A*" and "*b*" are constant matrices that need to be built.

As mentioned above, there are three variables that are to be controlled:

1. The output of the plant $\bar{y}(k)$
2. The temperature of input water supply $\bar{u}(k)$
3. The rate of change of input water supply temperature $\overline{\Delta u}(k)$

There are three constraint variables, $\bar{y}(k), \bar{u}(k),$ and $\overline{\Delta u}(k)$, but the constraint expression given by inequality (Equation 4-61) consists of only one variable, $\overline{\Delta u}(k)$. So, the other constraint variables are to be expressed as function $\overline{\Delta u}(k)$. Therefore, in this section the constraint matrices *A* and *b* are built by three steps.

First, since the output of the plant is the difference between reference set-point and room temperature, the desired $\bar{y}(k)$ for this system is less than or equal to zero, that is:

$$\bar{y}(k) \leq \bar{0} \qquad [4\text{-}62]$$

Alternatively, it can be expressed as follows:

$$\Psi_1 \bar{X}(k) + \Psi_2 u(k-1) + \Psi_3 \overline{\Delta u}(k) + \Psi_4 \bar{d}(\mathrm{k}) \leq \bar{0}$$

$$=> \Psi_3 \overline{\Delta u}(k) \leq -\left[\Psi_1 \bar{X}(k) + \Psi_2 u(k-1) + \Psi_4 \bar{d}(\mathrm{k})\right] \qquad [4\text{-}63]$$

Second, the input water temperature should be within the following range:

$$\overline{20} \leq \bar{u}(k) \leq \overline{65} \qquad [4\text{-}64]$$

Alternatively, it can be expressed as follows:

$$-[Xu(k-1) + V\overline{\Delta u}(k)] \leq -\overline{20}$$

$$=> -V\overline{\Delta u}(k) \leq Xu(k-1) - \overline{20} \qquad [4\text{-}65]$$

$$Xu(k-1) + V\overline{\Delta u}(k) \leq \overline{65}$$

$$=> V\overline{\Delta u}(k) \leq -Xu(k-1) + \overline{65} \qquad [4\text{-}66]$$

The above constraint can be expressed as:

$$\begin{vmatrix} -V \\ V \end{vmatrix} \overline{\Delta u}(k) \leq \begin{vmatrix} X \\ -X \end{vmatrix} u(k-1) + \begin{vmatrix} -\overline{20} \\ \overline{65} \end{vmatrix} \qquad [4\text{-}67]$$

Or, $F\overline{\Delta u}(k) \leq -F_1 u(k-1) - f$ [4-68]

The last constraint is for $\overline{\Delta u}(k)$, the minimum rate of change of temperature of input water supply is −5 °C, and the maximum rate is 5 °C, that is:

$$-\bar{5} \le \overline{\Delta u}(k) \le \bar{5} \qquad [4\text{-}69]$$

Alternatively, it can be expressed as follows:

$$\begin{vmatrix} -I \\ I \end{vmatrix} \overline{\Delta u}(k) \le \begin{vmatrix} -\bar{5} \\ \bar{5} \end{vmatrix} \qquad [4\text{-}70]$$

$$W\,\overline{\Delta u}(k) \le w \qquad [4\text{-}71]$$

Therefore, the integrated constraints can be expressed as Equation 4-72:

$$A\,\overline{\Delta u}(k) \le b$$

$$\begin{vmatrix} F \\ \Theta \\ W \end{vmatrix} \overline{\Delta u}(k) \le \begin{vmatrix} -F_1 u(k-1) - f \\ -\left[\Psi \bar{X}(k) + \Upsilon u(k-1) + \phi \bar{d}(\mathrm{k})\right] \\ w \end{vmatrix} \qquad [4\text{-}72]$$

4.4.6 Simulating the integrated predictive controller

Section 4.4 demonstrates the development of a space heating controller for estimating optimum supply water temperature using the concept of MPC. In the current state a control plan is formulated for next time steps by considering the uncertainty of weather and occupant heating load within the optimization model. Figure 4-28 shows the screenshots of the tool manager for setting the predictive controller.

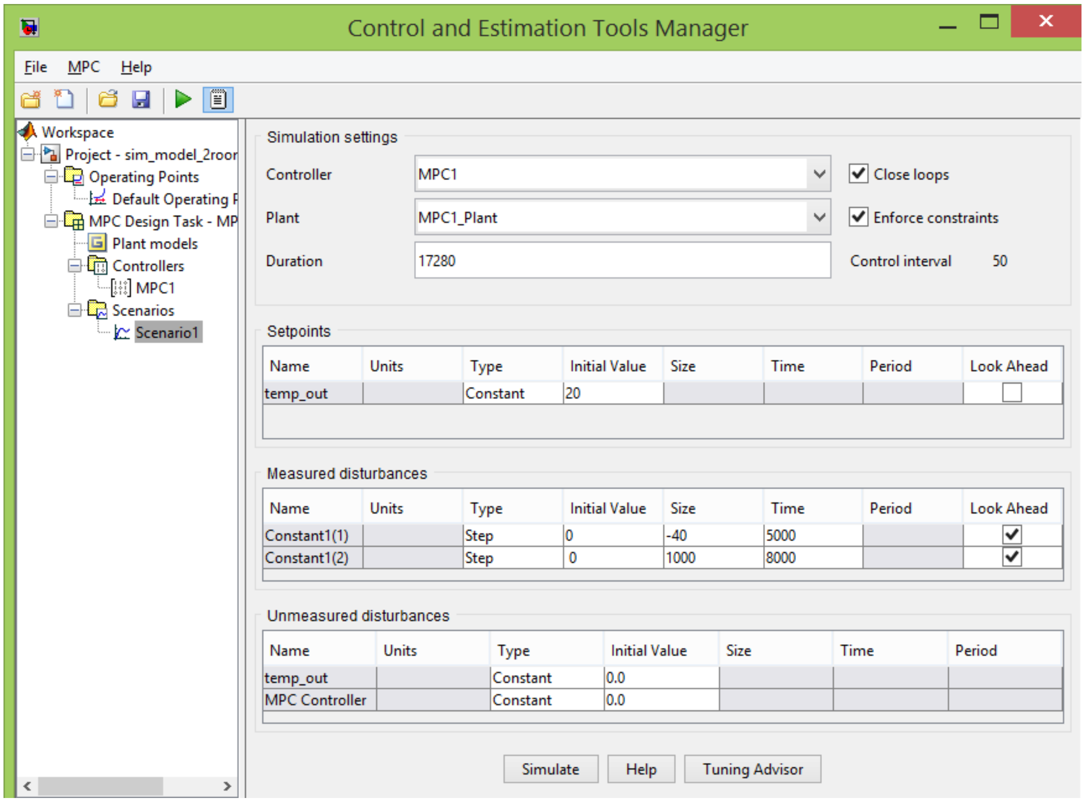


Figure 4-28: Screenshot of the tool manager for setting predictive controller

The developed predictive controller is simulated for five days (Figure 4-28). During the five days of the simulation period, the desired room temperature is set to 20 °C. If the controller is given the information that after 5,000 seconds the outdoor temperature will drop from 0 °C to −40 °C, and that after 8,000 seconds the occupant gain increases from 0 to 1,000 W, it will run the algorithm developed in this study to estimate the optimum supply water temperature. As can be observed in Figure 4-29, the predictive controller starts changing the supply water temperature beforehand (before the disturbance occurs) based on the predicted disturbances. The supply water temperature starts to increase as the outdoor temperature drops, and, in addition, the supply water temperature starts to decrease before the occupant gain increases (i.e., before the occupant heat load decreases).

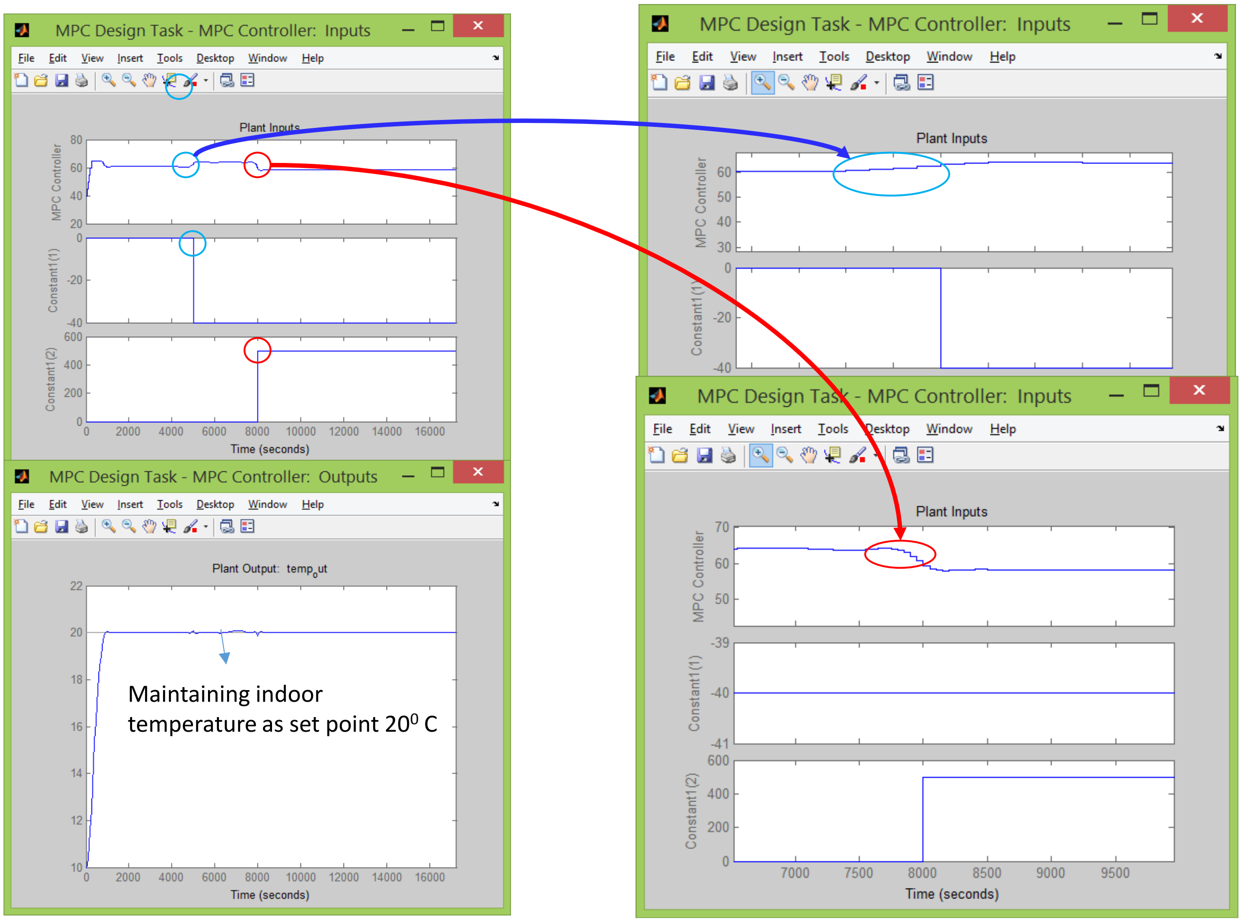


Figure 4-29: Simulation results showing the performance of the predictive controller with the uncertainty of weather and occupant load

4.5 Evaluating Design-alternatives for Improved Thermal Performance of Building Envelope

Based on the assumption (made in section 4.1) that the higher temperature difference between the outer and inner surfaces of the north-facing external walls causes higher heat loss through north-facing building envelope (leading to higher heating energy consumption in those units), there is higher potential to save heating energy in the north-facing units through improved thermal performance of the envelope. This section thus focuses on implementation of the framework (approach to improve thermal performance of north-facing building envelope) discussed in section 3.5. However, as mentioned in that section, before analyzing different design alternatives for north-facing building envelope, an established *mathematical model* (CIBSE method) is used to investigate the isolated impact of directional orientation on the thermal performance of the building envelope (given that multiple factors, including occupant activity pattern and comfort choices, may combine to influence the measured sensor value in section 4.1).

4.5.1 Mathematical model to identify the impact of varying orientations

In this section, the sensitivity of spaces of varying orientations is investigated by means of the mathematical model, and with that purpose, a north-facing unit and a south-facing unit on the second floor are used as case study. An established estimation method given by the Chartered Institution of Building Services Engineers London (CIBSE Guide A 2006; The CIBSE Method) is followed to investigate the effect of the climatic conditions (solar radiation, outdoor temperature) on the passive internal temperature and heat flux of the case study units with varying orientations. The method includes: (1) collecting solar radiation data (both direct and diffuse) for different orientations, (2) collecting outdoor air temperature, (3) estimating sol-air temperature, (4) estimating heat gains from all sources, and (5) estimating internal environmental temperature, following Equation 4-73 to Equation 4-77 (CIBSE Guide A 2006; The CIBSE Method).

Estimating solar heat gain:

$$Q'_s = SI'A_g \qquad [4\text{-}73]$$

where

Q'= Mean solar gain (W);

I'= Mean solar intensity (W/m^2); and

S= Solar gain factor.

Estimating casual gains:

$$Q_c' = \frac{(P \times t_1) + (L \times t_2) + -----}{24} \quad [4\text{-}74]$$

where

$Q_c' =$ Mean solar gain (W)

$P, L =$ Casual gain (W)

$t_1, t_2 =$ duration of $g_{c1,}\ g_{c2}$ ... ... (hours)

$$Q_c' = \frac{(\text{People}) + (\text{Lights}) + -----}{24}$$

Calculation of Sol-air temperature:

As mentioned in the IHVE Guidebook, “The Sol-air temperature is defined as the outside air temperature which, in the absence of solar radiation, would give the same temperature distribution and rate of heat transfer through a wall (or roof) as exists due to the combined effects of the actual outdoor temperature distribution plus the incident solar radiation” (IHVE Guidebook 1970).

The sol-air temperature is defined as:

$$t_{sa} = t_{oa} + R(\alpha I_T - \epsilon I_1) \quad [4\text{-}75]$$

where

$R(in\ m^2KW^{-1}) =$ Thermal resistance of the external $\frac{\text{surface}}{\text{air}}$ interface

$\alpha =$ Absorptivity for solar radiation of the considered wall, respectively

$\epsilon =$ Emissivity for infrared radiation of the considered wall, respectively

$t_{oa}\ (in\ o_C) =$ Outdoor air temperature

$I_T\ (in\ Wm^{-2})$ = Intensity of direct plus diffuse solar radiation on the outer surface of the wall

I_1 $(in\ Wm^{-2})$ = Intensity of long wave radiation from a thermal black body at temperature t_{oa}

Calculation of total heat gain and internal environmental temperature:

$$Q_t^{'} = Q_s^{'} + Q_c^{'}$$

$$Q_c' = \sum(A_c U_c + C_v)(T_{ei}' - T_{oa}') + \sum A_f U_f (T_{ei}' - T_{sa}') \quad [4\text{-}76]$$

where

T_{ei}' = Indoor Air Temperature

c and f refer to glazed and opaque surfaces, respectively

C_v = Ventilation conductance, which is evaluated from:

$$\frac{1}{C_v} = \frac{1}{0.33N_v} + \frac{1}{4.8\sum A} \quad [4-77]$$

Table 4-2 shows the outdoor temperature and solar radiation on the external façade of north-facing unit and south-facing units, their corresponding estimated sol-air temperature, and the calculated passive internal temperature (in °C). As observed, there is a significant difference with respect to the presence/extent of solar radiation between the external façade of the north-facing unit and south-facing unit, which results in higher sol-air temperature on the south orientation. Since the internal environmental temperature increases with the higher sol-air temperature, in the presence of solar radiation the south-facing unit achieves higher internal temperature than that of the north-facing room (assuming that other factors are the same). According to Table 4-2, there is a significant increase (around 3 °C) in passive internal environmental temperature for the south-facing room due to solar radiation.

Moreover, it is observed that, because of the lower solar radiation on the external façade of the north-facing unit (i.e., lower sol-air temperature), the heat loss is expected to be higher in north-facing units (if the maintained indoor temperatures in the north- and south-facing units are the same). Considering that lower solar radiation incident on the external façade of north-facing units has been observed to be a reliable influencing parameter for higher heat loss, and given the lower passive internal temperature (leading to higher heating energy consumption) in the north-facing units, a better design alternative for north-facing envelope with improved thermal performance is identified in the following section.

Table 4-2: Estimated sol-air temperature and passive indoor temperature

Orientation	Mean outdoor air temperature (°C)	Mean solar intensity (W/m^2)	Mean sol-air temperature (°C)	Mean internal environmental temperature (°C)
North-facing	11.3	84.66	12.29	15.96
South-facing		192.69	13.55	19.28

4.5.2 Simulation of design alternatives

Real-time field test may be an option for performance evaluation of potential design alternatives toward high-performance building envelope. However, evaluating isolated impacts of different design alternatives on energy load in a natural setting is a highly expensive and time-consuming undertaking. On the other hand, simulation is capable of studying the effect of one variable at a time, where the impact of a single change in one variable and its behavioural change can be observed by keeping other variables constant. In this research, simulation plays a significant role, since it categorically isolates the exclusive effect of the same element at different configurations and has the ability to analyze the impact of these design variables for any period of the year for any place. The findings of this simulation form the basis for measures to improve performance, as described later in this section.

Setting design alternatives for simulation:

In setting the design alternatives for simulation (to demonstrate how the thermal performance of north-facing units can be improved for future design reference), this study focuses on different alternatives for wall configurations and opening area. Since in the case study room opening area constitutes a significant share of the building envelope (approximately 30% of the total area), it is possible that the poorer thermal performance of these openings (compared to the insulated wall area) may hinder the efficiency of different wall configurations. As such, reducing the opening area may significantly decrease the energy consumption.

It should be noted that in this study those variables are selected which have already demonstrated (in previous studies) their contributions to improved thermal performance. Studies have shown that high-performance insulation has the potential to significantly improve energy efficiency by reducing heat loss through insulating materials with low thermal conductivity and improving the thickness of insulation layers (Ibrahim 2014; Verbeeck 2005; Enkvist 2007; EEW 2013). The present study thus establishes potential alternative wall configurations with different types of insulation, ensuring the minimum assembly R-value (RSI) of wood frame construction of R-15.6 (RSI 3.45) as recommended by ASHRAE-90.1 (2007).

Figure **4-30** shows the design alternatives assessed in this study.

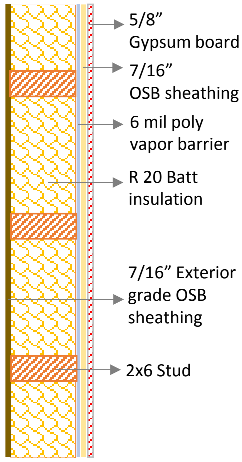
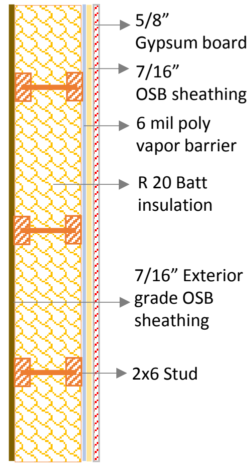
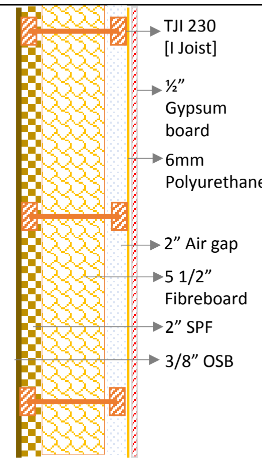
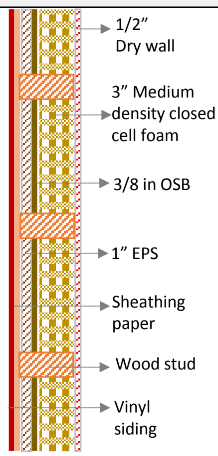
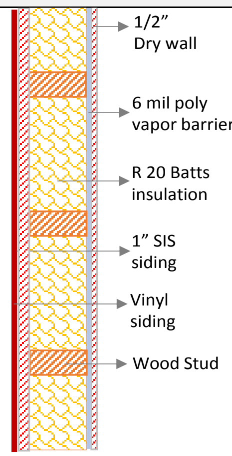
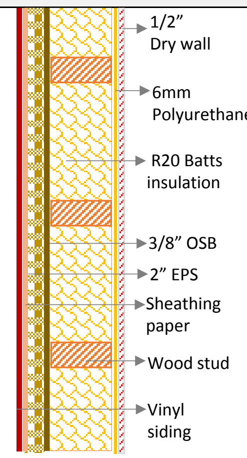
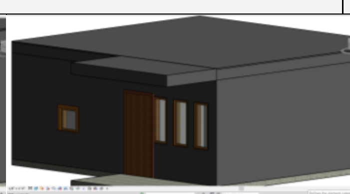
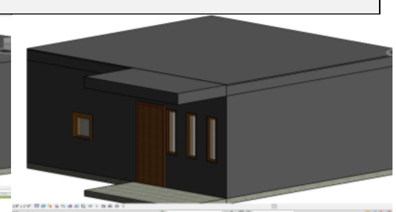
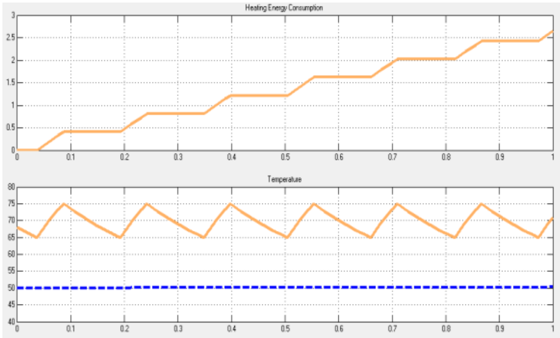
<table>
<tr><td rowspan="4">Wall alternatives</td><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Case study wall</td><td>Alternative 1</td><td>Alternative 2</td></tr>
<tr><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Alternative 3</td><td>Alternative 4</td><td>Alternative 5</td></tr>
<tr><td rowspan="2">Window alternatives</td><td>
Window area: 3.1 m^2
Three windows of 24″ × 48″, and one window of 33″ × 48″</td><td>
Window area: 2.5 m^2
Three windows of 20″ × 48″, and one window of 24″ × 48″</td><td>
Window area: 2.09 m^2
Three windows of 15″ × 48″, and one window of 23″ × 48″</td></tr>
<tr><td>Alternative 6</td><td>Alternative 7</td><td>Alternative 8</td></tr>
</table>

Figure 4-30: Design alternatives for thermal performance

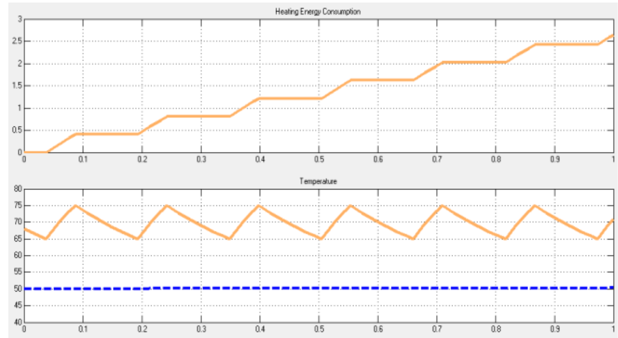
In the simulation, the conventional 2×6 wood studs of the case study wall system are replaced with I-Joist studs (Alternative 1) with the expectation that a reduced thermal bridging area will lead to better thermal performance. Replacing the case study wall system—with I-Joist wall studs—with one that has 16 in intervals and increased wall thickness is also investigated. Exterior rigid insulation alternatives such as structural insulated sheathing (SIS) and expanded polystyrene (EPS) foam are also investigated in combination with medium-density closed cell foam (sprayed foam) insulation and R20 batt insulation (fibreglass). In addition, based on the hypothesis that reducing opening area will significantly decrease the energy consumption, different window configurations are also simulated for the purpose of performance evaluation. In setting alternatives for window opening area, Building Code article 9.7.1.2., which establishes the general requirement of an unobstructed opening with a minimum area of 0.35 m^2 (3.77 ft^2 or 543 in^2) where no dimension should be less than 380 mm (15 in), is followed (Alberta Building Code 2006).

Parametric study through simulation:

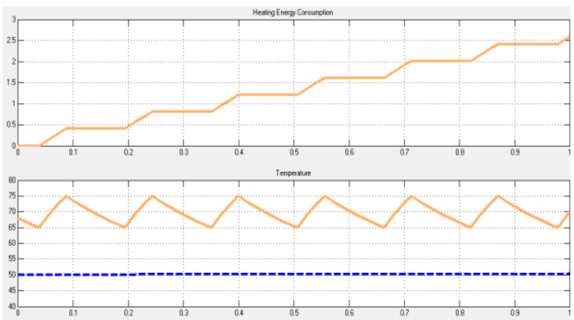
As mentioned in the previous section, along with the case study window and wall configuration, five alternative walls and three alternative window configurations are selected for evaluation. It is observed (Figure 4-31) that changing only stud type (Alternative 1) and insulation type (Alternative 3, 4, and 5) does not affect energy consumption for a small area for a small period of time (1 hour), whereas increased wall thickness and insulation can reduce space heating energy consumption by 150 Wh (Watt-hour) when compared to the original design condition.



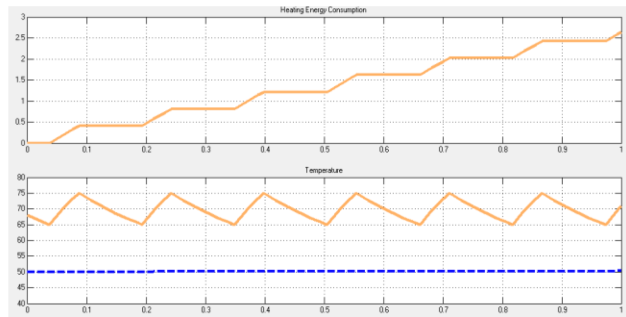
Case study: Window size: 3.7 m^2
Energy consumption: 2.65 kWh



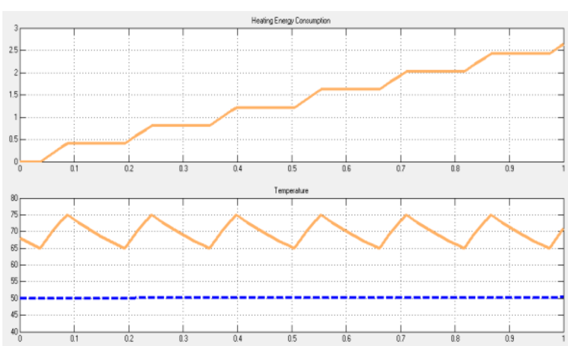
Alternative 1
Energy consumption: 2.65 kWh



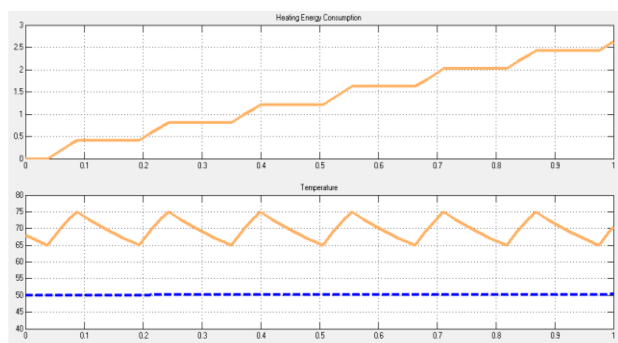
Alternative 2
Energy consumption: 2.5 kWh (saving: 150 Wh)



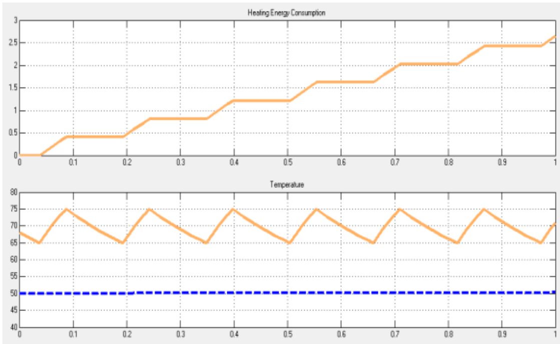
Alternative 3
Energy consumption: 2.65 kWh



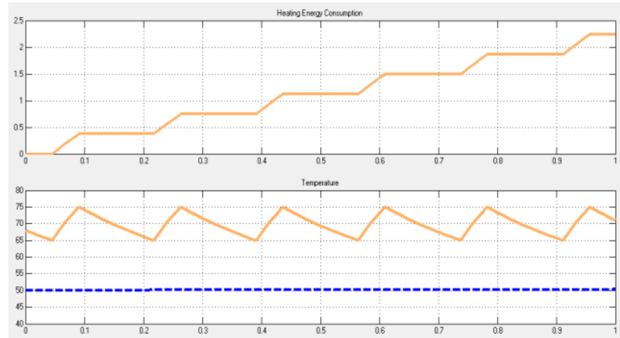
Alternative 4
Energy consumption: 2.65 kWh



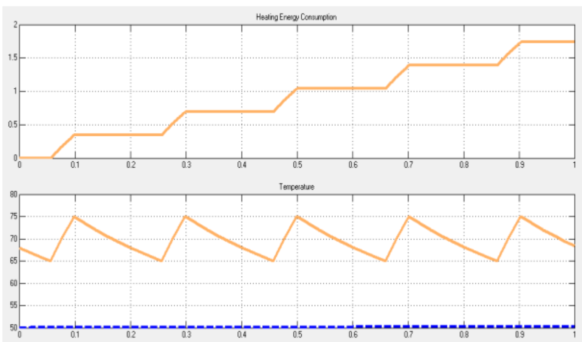
Alternative 5
Energy consumption: 2.65 kWh



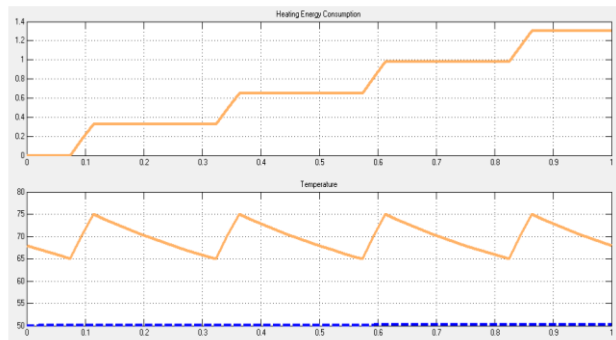
Case study: Window size: 3.7 m^2
Energy consumption: 2.65 kWh



Alternative 6: Window size 3 m^2
Energy consumption: 2.25 kWh (saving: 400 Wh)



Alternative 7: Window size 2.5 m^2
Energy consumption: 1.75 kWh (saving: 900 Wh)



Alternative 8: Window size 2.0 m^2
Energy consumption: 1.3 kWh (saving: 1,350 Wh)

Figure 4-31: Comparison of design alternatives

However, as expected, it is observed that, when compared to the existing design, the design alternatives (smaller opening area) for opening area show better results in terms of energy consumption, ranging in savings from 400 Wh and 950 Wh with Alternative 6 and Alternative 7, respectively, to 1,400 Wh with Alternative 8. While simulating different design alternatives, the energy consumption by heating system is measured when the system has to maintain an indoor room temperature within the range of 18 °C to 24 °C.

As observed from the simulation, even though design alternatives for potential wall configuration do not show much positive effect on energy savings for the case study unit, reducing opening area as a design variable leads to a significant decrease in energy consumption. However, it is recognized that design variables are not interdependent within the context of IEQ, and that changing one design feature to improve one factor of IEQ may significantly affect the other IEQ factors. For example, the decision to decrease opening area can lead to a reduction in heat loss (improved energy efficiency), though with results (reduced daylight) that may not coincide with the original objective.

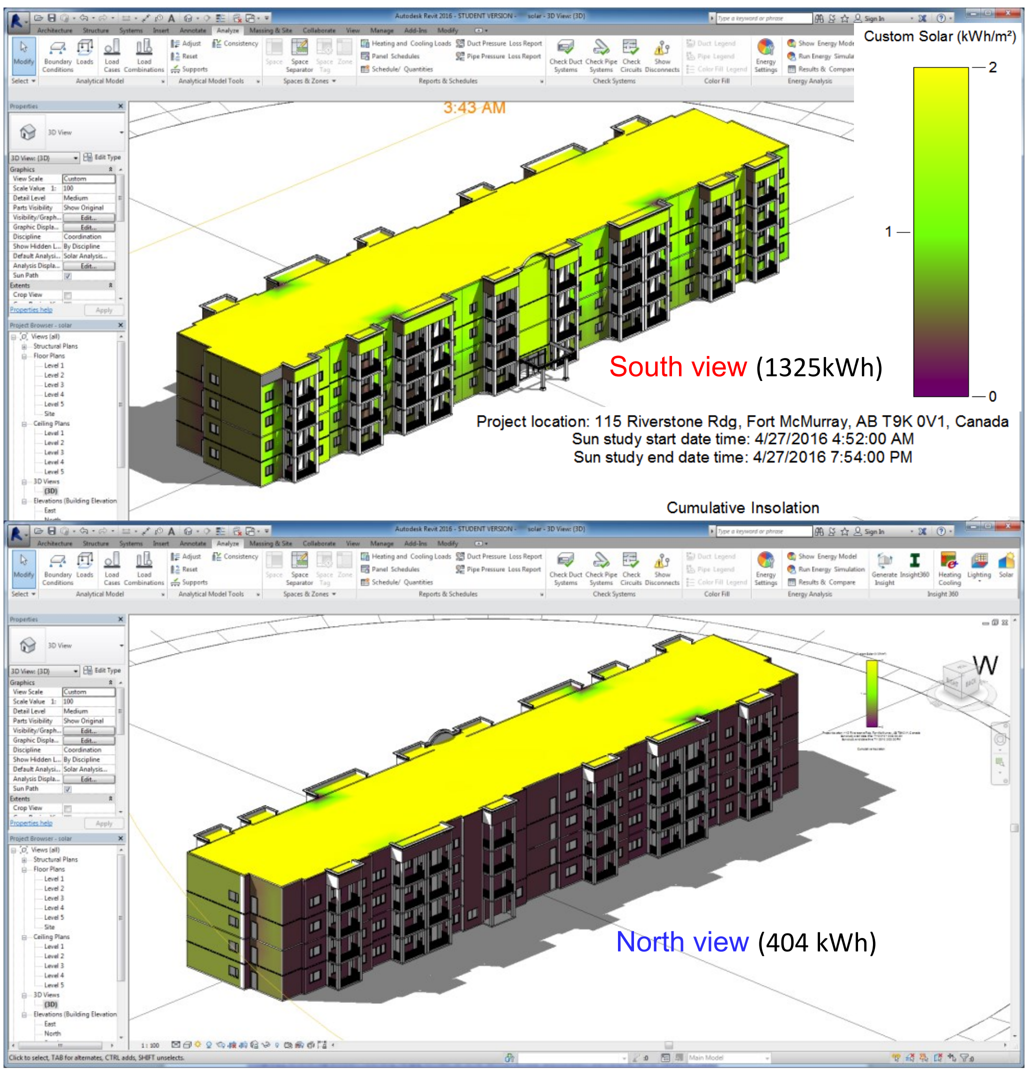


Figure 4-32: Solar radiation incident on the external façade of north and south envelope

Considering the fact (from the mathematical model and Figure 4-32) that daily solar radiation on the external façade of north-facing units is lower (404 kWh) than on south-facing units (1,325 kWh), it is assumed that reducing the opening area in the north-facing units to improve thermal performance will affect the natural indoor illumination level in the case study room. As such, the impact of reduced opening area on daylight inclusion within the case study unit is evaluated as follows.

In order to investigate the nature of the luminous environment (natural illumination level) in the case study room, a simulation model is developed using Revit Daylighting Analysis simulation tool with the design alternatives of window opening (Alternative 6, 7, and 8). The indoor illumination level is recorded at a plane 2.5 ft above the floor level representing the work plane. The following criteria are utilized to provide quantitative judgment of the simulated values:
(1) that the area of the room is below standard illumination levels (300 Lux) (IESNA 2000); (2) that the room is within acceptable illumination level (300 to 500 Lux), which is the recommended level mentioned in IESNA for spaces in which occupants are likely to be carrying out paper-based tasks (IESNA 2000); (3) the pattern of daylight level transmitting from the window into the room; and (4) the maximum and minimum range in each space, which indicates the uniformity ratio within the space and its glare potential.

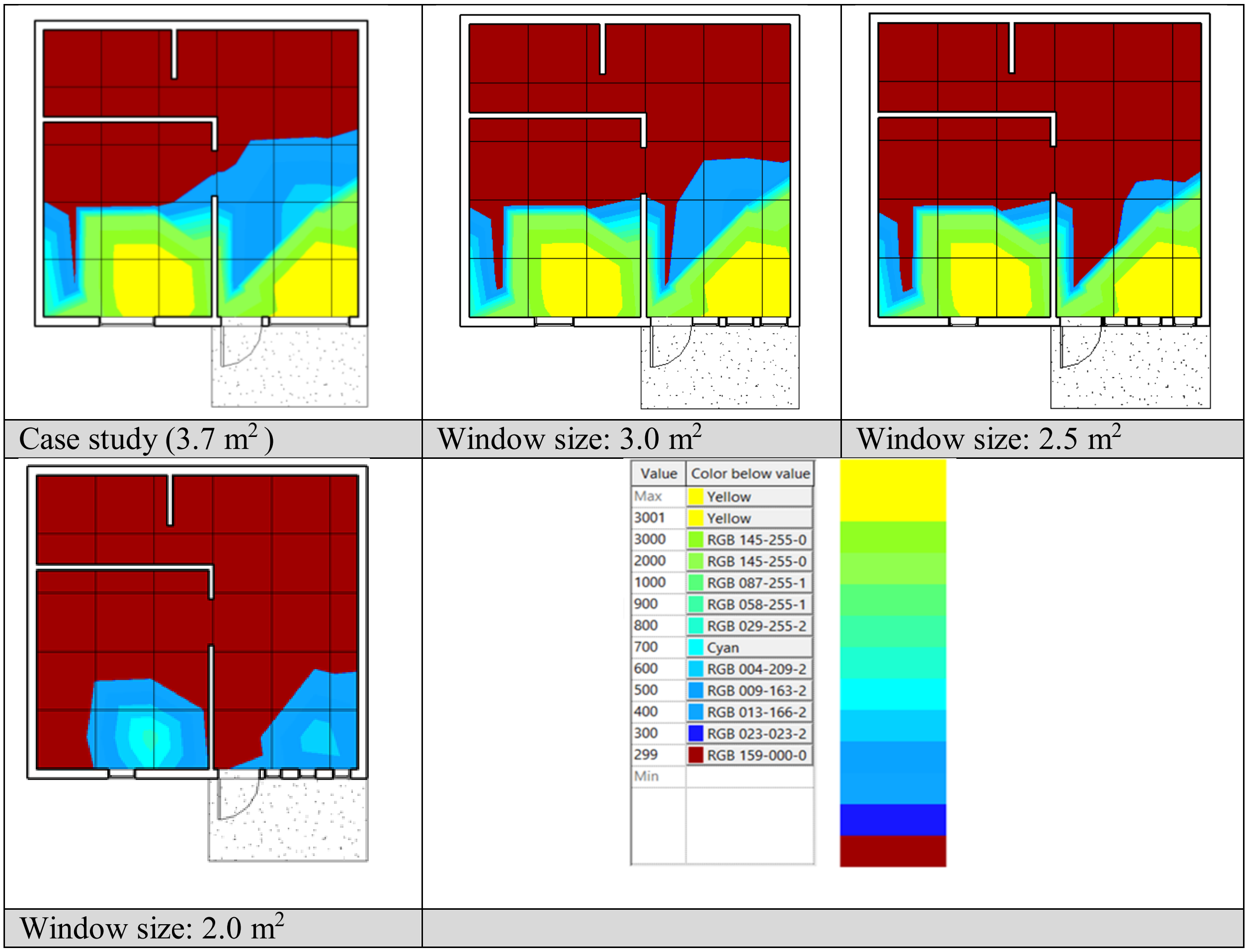


Figure 4-33: Indoor illumination of case study room through simulation

In consideration of all these factors, the simulated results (Figure 4-33) show that Alternative 8 (window area 2.0 m^2) is not able to maintain IESNA standards. However, Alternative 7 (window area 2.5 m^2) can be considered acceptable since most of the workspace in the bedroom and living room receives the required level of illumination. For a layout like the one in the case study unit, it should be noted, it is not expected that the kitchen space and washroom will be provided with natural lighting. However, since different design variables (orientation, layout, building envelope configuration, etc.) are identified to be the reliable influencing factors for energy efficiency in building sectors, holistic understanding (within different phases of the life cycle) of the relationship between different design variables and a facility's energy efficiency is required and should be pursued in future work.

Chapter 5 : RESULT-PERFORMANCE EVALUATION OF OPERATIONAL STRATEGY

As mentioned in the literature review and also as observed in the analysis of the sensor data, there is a gap between the heating energy produced by the building management system (BMS) and the actual heating energy consumed by the occupants, indicating the availability of additional produced energy in the system. It should be considered that this extra available heating energy in the system causes significant heat loss to the surroundings (heat loss through storage tank and supply pipes). Furthermore, producing and maintaining the extra available heating energy in the system causes additional energy consumption from the facility's space heating system. Therefore, this research focuses on estimating optimal heating load in order to produce heating energy proportionally, thereby optimizing the overall space heating energy consumption.

Given the hypothesis that integrating predictive occupant information (along with weather disturbances and thermal performance of building envelope) within a control strategy may assist BMS and facility managers in producing optimum heating energy (by minimizing extra energy), it is expected that the developed predictive user-centric space heating control model (integrating predictive occupant information, weather uncertainty, thermal performance of building envelope) will optimize space heating energy consumption. To validate this hypothesis, this chapter compares the simulation results of the traditional control system with those of the developed optimization control model.

5.1 Comparison and Performance Evaluation Criteria

Given that a higher amount of supplied/produced energy leads to higher energy consumption by the heating system, the controller that uses a lower amount of supply energy (energy production) to meet user demand is considered the better controller in terms of energy efficiency and performance. Therefore, this section compares the amount of supplied/produced energy (to meet user heating demand) between the proposed user-centric control strategy and traditional control schemes.

In carrying out performance evaluations and comparisons by estimating the amount of energy supplied/produced in the system for different control strategies, this research considers two types of energy consumption/usage: (1) the amount of produced/supplied energy that is wasted due to heat loss through the heating distribution pipes or hot water storage tank; and (2) the amount of produced/supplied energy that is actually consumed to meet occupant heating demand in the units. Energy consumption for producing/generating a certain amount of heating energy (that is to be supplied) accounts for a large part of a facility's overall space heating energy consumption, and being able (through the optimization model) to reduce the amount of supply energy (while meeting user demand) will reduce the overall heating energy consumption substantially. However, it should be noted that savings from the decrease in the amount of energy consumption used for producing redundant energy in the system is not considered in the comparison here of the two control schemes.

Moreover, this study does not aim to reduce actual heating energy consumption by compromising occupant comfort choices or actual heating demand. Rather, it aims to reduce the redundant heat available/produced in the system. As such, the comparison between traditional and predictive control strategies is conducted in terms of amount of available/produced heating energy and the amount of available energy in the system.

5.2 Estimating Energy Consumption

With a water-borne heating system, BMS supplies heating energy (hot water) to the users through a radiator coil. The radiator metal is heated from the water flowing through it, and it in turn heats the room air. In this process, the supplied hot water loses its energy (if there is heating demand from occupant), which is defined as the actual heating energy consumption by the occupant. To estimate that energy, this study multiplies the properties of water (e.g., specific heat capacity, density, and flow rate) with the temperature difference between water flowing into and out of the radiator. The expression for estimating actual energy consumed (energy loss or heat dissipation through radiator coil from supplied hot water) by occupants is given in Equation 5-1. Implementation in Simulink of the equation for actual energy consumption of a room is shown in Figure 5-1. As mentioned above, along with the actual energy consumption by occupants in different rooms, this study estimates heat loss through heating distribution pipes and hot water storage tanks. Adding this estimated heat loss through pipes and storage tank with the actual energy consumption, the amount of energy produced by the BMS for different control schemes is determined. The Simulink block for estimating energy production by the BMS is shown in Figure 5-2, where the energy usage at every time-step is summed up in order to estimate the energy consumed over a certain period of time.

$$\sum_{i=1}^{n} Q = \sum_{i=1}^{n} \rho_{w(i)}\, c_{w(i)} [X_{supply(i)} - \{ (1-\alpha(i))\, X_{supply(i)} + \alpha(i)\, X_r \}] \qquad [5\text{-}1]$$

where

Q = Energy consumption

X_r = Radiator metal temperature

X_{supply} = Supply water temperature

X_{return} = Return water temperature

ρ_w = Density of water

c_w = Specific heat capacity of water

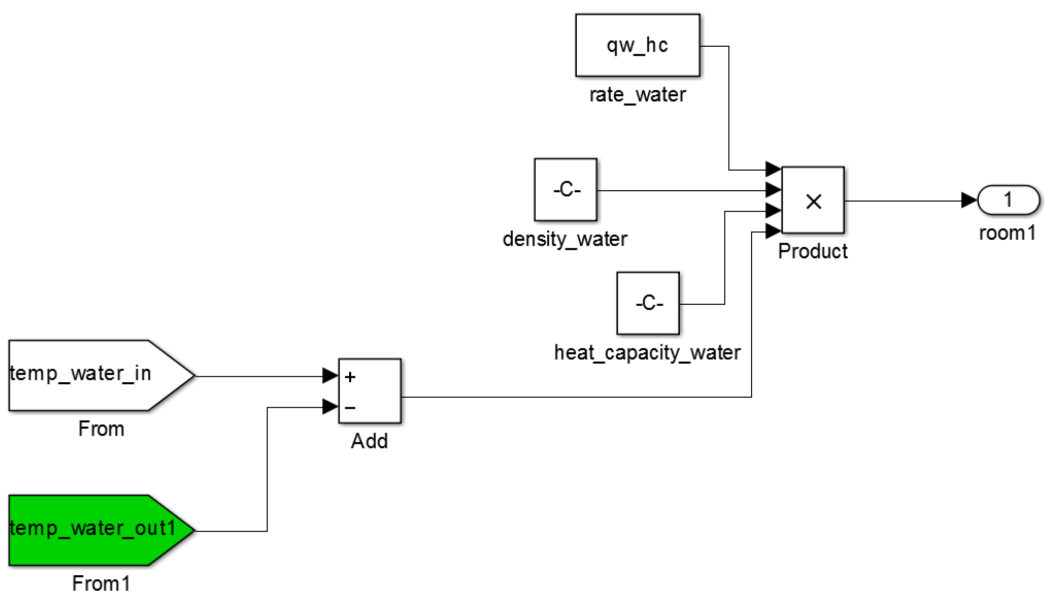


Figure 5-1: Simulink diagram for estimating energy consumption in individual unit

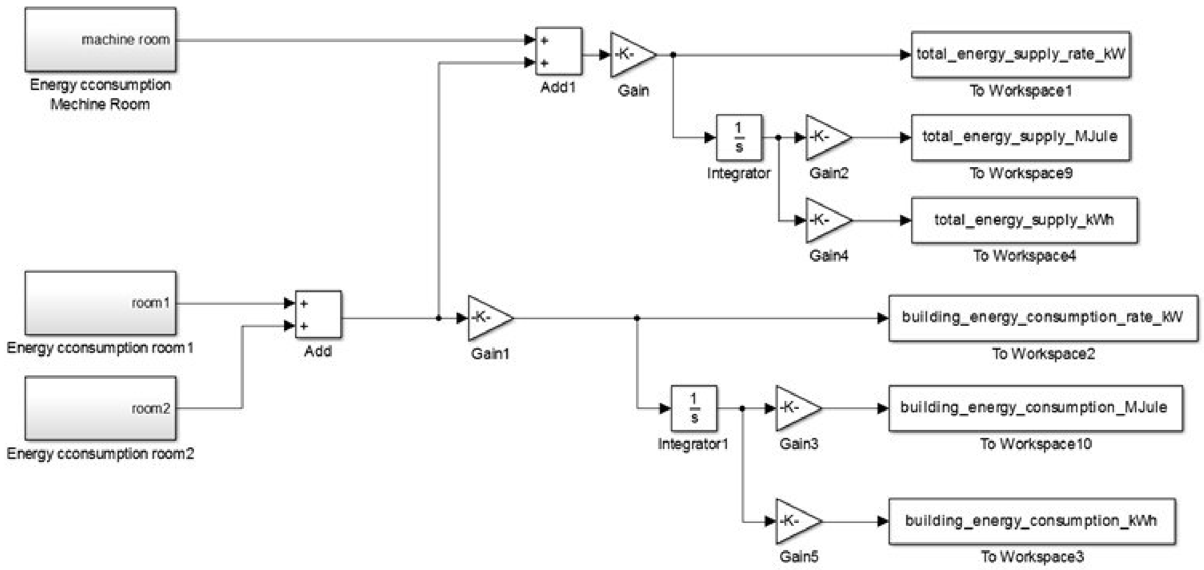


Figure 5-2: Simulink diagram for estimating energy production by BMS

5.3 Results Comparison

Since the developed predictive user-centric space heating control model integrates uncertainty of weather and occupant load (through feedforward connection) within its space heating operational strategy, this section aims to evaluate whether, using the predictive knowledge of uncertainties, the amount of space heating energy production can be optimized and space heating energy consumption compared to the traditional control strategy can thereby be reduced. It should be noted that in some cases predictive knowledge of uncertainty can deviate from the actual state. The performance of the developed model is thus checked (by adjusting with feedback connection) to identify any cases in which the prediction of uncertainty is incorrect. For this purpose, the following cases are considered in order to compare the energy performance of the control strategies.

Case 1: This case is used to evaluate the performance of the developed predictive user-centric space heating control strategy when the space heating controller is assisted with reasonably accurate predictive knowledge of uncertainties. In this case, both the predicted state and actual state of outdoor temperature range from −19 °C to −24 °C. The predicted occupant load and the actual occupant load range from 0 W to 600 W. As can be observed in Figure 5-3, with the predictive knowledge of outdoor air temperature at time 20:00 (which is a drop of outdoor temperature from −21 °C to −23 °C), the developed controller begins optimizing the required amount of supply energy (to maintain the desired comfort choices), and thus begins increasing the amount of supply energy (increase in temperature of supply water) beforehand. The simulation results also validate that the developed controller is capable of optimizing the amount of supply energy required when provided with the predictive knowledge of occupant load, as the developed controller begins decreasing the amount of supply energy (decrease in temperature of supply water) beforehand based on the predictive knowledge of occupant load states at 07:00 and 17:00 (which represents a sudden increase in occupant load from 0 W to approximately 500 to 600 W).

The simulation results show that, with the predictive controller, the amount of energy production follows closely with the actual heating demand, thereby reducing the gap between demand and supply. With the existing traditional strategy, in contrast, the amount of space heating energy production indicates a discrepancy (larger gap between demand and supply) with the holistic actual demand/load. However, the traditional strategy tracks the weather load precisely. Since the existing control strategy is designed to consider only current outdoor temperature while producing/supplying heating energy, as observed in Figure 5-4 the traditional controller increases the temperature of the supply water (increase in the energy production) once the outdoor temperature decreases below a certain temperature (previously set). This is not assisted by any predictive knowledge of weather load, occupant load, or thermal performance. Therefore, even with a lower occupant heating demand state, the traditional controller estimates higher supply need considering only the current state of the lower outdoor temperature in the time periods 07:00 to 09:00 and 17:00 to 20:00. With the outdoor temperature ranging between −21 °C and −23 °C, the traditional controller supplies 65 °C hot water for space heating. The predictive controller, meanwhile, by taking advantage of the presence of internally generated heat and actual thermal performance, reduces the supply water temperature to ~45 °C. Because of the presence of extra heat, the valve opening in the traditional controller is 0.13, whereas, the valve opens to full efficiency (1.00) based on the optimized heat with the predictive controller. The large gap (see Figure 5-4) between the supply and demand indicates that the amount of heating energy produced with the traditional control strategy is redundant as opposed to the actual heating need, which causes significant heat loss through surroundings, thus causing higher heating consumption from facility.

Estimation and comparison of the total heating energy produced/supplied (by BMS) through the controllers for a period of 24 hours show that the traditional controller consumes 230 kWh of heating energy, whereas the predictive controller consumes 140 kWh, a savings of 90 kWh of energy per day (Figure 5-5). The results observed from case 1 validate that the existing traditional control strategy is unable to take advantage of knowledge pertaining to a lower occupant demand state, thus resulting in the production of more energy than needed. Considering that the traditional controller increases the supply water temperature with lower outdoor temperature whereas the user-centric predictive controller takes advantage of the occupant load when determining supply water temperature, a significant difference can be expected in the performance of the two controllers when the outdoor temperature falls below a certain temperature (previously set), and internally generated heat is present.

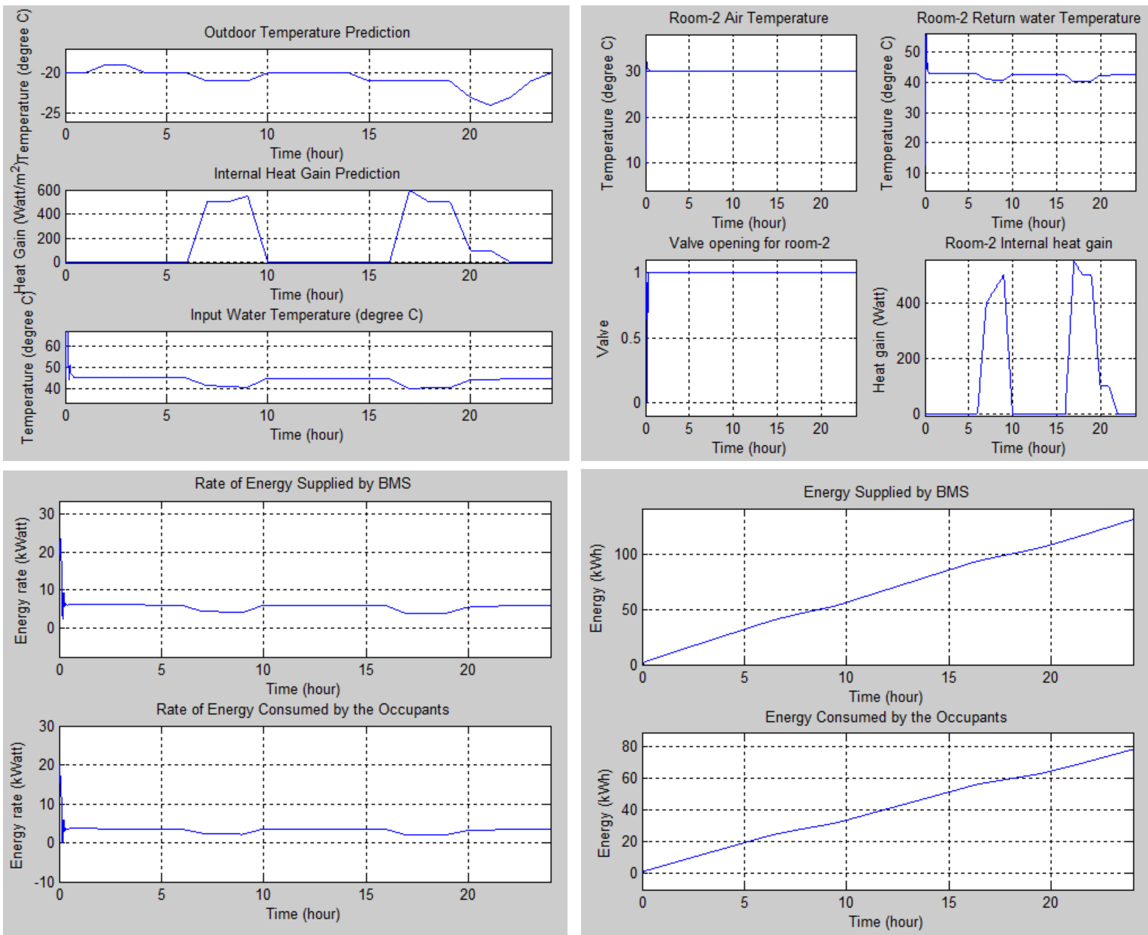


Figure 5-3: Simulation results for user-centric predictive strategy (Case 1)

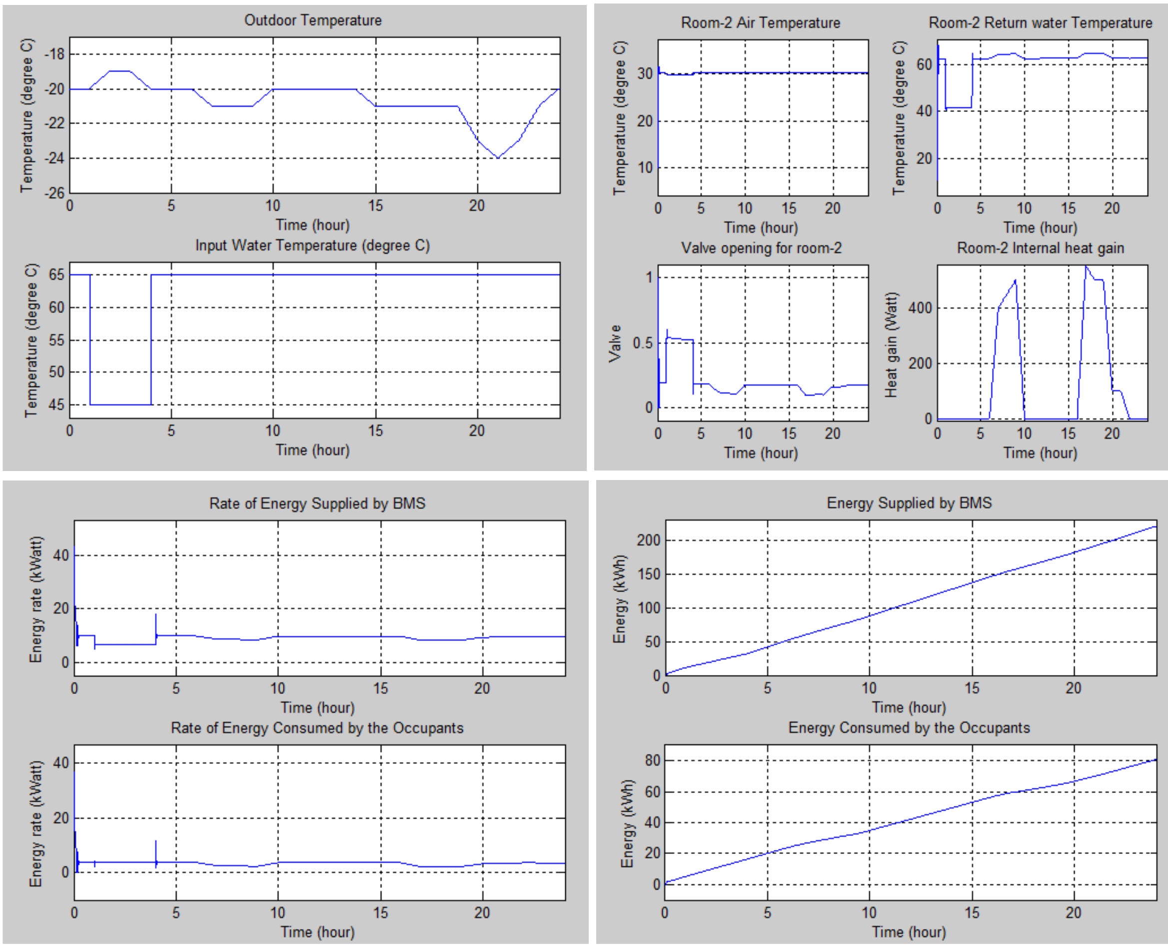


Figure 5-4: Simulation results for traditional strategy (Case 1)

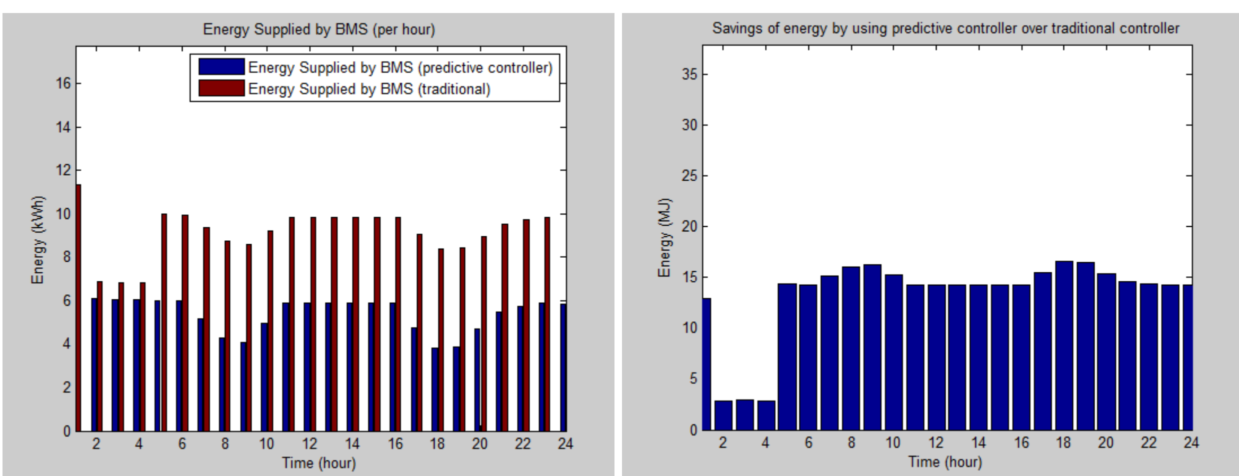


Figure 5-5: Comparison of energy consumption between traditional and user-centric predictive control strategies (Case 1)

Case 2: As mentioned above, it is possible that the predictive knowledge (of uncertainties in weather or occupant load) will deviate from the actual state. A case is thus simulated in order to evaluate how the developed predictive controller performs while adjusting the model (through feedback) to address the deviated predictive knowledge without affecting occupant comfort. As observed from Figure 5-6 and Figure 5-7, in case 2, the developed controller is fed incorrect predictive information (intentionally for simulation purposes) of an outdoor temperature of −20 °C (meaning that, expecting lower weather load / supply need by 16:00), whereas during that time (at 16:00) the actual outdoor temperature is recorded as −21 °C (greater supply energy need). In addition, in another time period (05:00) (Figure 5-7) the controller is provided with an incorrect prediction of occupant load of 450 W (meaning that, a lower heating need from occupant is expected), while the actual state of occupant load is zero (meaning that, in reality, no advantage from internally generated heat will be achieved). From the simulation results, it is observed that the controller begins optimizing the amount of supply energy (temperature of supply water) based on the predictive knowledge of the uncertainty (Figure 5-8). However, it can adjust the temperature effectively soon enough to ensure occupant desired comfort choice.

As in the previous case, the large gap (observed in case 2, Figure 5-6) between the supply and demand indicates that the amount of heating energy produced by the traditional control strategy is redundant as opposed to the actual heating need, thus causing a valve opening in the range of 0.13 to 0.2 in the traditional controller. In contrast, the valve opens to full efficiency (1.00) based on the optimized heat with the predictive controller. Moreover, estimation and comparison of the total heating energy produced/supplied by the BMS through the controllers for a period of 24 hours show that the traditional controller consumes 250 kWh of heating energy, whereas the predictive controller consumes 150 kWh, a savings of 100 kWh of energy per day. The results for case 2 validate that the developed predictive control strategy is able to adjust the model (through feedback) to deal with any incorrect prediction, resulting in optimal energy production.

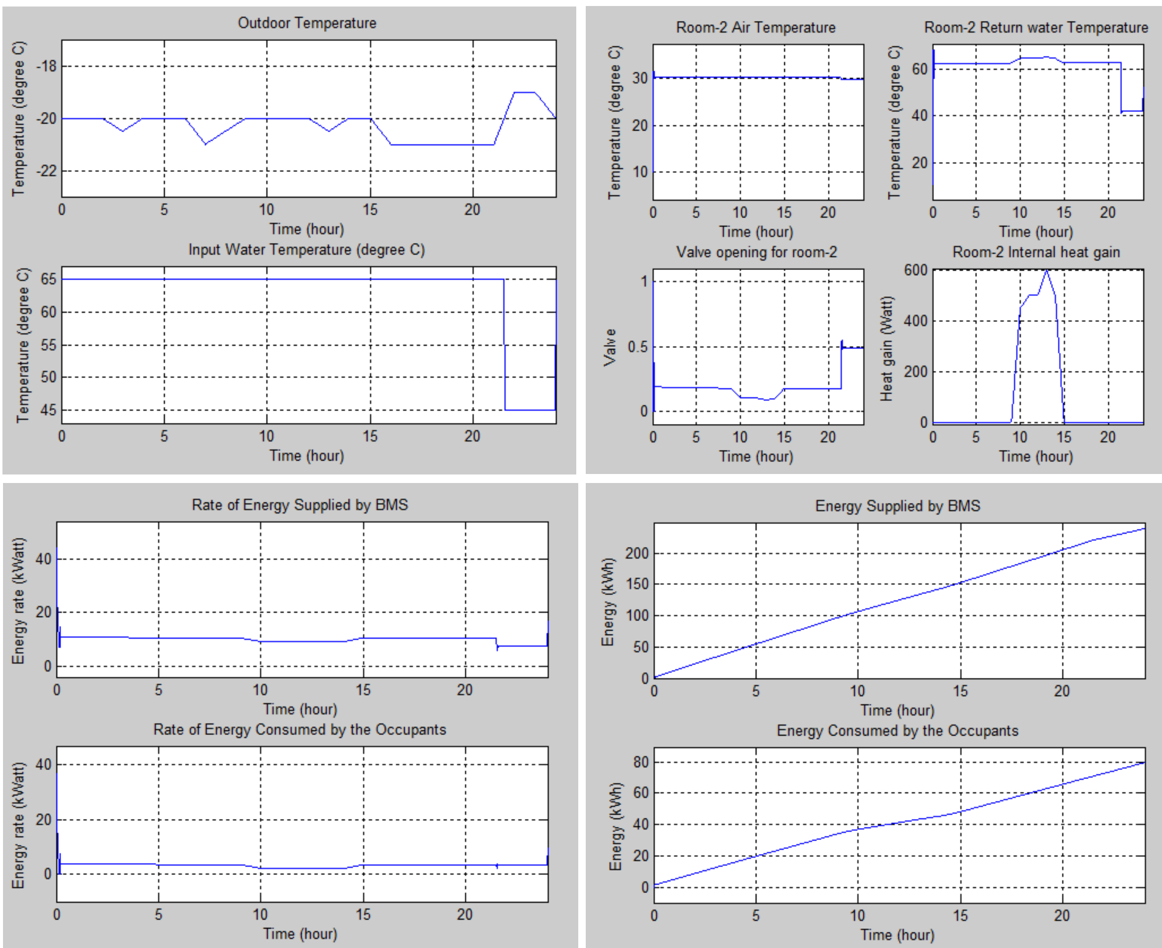


Figure 5-6: Simulation results for traditional strategy (Case 2)

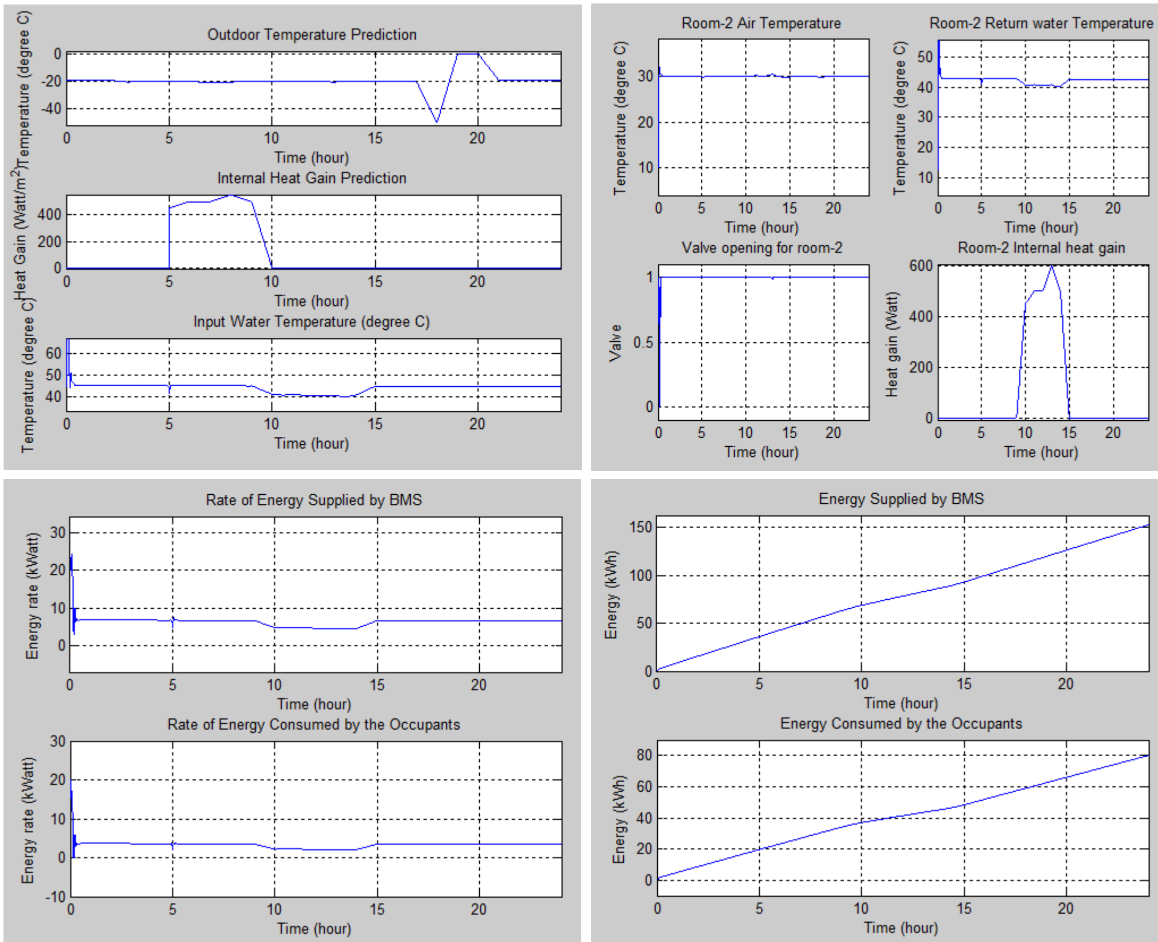


Figure 5-7: Simulation results for user-centric predictive strategy (Case 2)

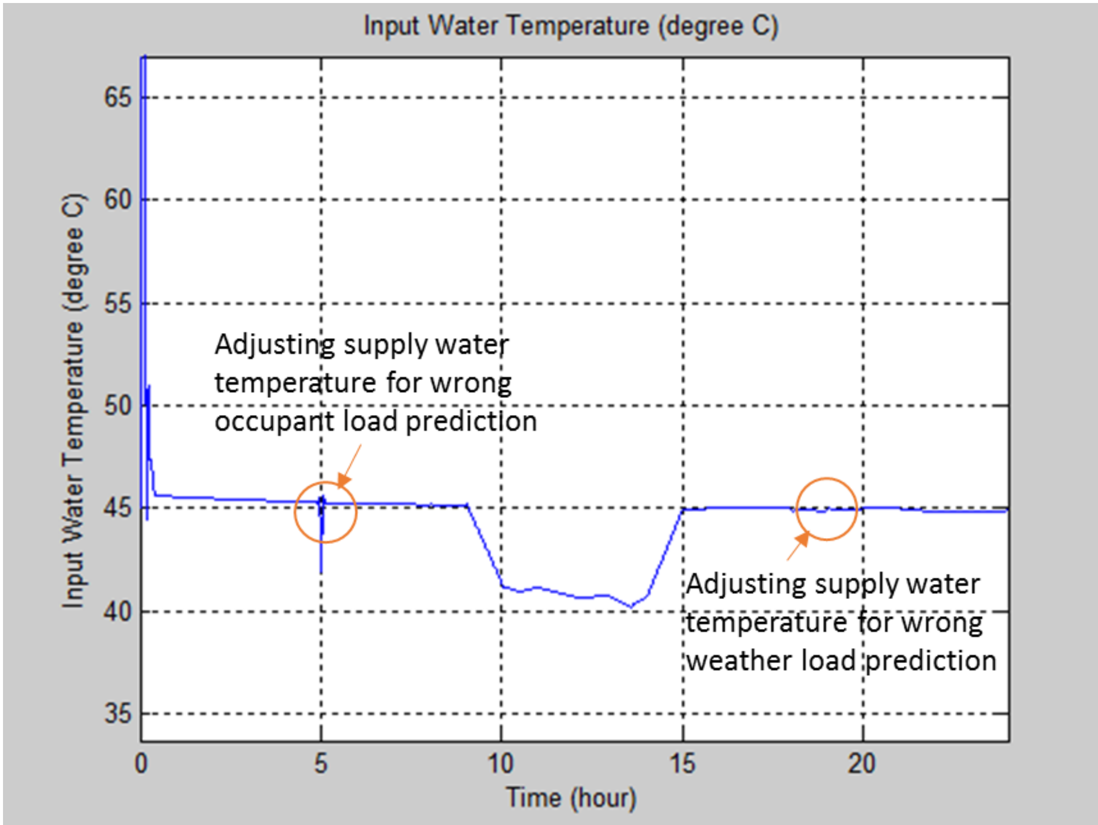


Figure 5-8: Supply water temperature for user-centric predictive strategy (Case 2)

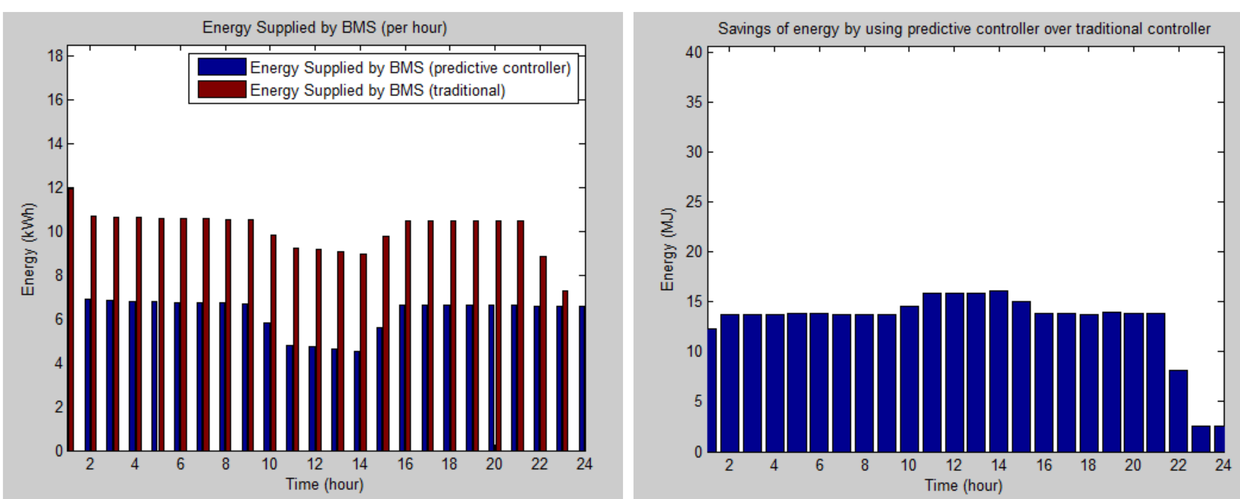


Figure 5-9: Comparison of energy consumption between traditional and user-centric predictive control strategy (Case 2)

Chapter 6 : CONCLUSION

In recent years, many approaches have been undertaken to develop energy-efficient control strategies (for indoor temperature control) to reduce space heating energy consumption. One of the challenges in developing energy-efficient space heating control and operational strategies is to strike a balance between meeting user heating demand while reducing space heating energy consumption. In most cases, to ensure user comfort, practitioners design and develop control strategies based on the worst-case scenario. This approach of operating a space heating model at its full design load (ignoring the facility's actual heating demand state) results in over-consumption of energy.

Some control strategies (mostly for commercial facilities) have attempted to take into account user information, and including this information within space heating control strategy has been observed to reduce space heating energy consumption. However, in terms of developing a user-centric control model, there are some distinct dissimilarities (with respect to user patterns) between multi-family residential facilities (characterized by uncertainty in schedule, including varying demand load from varying households with varying comfort choices, and multiple desired set-point temperatures at any given time) and commercial facilities (characterized by comparatively fixed schedule and comparatively known/predictable user demand load patterns). This study thus provides a unique framework for developing a user-centric space heating control/operational strategy for multi-family residential facilities in cold-climate regions. The following section discusses the contributions made in this study.

6.1 Contributions

Developed data analysis framework for identifying the relevant factors affecting multi-family residential facility's space heating energy consumption:

Given that a multi-family residential facility poses several challenges (due to the complex nature of occupant usage patterns) when developing an energy-efficient user-centric space heating operational strategy, this research develops a comprehensive approach based on the following three steps: (1) identifying the relevant factors affecting a multi-family residential facility's space heating energy consumption through a sensor-based occupancy-phase data analysis framework; (2) following the observation made from the data analysis, defining the scope to address challenges related to multi-family facility space heating energy consumption; and (3) assisting facility managers and BMS with user-centric energy management strategies for optimizing space heating energy consumption from multi-family residential facilities in cold-climate regions.

This research demonstrates the data analysis framework to improve understanding of the nature of and issues related to a multi-family residential facility's space heating energy consumption during occupancy. The data analysis framework focuses on establishing correlations among occupant activities (through energy usage data), weather conditions, indoor air quality, heating energy consumption, and efficiency of the heating system. Then, based on the extracted information, the framework assists in determining appropriate measures for optimizing a multi-family residential facility's energy consumption by addressing (1) thermal performance of the building envelope, (2) energy usage patterns of the occupants, and (3) operational strategy.

A framework to develop a multi-family residential facility's occupant pattern model: (*to be considered within space heating control strategy)*

This research develops an occupant pattern model for predicting a multi-family residential facility's next-state occupant load with relevant occupant information to be incorporated into the user-centric space heating control strategy (for optimizing energy consumption). Considering the challenges pertaining to (a) extracting relevant occupant information (privacy concerns, cost of installing and maintaining sensors in all the units of a multi-family facility), and (b) the complex nature of occupant patterns (characterized by uncertainty in schedule, and variance in demand load from household-to-household), this research introduces a framework that focuses on identifying occupant factors (analyzing correlations between occupant pattern and space heating energy consumption) through a sensor-based energy usage monitoring approach (considering motion camera can cause privacy concerns) from sample representative groups (considering the cost for installing and maintaining sensors in all the units). Categorization of sample representative groups is carried out by first selecting sample case study units (based on physical characteristics) and later grouping them (based on energy usage pattern) as sample energy usage groups representing the energy usage patterns of a multi-family residential facility. Following the development of a framework for identifying the occupant factors that have a significant correlation with occupant load, this study adopts a unique approach of considering occupant energy usage pattern as well as heat pump performance in order to measure occupant load. This approach includes predicting the pattern of (a) internally generated heat associated with occupant activities (by learning the pattern of energy usage and CO_2 level from sample representative group), and (b) the heating demand pattern of the building (by learning the pattern of heat pump performance); based on the predicted information, this approach estimates the next-state occupant load to be considered for producing/supplying heating energy to the multi-family residential facility. To the best of the author's knowledge, the approach adopted in this study to develop a framework for multi-family residential facilities to predict the next-state occupant load (by systematically considering internally generated heat associated with occupant activities, CO_2 level associated with occupant presence, and heating system SP and FR state associated with the building's holistic demand state) is a unique approach in the literature.

A framework to develop user-centric predictive post-design space heating control strategy for multi-family residential facility:

As mentioned above, considering only current outdoor temperature and ignoring occupant information (such as occupant load) in space heating control strategy makes the system inefficient and leads to the consumption of more heating energy than is necessary. For the purpose of developing a user-centric space heating model that considers occupant heating load (along with weather load and thermal performance of building envelope) while producing/supplying heating energy, this study develops a framework to optimize the amount of supply energy (set-point temperature of the supply water). The proposed framework makes the system more energy-efficient, reducing energy consumption by preventing redundant heating energy production and the excess heat loss through the surroundings).

Considering the issues inherent in developing a user-centric space heating model for a multi-family residential facility, this research establishes a framework for the development of a controller with feedforward connection that considers predictive knowledge of uncertainties (given that the heating system, unlike lighting control, is not a fast-reacting system); feedback connection (since prediction can deviate from the actual state); and a unique approach of taking error (difference between desired comfort choice and current state) as the feedback (given that a multi-family facility receives multiple set-point temperatures at any specific time) to ensure occupant comfort. To the best of the author's knowledge, this is the first attempt in the literature to develop a framework for multi-family residential facilities that adopts a sensor-based monitoring approach to study occupant energy usage pattern and system efficiency, and then integrates the multi-family residential facility's occupant load pattern (along with weather uncertainties and thermodynamic performance of building envelope) within a space heating control/operational strategy for developing a user-centric predictive space heating control model for multi-family residential facilities in cold-climate regions.

6.2 Suggestions and Future Scope

Strategies are developed in this research to aid the decision-making process with regard to building energy management and occupant comfort. The author in this study suggests implementing these strategies (some as current and some as future scopes) for the purpose of optimizing the amount of space heating energy consumption as well as overall energy management while sustaining occupants' comfort.

Adjusting the set-point temperature of supply water temperature:

This study develops a post-design user-centric predictive space heating control model by facilitating a method for facility managers and BMS to interact with occupants' information (along with weather uncertainty and thermodynamic performance). The author suggests implementing the developed predictive user-centric control model in a multi-family residential facility's heating system, with the expectation that optimizing the amount of space heating energy production (the set-point temperature of the supplied water) will make the system more energy-efficient by preventing redundant heating energy production and excess heat loss through the surroundings.

Improving thermal performance of building envelope (for future design reference):

The observed relationship between heat flux and heating energy consumption is such that, in general, units with higher heat flux have higher heating energy consumption. Since the comparatively lower thermal performance of north-facing units of the case study facility is observed to have a significant impact on the space heating energy consumption of north-facing units, suggestions are made for improving thermal performance of the north-facing building envelope through efficient strategies (for future reference during the design phase). This study investigates the thermal performance of different design alternatives (different wall and opening configurations) for north-facing building envelope in order to determine the extent to which changing the thermal parameters of wall systems and the configurations of openings can reduce thermal loss and improve efficiency in north-facing building envelope. It is found that changing wall configurations (increasing thickness of the insulation with I-stud and air gap) can reduce space heating energy consumption by 150 Wh. In addition, it is observed that, when compared to the existing design, the design alternatives for opening area show better results in terms of energy efficiency, with savings ranging from 350 Wh to 850 Wh. Therefore, the author suggests using different design alternatives (different wall and opening configurations) for north-facing units in future design.

Adjusting room set-point temperature during absence of occupants:

Long-term absences (e.g., vacancy) and short-term absences (e.g., vacation), which are a common phenomenon in multi-family residential facilities, point to the possibility of relatively lower heating demand compared to full heating load of a facility. Researchers at the Canadian Centre for Housing Technology identify that a significant amount of energy savings can be achieved through thermostat temperature settings; 13% reduction in gas usage and 2.3% savings in electricity usage can be achieved by setting the temperature to 16 °C when the dwelling is unoccupied, for instance (Canada Mortgage and Housing Corporation 2005). Since the developed space heating control model in this study takes error (difference between desired room temperature and current room temperature) as feedback to optimize the amount of energy production, this study suggests that reducing the desired set-point room temperature in the units (with long-term and short-temp absences) will reduce the space heating energy consumption. Therefore, the author proposes integrating the absence information within a space heating energy management strategy to optimize the amount of energy production and supplied energy.

The developed occupant pattern prediction model predicts the next-state indoor CO_2 level from sample representative groups (indicating presence/absence of occupant). However, it should be noted that learning occupant presence/absence patterns for each individual unit requires the installation of sensors in all the units, which may not be feasible considering the installation and maintenance costs. Therefore, this study alternatively suggests that building management take measures to promote energy-saving behaviour (reduced thermostat temperature settings while not present) among occupants. In this regard, real-time energy feedback information can be a powerful impetus for behavioural change.

Appliance scheduling:

Based on the analysis conducted with the monitoring data, it is observed that occupant activities occasionally follow weather- and time-dependent energy usage patterns. It is observed that (as discussed and demonstrated in section 4.3), the developed time-ordered occupant energy usage pattern model can predict upcoming actions using observed historical data. It can be expected that the developed time-ordered occupant energy usage pattern model will assist in the development of a BMS that estimates future energy demand, and that the predictive energy demand estimation can be used to develop an appliance scheduling scheme by taking advantage of the time-varying retail pricing of electricity.

Setting different usage limits for different user groups:

In many cases, utility costs (space heating, electricity) are included in monthly rental costs of a given unit in a multi-unit facility. Thus, unlike with single-family detached homes where occupants pay for utilities in addition to mortgage or rental costs, tenants in multi-family facilities may not have a financial incentive to reduce energy consumption (Levinson 2004). Studies indicate that tenants behave differently when they rent apartments with utilities included, as opposed to having to pay energy costs separately from rent (Sjögren 2007). In this context, the present study suggests a separate utility payment for the units of multi-family facilities. The present research investigates the energy usage pattern for different user groups (while defining sample representative groups for occupant model) in order to identify the impact of unit size (floor space) unit height (floor level), and directional orientation on energy usage. Based on the extent of these influencing factors, the BMS and facility managers can suggest different energy usage limits for different user groups, and can pursue appropriate measures if the energy usage continuously exceeds the established threshold of energy usage.

Automated ERV usage and behavioural awareness:

Studies show that elevated CO_2 levels may cause health problems (Wyon and Wargocki 2006). In the case study building it is identified that units with higher ERV usage have relatively lower CO_2 concentration, while units with lower ERV usage have higher CO_2 concentration (Sharmin et al. 2014). Since the ERV system is operated manually in the case study building, it is believed that lack of awareness of how to effectively use the ERV system has influenced the higher indoor CO_2 level. This study suggests that the units with higher CO_2 levels and the corresponding influencing factors be monitored and identified on a continuous basis, and that necessary steps be taken such as enforcing the usage of ERV in the interest of occupant health. As mentioned above, the developed occupant pattern prediction model is able to predict next-state indoor CO_2 level from sample representative groups (as Figure 4-18 shows that hours 19:00 and 20:00 indicate non-standard indoor CO_2 level). However, as an alternative to installing sensors in each unit of a multi-family facility (considering the high cost of installation and maintenance of the sensors), this study suggests that building management encourage behavioural awareness of the users.

The framework presented in this study demonstrates a sensor-based occupancy-phase data monitoring approach that, by identifying and establishing the relationships among various measured components, determines the influencing factors pertaining to any inefficiency in the energy performance of a multi-family residential facility. Thus, by identifying correlations among occupant load pattern, thermal performance of building envelope, operational strategies, and their association with energy consumption, it extracts useful information to assist facility managers and BMS in improving system efficiency. The knowledge generated from this study can be further applied to predict occupant electricity load (to operate different appliances) and, by aggregating the energy demand for all occupants in the multi-family building, can assist with the development of an appliance scheduling scheme based on time-varying retail pricing. Furthermore, as suggested in this section, installing sensors to all the units is expected to result in changes in building operations (automated ERV usage to maintain standard indoor CO_2 level, thermostat control by BMS in case of long vacancy) through the use of controls that automatically adjust to environmental requirements. The knowledge can further be used to improve thermal performance of building envelope for future design reference.

It should be noted that the major contribution of this study is the development of the integrated predictive user-centric space heating control model for multi-family residential facilities in cold-climate regions. The developed model in this study holistically considers the uncertainty related to occupant load (with the multi-family residential facility occupant pattern prediction model developed in this thesis), along with weather uncertainty and thermodynamic performance. This forms the basis upon which to estimate actual heating load of the multi-family facility and thereby optimize the space heating energy production. Through the combination of this knowledge, facility managers and BMS will be able to minimize the consumption of energy resources while maintaining a comfortable IEQ level. It is expected that the approach demonstrated in this research can be applied within a multi-family residential facility's energy management system to achieve financial and environmental benefits.

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