Doctor of Philosophy

Context-based Control Strategies for Improving Energy Efficiency in Multi-zone Buildings

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Abstract

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With the increasing concern about energy saving, demand-side management has been widely implemented during the building life cycle. In the design phase of buildings, technical improvements in the insulation of its envelope and the efficiency of mechanical and electrical equipment significantly contribute to energy saving in building. Also, the energy-efficient operation of mechanical and electrical equipment is a permanent solution to

achieve energy saving in the operation phase of buildings. Among these alternatives, recent efforts have focused on the operational solution due to a significant energy saving potential with relatively less effort.

Due to the importance of control strategies in demand-side management, a substantial amount of studies has been conducted to investigate the amount of energy saving from heating, ventilating and air conditioning (HVAC) scheduling techniques in buildings. Unfortunately, despite the previous achievement, the two main problems still exist in establishing optimal HVAC control strategies in multi-zone buildings. First, almost all studies have scheduled the operation of HVAC systems at the zone level. Although the zone-based HVAC scheduling provides a significant reduction in energy consumption, there still remain limitations in maintaining occupants' thermal comfort. This is because a zone may consist of multiple rooms having different energy use patterns. Furthermore, its practical applications are limited due to a time-consuming process to set up control parameters in multiple zones. Second, little is known regarding the effect of contextual variables on energy saving from HVAC scheduling techniques in multi-zone buildings. Although only few studies have investigated how dynamic environment-related variables affect energy saving from HVAC scheduling techniques, they assumed that all zones have identical energy use patterns.

Thus, it is impossible to establish optimal control strategies that can maximize energy saving from HVAC scheduling techniques in in multi-zone buildings.

As an effort to address these problems, this research aims to investigate how temporal and weather variables affect energy saving from HVAC scheduling techniques in multi-zone buildings. In order to achieve this objective, representative end-user groups (EUG) are identified in dormitory buildings of a university in Seoul, South Korea. Then, the following two models are developed depending on their purposes. First, a data mining-based model is constructed to predict baseline energy consumption for EUGs. Second, a thermodynamic model is developed to simulate post-retrofit energy consumption under controlled conditions by HVAC scheduling techniques. Then, based on the developed models, energy performance simulation is conducted to evaluate the amount of energy saving from HVAC scheduling techniques in different temporal and weather contexts.

From the results of energy performance simulation, the two key findings are summarized as follow. First, global temperature and on/off control of HVAC systems, as HVAC scheduling alternatives, produce the significant amount of energy saving in the case buildings. This implies that the buildings exhibit characteristics of low energy efficiency in heating seasons. Second, the HVAC scheduling techniques produce different energy saving potentials

depending on outdoor temperature and course period. In other words, this indicates that establishing optimal control strategies is dependent on the given contexts. However, there is not always a consistent relationship between contextual variables and optimal HVAC control strategies in multi-zone buildings.

The main contribution of this research is to improve our understanding of the effect of temporal and weather variables on energy saving from HVAC scheduling techniques in multi-zone buildings. More specifically, this research provides a first look into the contextual behavior of representative end-user groups in multi-zone buildings. Additionally, this research contributes to an enhancement of the knowledge about how the characteristics of representative end-user groups affect the performance of building energy use prediction. Lastly, the developed models enable facility managers to schedule the energy-efficient operation of HVAC systems without compromising occupants' thermal comfort in multi-zone buildings.

Keywords: Energy Saving, Demand-Side Management, Multi-Zone Building, Control Strategy, Data Mining, Machine Learning, Energy Simulation

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Chapter 1. Introduction

1.1 Research Background

The environmental crisis has engendered concern for energy saving in buildings (Metz et al. 2007). In the United States and Europe, buildings contribute 40% of the total energy used in those countries (EIA 2012; EC 2015). In Asian countries, the building sector is responsible for 18% in South Korea (KEMCO 2014), 26.5% in China (Chena et al. 2011), and 25% in Japan (ECC 2013). Although the percentage of building energy use varies by country, it is obvious that the building sector is a significant final energy consumer, and is thus required to reduce its energy consumption.

During the past few decades, much attention has been given to demand-side management (DSM)[1)] to mitigate the environmental impact of energy consumption in buildings. Basically, the DSM can take the following two measures. The first measure includes technical improvement, such as enhancing the insulation of the building envelope (Romani et al. 2015), and purchasing high efficiency mechanical and electrical (M/E) equipment, such

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[1)] Demand-side management is defined as a means of modifying or reducing the overall energy demand (Kiliccote and Piette 2006).

as heating, ventilating and air-conditioning (HVAC) systems (Gustafsson et al. 2014). The second measure corresponds to the operational solutions that can be used during the operation of buildings, such as control strategies of M/E equipment (Escrivá-Escrivá et al. 2010), and occupants' behavioral change toward energy saving (Iyer et al. 2006).

Among these approaches, recent studies have focused on control strategies due to a significant energy saving potential with relatively less effort (Zeng et al. 2015). According to the results of empirical experiments (Lindelö and Morel 2006), occupied commercial buildings spend excessive energy due to the unnecessary usage of lightings in the day time. The substantial amount of energy is also spent by turning HVAC systems on during unoccupied hours (Anderson et al. 2015; Masoso and Grobler 2010). These observations indicate that a significant amount of energy can be reduced by controlling the operation of M/E equipment (e.g., interrupting the operation of HVAC systems while unoccupied, adjusting supply air temperature of HVAC systems during occupied periods). Furthermore, despite the technical improvement in building's physical characteristics and M/E equipment, there would still remain energy overconsumption if end-users are not responsible for utility cost (e.g., occupants in commercial buildings).

Given the importance of control strategies in demand-side management, a substantial amount of studies has been investigated the performance of HVAC control strategies in buildings. This is important because HVAC systems account for more than 50% of the energy consumed in buildings (EIA 2011). Further, this has been prevalent due to the fact that the energy-efficient operation of HVAC systems on average contributes to 20% of energy consumption in buildings.

In the extensive literature on HVAC control strategies, the main goal is to minimize energy consumption while maintaining indoor environment within an acceptable thermal comfort range. This is important because built environment significantly affects the health and productivity of the occupants (Dounis and Caraiscos 2009). As a consequence, several HVAC scheduling techniques have been examined to establish optimal control strategies that can maximize energy saving in buildings. The most common HVAC scheduling technique is to adjust global temperature setpoint for improving energy efficiency in buildings. As summarized by Yang et al. (2014), HVAC energy consumption was reduced by 6% to 33.6% against the reference period. Also, on/off control of HVAC systems has been widely discussed to avoid energy overconsumption in unoccupied buildings. For example, Escrivá-Escrivá et al. (2010) has confirmed that the four basic on/off control strategies provide a significant potential to reduce the amount of electrical energy. In recent years,

with a development in smart metering systems, much attention has been given to HVAC controller algorithms, which provide operating environments for HVAC control (Haniff et al. 2013). Compared to the conventional algorithm (SBC) which is dependent on predefined occupancy schedules, the rule-based controller (RBC) operates HVAC systems depending on real-time occupancy measurements. Further, model predictive controller (MPC) optimizes the operation of HVAC systems with respond to future environmental change (e.g., occupancy status, outdoor temperature) (Dobbs and Hencey 2014).

1.2 Problem Statement

Unfortunately, despite the previous achievement, the two main problems still exist in establishing optimal HVAC control strategies in multi-zone buildings.

First, occupants' thermal comfort is rarely addressed when establishing HVAC control strategies in multi-zone buildings. In general, the main goal of HVAC control strategies is to maximize energy saving without compromising occupants’ thermal comfort. This is important because buildings have various end-user groups which spend a different amount of energy over time. Kwac et al. (2014) has observed that 20 most frequent load patterns exist among

households although their buildings are used for a single purpose of residence. Further, as discovered by Miller et al. (2015), educational and commercial buildings consist of several performance clusters that are characterized by daily energy consumption. Consequently, these observations indicate that HVAC control strategies should be personalized depending on end-user group to achieve energy saving with satisfying their thermal comfort.

In an effort to satisfy the prerequisite, many researchers to date have proposed zone-based HVAC control. This control approach is to independently operate HVAC systems depending on zone (e.g., floor level, room type or adjacent rooms) which is a basic area for indoor climate control. For example, a university in Seoul, South Korea controls the operation of HVAC systems depending on the function of rooms (e.g., administration, research, lecture and meeting). However, although the zone-based HVAC control strategies provides a significant reduction in energy consumption, there still remain limitations in maintaining occupants' thermal comfort in multi-zone buildings because a zone may consist of multiple rooms that have different energy use patterns. Further, its practical applications are limited due to a time-consuming process to set up control parameters (e.g., temperature setpoint, on/off) across multiple zones.

Second, little is known regarding investigating the effect of weather and temporal variables on energy saving from HVAC scheduling techniques in multi-zone buildings. In general, spatial, temporal, weather and demographic variables significantly affect occupants' energy use behaviors and thus lead to a variation in energy use (van Raaij and Verhallen 1983). Therefore, buildings will show different distributions of end-user groups depending on contextual variable (see Fig. 1-1). Further, it can be expected that optimal control strategies that maximize energy saving from HVAC scheduling techniques vary depending on contextual variables. For example, while some end-user groups that consume significant amounts of unoccupied energy are prevalent on weekdays, they are rare on weekend. As a consequence, interrupting the operation of HVAC systems in vacant rooms would be more effective on weekdays than weekends.

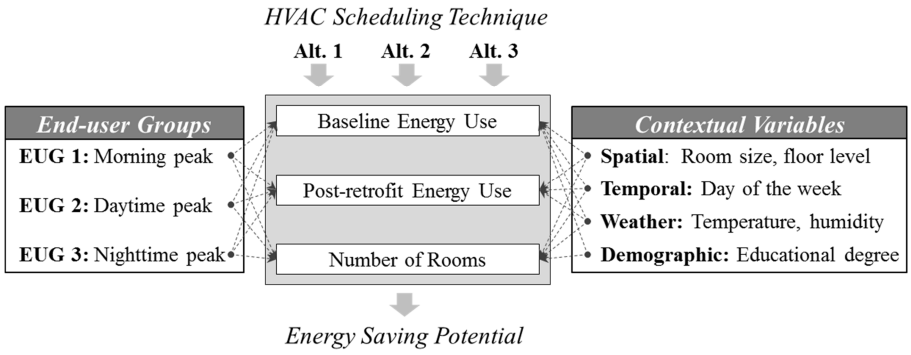


Figure 1-1. Relationship among Contextual Variables, End-user Groups and Energy Saving Potential in Multi-zone Buildings

Until recently, many studies have explored the spatiotemporal effect (e.g., day of the week, month of the year) of HVAC controller algorithms on energy saving (Erickson et al. 2011; Oldewurtel et al. 2013; Brooks et al. 2015; Pritoni et al. 2016). In addition, few studies have evaluated the energy saving potential of occupancy-driven HVAC controllers in different geographical and climatic contexts (Erickson et al. 2011; Goyal et al. 2013). However, investigating how contextual variables affect energy saving from different HVAC scheduling techniques in multi-zone buildings is not well understood. In the limited studies where the effect of HVAC scheduling techniques has been investigated, Escrivá-Escrivá et al. (2010) have not shown the variation in energy saving by contextual variables. Also, although Ghahramani et al. (2016) has investigated how dynamic environment-related variables affect energy saving from optimal selection of two control parameters such as temperature setpoint and deadband, it is impossible to understand the their contextual effects on energy saving in multi-zone buildings due to the assumption that all zones have identical energy use patterns.

1.3 Research Objectives and Framework

The primary purpose of this research is to investigate how temporal and weather variables affect energy saving from HVAC scheduling techniques in multi-zone buildings. The following are more specific objectives of this research.

a) To identify representative end-user groups in multi-zone buildings: Despite the large body of work attempting to investigate representative end-user groups in buildings, a poor understanding of their characteristics (e.g., energy use patterns, the percentage of total rooms) in different contexts remains. This identification process will provide a basis to select appropriate HVAC scheduling alternatives in multi-zone buildings.

b) To develop a data miming-based prediction model for baseline energy consumption in multi-zone buildings**:** The knowledge of energy use can help to optimize the operation of HVAC systems in buildings. However, despite the related works on building energy use prediction, there still remain limitations of addressing the characteristics of representative end-user groups in multi-zone buildings. The developed model will improve our understanding of how the characteristics of end-user group on prediction accuracy.

c) To create a thermodynamic model for post-retrofit energy use prediction in multi-zone buildings: Although energy simulation programs are prevalent to estimate post-retrofit energy consumption under controlled indoor environment, they rarely elaborate thermodynamics in different weather contexts. The developed thermodynamic model will be useful for post-retrofit energy use prediction in a given context.

d) To investigate the amount of energy saving from HVAC scheduling techniques in multi-zone buildings: It is not clear at this time how contextual variables affect energy saving from HVAC scheduling alternative in multi-zone buildings. Through simulation experiments using the developed models, it is possible to improve our understanding of the contextual effect of HVAC scheduling techniques on energy saving in multi-zone buildings. Also, this will provide information about optimal control strategies in different weather and temporal contexts.

In order to achieve these diverse research objectives, an interdependent research framework has been developed that integrates the outputs of each research phases (see Fig. 1-2). Based on the field-collected data from case buildings, representative end-user groups are identified in the research phase 1. Then, in order to predict baseline energy use for end-user groups, a data mining-based model is developed using their occupancy-related

characteristics in the research phase 2. Lastly, after constructing a thermodynamic model for post-retrofit energy use prediction in the research phase 3, energy performance simulation is performed using the outputs of previous research steps.

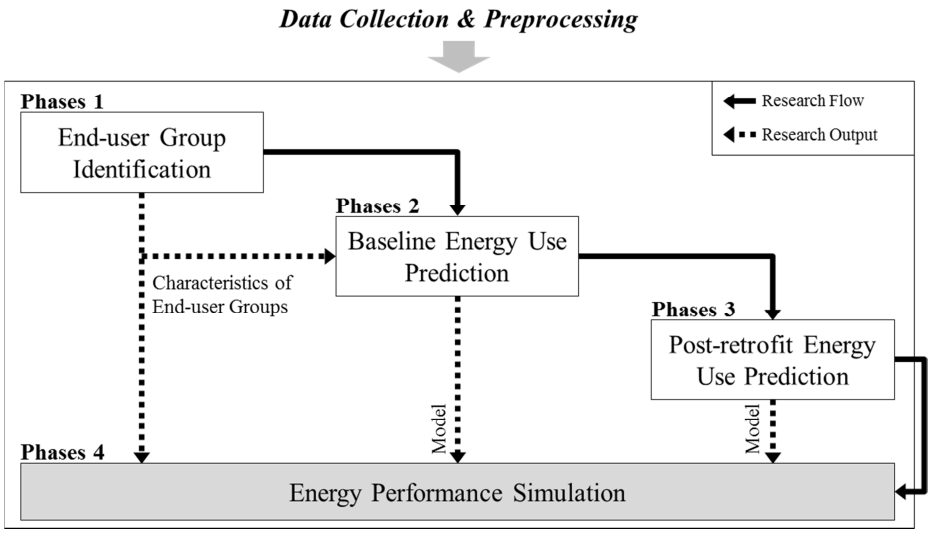


Figure 1-2. Interdependent research framework

1.4 Dissertation Structure

The organizational structure of this dissertation is established using eight Chapters (see Fig. 1-3). Chapter 1 and 8 provide the introduction and conclusion to this work and the interior Chapters each address a research issue in the aforementioned research framework. The following is a list of the chapters.

Chapter 1: Introduction. This chapter introduces the background, problem statements, objectives and approaches of the entire research effort.

Chapter 2: Preliminary Research. This chapter provides a comprehensive overview of demand-side management in buildings. Also, the extensive literatures on HVAC control strategies are reviewed. Then, research on building energy use prediction is introduced.

Chapter 3: Conceptual Framework for Energy Performance Evaluation. This chapter develops a conceptual framework for evaluating energy saving from HVAC scheduling techniques in multi-zone buildings. For the developed framework, a decomposition approach for quantifying total energy saving from HVAC scheduling techniques is proposed. Also, after data

collection from case buildings, energy performance evaluation methods are determined by comparing existing technology alternatives.

Chapter 4: End-user Group Identification in Multi-zone Buildings. This chapter presents an exploratory analysis on representative end-user groups in multi-zone buildings. The study focuses primarily on quantifying the amount of daily and hourly energy consumption across all the end-user groups. Then, the distribution of end-user groups is investigated depending on spatial, temporal and weather conditions.

Chapter 5: Baseline Energy Use Prediction using Occupancy-related Characteristics. This chapter introduces a data mining-based energy use prediction model which addresses the characteristics of representative end-user groups in multi-zone buildings. After constructing the model, its performance is evaluated through comparing actual and predicted energy use on a daily basis.

Chapter 6: Post-retrofit Energy Use Prediction using Thermodynamic Modeling. This chapter presents five key requirements to elaborate thermodynamic behaviors in the indoor environment. Then, a thermodynamic model is constructed using mathematical methods for heat transfer calculation.

Chapter 7: Energy Performance Simulation for Multi-zone Buildings. This chapter conducts simulation experiments using the developed models. Simulation results are also discussed to improve our understanding of how contextual variables affect energy saving from HVAC scheduling techniques in multi-zone buildings.

Chapter 8: Conclusions. This chapter summarizes the findings and main conclusions from the previous chapters. Future works are also outlined.

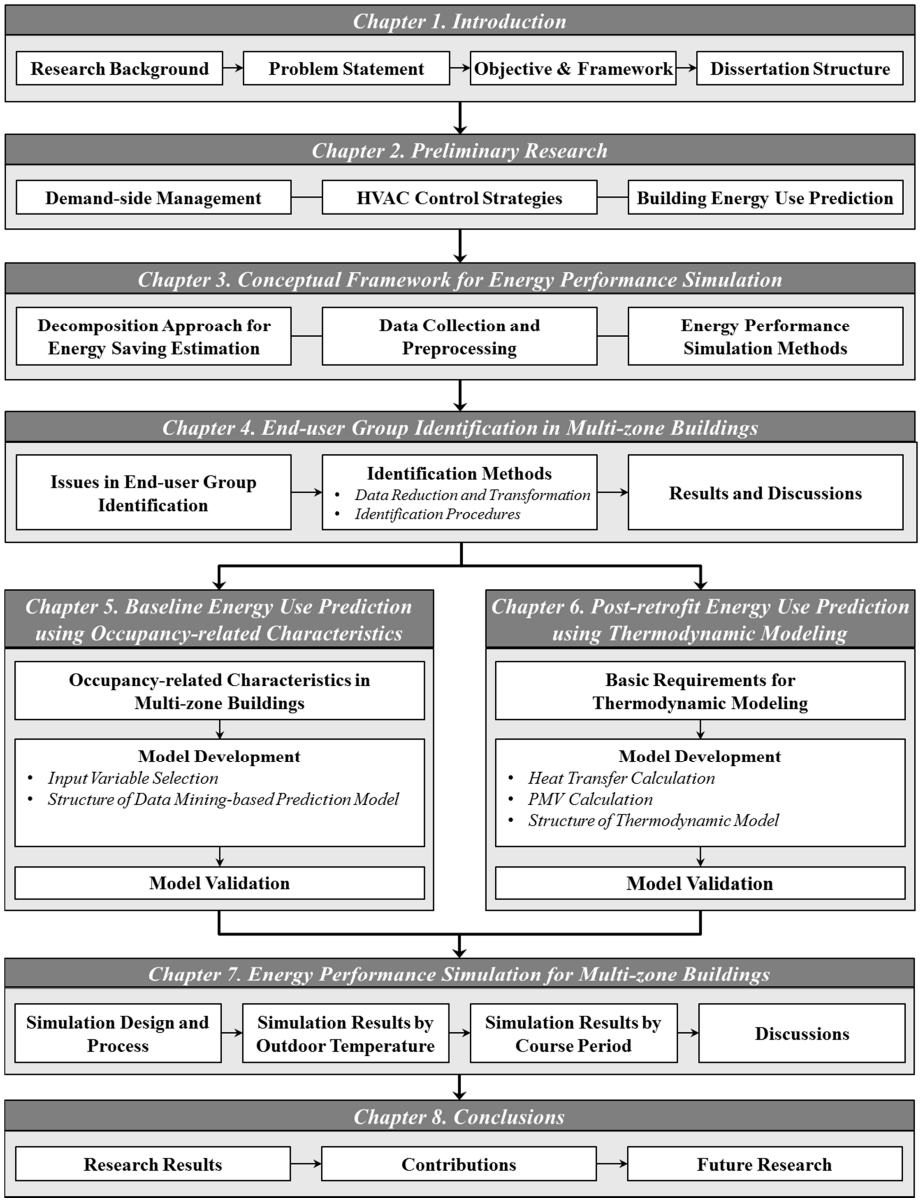


Figure 1-3. Dissertation Structure

Chapter 2. Preliminary Research

This chapter provides a comprehensive overview of demand-side management in buildings to improve our understanding of its current practices. For this, literature reviews are first performed to establish theoretical foundations for demand-side management in buildings. Next, this research analyzes related works on HVAC control strategies in buildings to investigate the limitations of its state-of-the-arts. Then, research on building energy use prediction is introduced.

2.1 Demand-side Management in Buildings

Since the mid-1980s, demand-side management (DSM) has been traditionally adopted as a solution of reducing energy consumption in industrial, commercial and residential sector. For instance, at that time, the U.S. had annual DSM expenditures of billions of dollars and thus resulted in a significant amount of electrical energy saving. Although national activities have decreased since then, a number of instances emphasize the importance of DSM programs to reduce the demand for electricity.

2.1.1 Overview of Demand-side Management in Buildings

Initially, most of the literature and case studies on demand-side management (DSM) correspond to the planning, implementation, and monitoring of electrical utility program that is designed to influence electrical energy use for end-users with various ways (e.g., a desired change in energy use patterns through load management). Recently, DSM is even more compassing than this definition because it includes the management of all forms of energy at the demand-side, not just electricity. Furthermore, such demand-side management programs have been implemented by various stakeholder groups (e.g., government organizations, natural gas suppliers, nonprofit groups, and private parties).

Among the different demand end use categories, building sector has paid a significant attention to adopting DSM programs due to its significant portion of the final energy consumption (Kiliccote and Piette 2005). As shown in Table 2-1, the programs can be summarized depending on the following two purposes.

Table 2-1. Examples of Energy Efficiency and Demand Response

Phase	Energy Efficiency	Demand Response
Design	• Energy-efficient HVAC Systems • Improved Insulation of Roof Spaces	• Dynamic Control Capability
Operation	• Integrated HVAC System Operation	• Demand Limiting • Demand Shifting • Demand Shedding

a) Energy Efficiency: DSM for increasing energy efficiency of buildings lowers overall energy consumption while maintaining the same level of thermal comfort in buildings (see Fig. 2-1). The change in load shape contributes to environmental protection as well as utility cost savings. In building sectors, energy efficiency measures typically include installing energy efficient equipment or construction materials, and operating buildings efficiently.

b) Demand Response: Demand response can be defined as short-term modifications in energy use patterns for end-users in response to dynamic environmental factors (e.g., energy price). Fig. 2-1 shows the range of typical demand response programs. Demand limiting refers to shedding loads when pre-determined peak demand limits are expected to exceed. Demand shifting

is to change the time that energy is used. Demand shedding is a temporary reduction or curtailment of peak energy use.

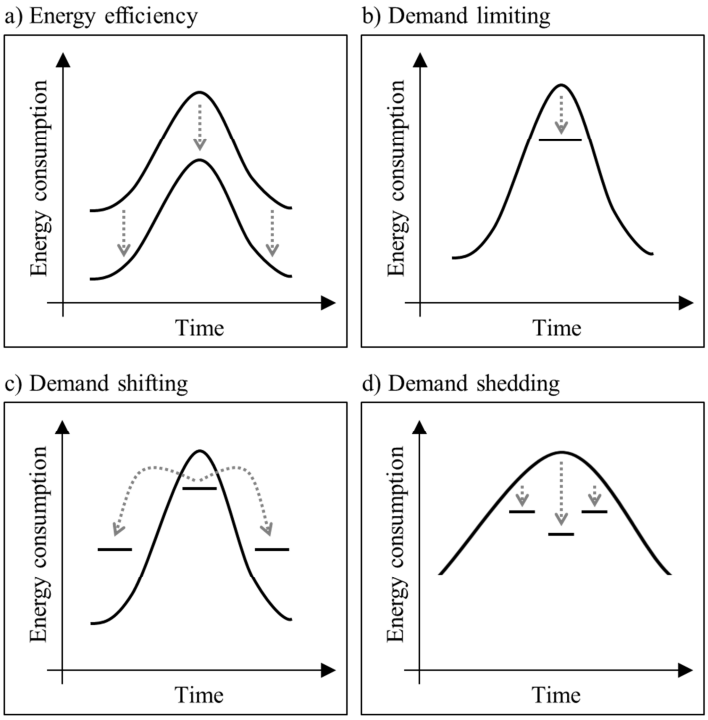


Figure 2-1. Four generic load shapes through demand-side management

When the DSM programs are applied for energy saving in buildings, facility managers have various beneficial effects including mitigating electrical system emergency, reducing the number of blackouts and increasing system reliability. Significant cost benefits can be also given to end-users through reducing their energy consumption. In particular, when the programs are used in commercial buildings, it provides more contribution to achieving

not only energy saving, but also establishing comfort environment which maximizes human productivity (Akimoto et al. 2010). Further, improving thermal, visual and acoustic environmental qualities contributes to our health and well-being (Grondzik et al. 2010).

2.1.2 Demand-side Management Planning Framework

In general, the following six steps should be taken to implement the effective DSM program in buildings (see Fig. 2-2):

a) Objective Setting: At the beginning of the DSM planning framework, the first step is to establish strategic objectives which generally include reducing energy use or improving comfort environment.

b) Initial Site Inspection: Improving the effect of DSM programs requires a thorough understanding of energy consumption in buildings. For this, the facility managers should collect all the necessary information about building characteristics (e.g., building type, building floor area), equipment (e.g., HVAC and lighting systems), and historical energy use data.

c) Alternative Generation: The third step is to identify technical and operational alternatives for each target end use (e.g., residential space heating, commercial lighting). This process should consider the suitability of the alternatives for satisfying the strategic objectives. For example, if the objective of DSM program is to reduce heating and cooling energy consumption while unoccupied, interrupting the operation of HVAC systems in vacant buildings would be an appropriate choice.

d) Energy Saving Estimation: The facility managers estimate energy saving potential to investigate the benefits from the DSM programs in buildings. Compared to lighting control strategies which can be a relatively straightforward process, establishing HVAC control strategies requires to estimate energy saving with various factors due to their complicated relationship with HVAC systems and technical alternatives. Therefore, the development of a simulation tool for predicting energy saving potential of technical alternatives is desired.

d) Selection of the Most Viable Alternative(s): Based on the results of energy saving estimation, the fifth step is to select the most viable alternatives(s) for the DSM programs in buildings.

f) M&V for Demand-side Management Programs: Much effort should be made to measure and verify the planned DSM in buildings. Through identifying deviations from expected performance, it is possible to foster advanced planning and organization within DSM programs.

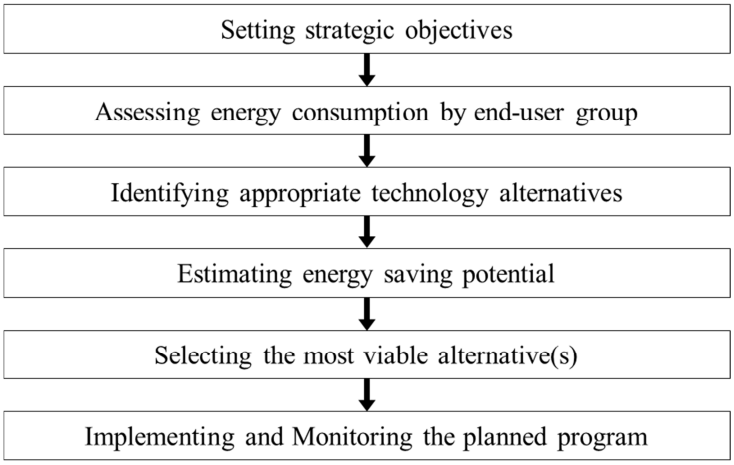


Figure 2-2. Demand-side management planning framework

2.2 HVAC Control Strategies

2.2.1 HVAC Scheduling Techniques

In general, HVAC scheduling techniques include manipulating a) global temperature setpoint and b) on/off states of HVAC systems (Haniff et al. 2013).

a) Global Temperature Control: In the literature, the most common HVAC scheduling techniques that have been proposed to date are global temperature setpoint adjustment in all zones. This has been prevalent due to its convenient combination with other techniques such as interrupting the operation of HVAC systems and pre-conditioning building zones. Ward and White (2007) have investigated that as the temperature setpoint increases by 1 degree Celsius during the summer season, the static approach produces energy saving with a range of 5 to 10%. Roussac et al. (2011) showed that the dynamic approach reduces more daily HVAC energy use than that of the static control strategy at 6.3% compared to 6.0%. An adaptive comfort temperature control model developed by Mui et al. (2003) contributed to a 7% of total energy saving in office buildings. Sehar et al. (2016) achieved a maximum energy saving at of 13.8 % a peak time through optimally increasing the cooling set points in all zones.

Additionally, the daytime or nighttime setback strategies have been used to ensure that all zones can become comfortable within an acceptable time before occupants arrive. This scheduling technique manipulates the temperature setpoint of HVAC systems during unoccupied hours. Ma et al. (2012) applied three types of night setback strategies to a commercial building with moderate thermal mass. Through simulation experiments, it was observed that weekly energy saving of HVAC systems ranges from about 15%

to 30%. Lee and Braun (2008) achieved a significant reduction in peak cooling demand in small, medium and large commercial buildings using three demand-limiting methods. A measured occupancy-based setback controller proposed by Goyal et al. (2013) resulted in 42-59 energy savings over the baseline controller. Moon et al. (2017) founded that two artificial neural network models that investigates the required time for increasing the current indoor temperature to the setback temperature reduce more cooling energy compared to the conventional setback control.

b) On/Off Control: The basic HVAC scheduling technique is to manipulate the operation of HVAC systems using on/off controller. As summarized in Escrivá-Escrivá et al. (2010), this corresponds to the following four alternatives. The first one is the pre-conditioning of building zones which shifts the load from to off-peak demand hours. This does not lead to a reduction in energy consumption, but achieves economic saving due to a dynamic change in energy price. Escrivá-Escrivá et al. (2010) suggested a pre-heating control during unoccupied hours (e.g., 7-9 a.m.) to reduce energy cost in buildings. Although energy consumption slightly increased through pre-heating, it saved up to 13.91% of energy cost for the HVAC systems. Xue and Shengwei (2012) proposed an interactive building load management framework which utilizes building thermal mass to store cold energy under

dynamic pricing scheme. The proposed framework contributed to the maximum load shift of 7.67% from working hours to non-working hours.

Second, interrupting the operation of HVAC systems helps reduce energy consumption in buildings. Basically, this is useful to avoid unnecessary energy consumption during unoccupied hours such as weekends and night in commercial buildings. Further, additional energy saving can be achieved through the thermal inertia of buildings. Escrivá-Escrivá et al. (2010) investigated how interrupting the HVAC operation affects daily energy consumption. When switching off HVAC systems during the warmest period (e.g., from 12 p.m. to 1 p.m.) of the day, energy consumption was reduced by up to 5.6%. Early switch off of HVAC systems, which interrupts its operation before occupants leave the buildings, also produced energy saving ranged from 4.48% to 11.19%. Additionally, the significant amount of energy saving was observed when combining the individual techniques.

2.2.2 HVAC Controller Algorithms

In general, HVAC control strategies should maintain indoor environment such as temperature in a given comfort rage while minimizing energy consumption in buildings. For this, many conventional HVAC control are

implemented using schedule-based controller (SBC). This controller does not use occupancy measurement, but predefined occupancy schedules. For instance, as shown in Fig. 2-3, commercial buildings are mainly conditioned from 9:00 A.M. to 6:00 P.M. because almost occupants are present during the period. However, since fixed schedules do not account for the variation in occupancy patterns, early or late occupants feel uncomfortable in their indoor environment.

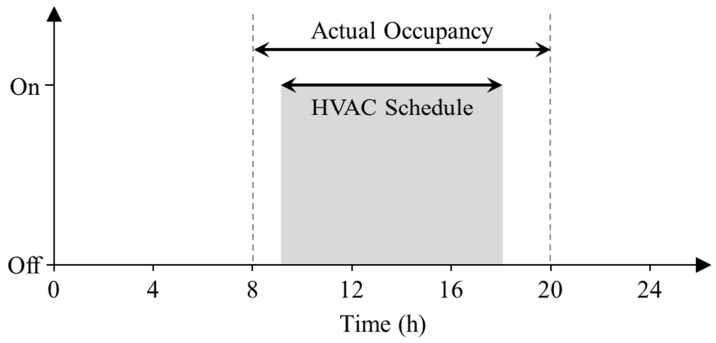


Figure 2-3. An Example of Schedule-based HVAC Controller

Additionally, with advances in technology, researchers have paid more attention to rule-based controller (RBC) which implements all HVAC controls depending on real-time occupancy measurements. For example, Fig. 2-4 shows that the temperature setpoint varies according to actual occupancy status. Most importantly, this approach facilitates an independent HVAC control by zone to provide thermal comfort for all the occupants living in

buildings. However, the RBC might take a while for the indoor temperature to return to a comfortable range after occupants arrive.

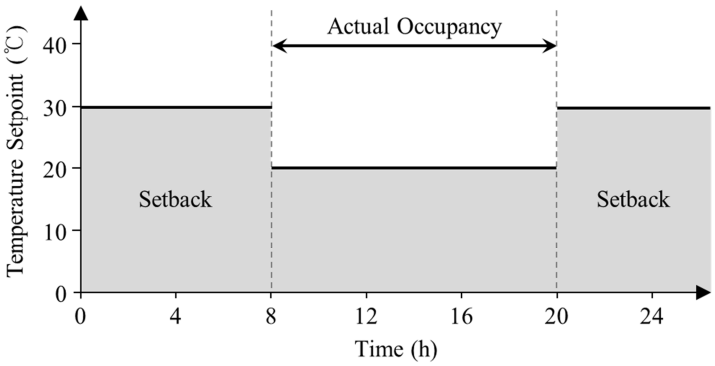


Figure 2-4. An Example of Rule-based HVAC Controller

Recently, model predictive controller (MPC) has been widely used to optimize the operation of HVAC systems in buildings. The MPC includes optimization and prediction features which make it possible to response to future environmental change (e.g., occupancy status, outdoor temperature) in advance. For example, as found in Fig. 2-5, this controller slightly raises temperature setpoint of HVAC systems to the desired value until occupants are expected to leave their zones or rooms. While the MPC can minimize energy waste (e.g., before leaving) and thermal discomfort (e.g., when arriving) by thermal lag, it requires a high level of expertise and computation time to implement, and thus results in an impediment to more wide spread application (Valencia-Palomo and Rossiter 2012).

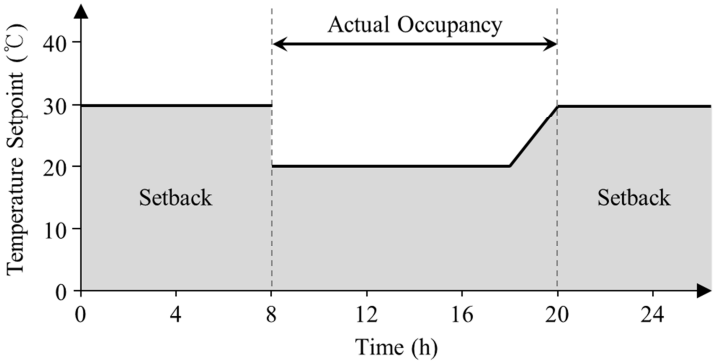


Figure 2-5. An Example of Model Predictive HVAC Controller

2.3 Buildings Energy Use Prediction

Building energy use prediction is essential to achieve energy saving during the operation phase because the knowledge of energy use can help to optimize the operation of energy-using equipment (Jain et al. 2014; Monfet et al. 2014; Yang et al. 2005). Once the energy use in a building is identified, it is possible to develop appropriate energy saving strategies and thus achieve energy saving in the following three ways. First, by identifying the energy use in buildings, facility managers are able to determine the starting/finishing time of heating, ventilating, and air conditioning (HVAC) systems to prevent energy waste in buildings. Second, it is possible to avoid reaching peak energy demand by pre-heating/cooling of buildings. Third, adjusting the temperature setting point during the peak energy periods can save energy.

In the extensive literature on building energy use prediction, various influential factors have been considered to improve its performance. The major factors include weather, building characteristics, equipment, and occupant-related characteristics (Jovanović et al. 2015; Kwok et al. 2011; Neto and Fiorelli 2008; Yezioro et al. 2008). Among these factors, recent studies have emphasized the importance of occupancy data (e.g., occupancy schedule) since occupants in buildings interact with energy-using equipment and devices (Yezioro et al. 2008; Li et al. 2015). Furthermore, technical advancement allows us to obtain actual occupancy data, which consequently contribute to building energy use prediction (Sandels et al. 2015; Virote and Neves-Silva 2012). From their experimental results, it was found that the improved performance of building energy use prediction models could be obtained by considering occupancy as input variable for the prediction models.

To date, a number of building energy use prediction models have been developed in the literature, based on three major approaches: thermodynamic modeling, statistical and artificial neural network (ANN). Thermodynamic models aims to predict the energy performance (e.g., energy use, thermal comfort) of a given building. In general, it enhances our understanding of how buildings respond to dynamic built environment, and identifies potential problem caused by interference between design and performance parameters (Maile et al. 2007). Particularly, the primary strength of thermodynamic

models is their ability to predict thermodynamic behaviors previously unobserved conditions (Coakley et al. 2014). For these reasons, many studies have adopted a thermodynamic model to investigate the effect of different design alternatives and control strategies on energy consumption in buildings. Ghahramani et al. (2016) modeled office buildings by Energy Plus, released by U.S. DOE, to quantify the influence of building size, construction category, climate, occupancy schedule, temperature setpoint and deadband on HVAC energy consumption. Afram and Janabi-Sharifi (2015) developed gray-box models of residential HVAC systems, simulated in Simulink environment, as a tool to implement various energy conservation strategies in design and operation phase. Nematchoua et al. (2015) constructed a thermal model using MATLAB-Simulink simulation to determine economical and optimum thermal insulation thickness for buildings.

Statistical models predict building energy consumption using historical data together with the measured input data (Sandels et al. 2015). While the structure of this approach is well understood due to the simplicity of the model parameters, much effort is needed to overcome the autocorrelation and multi-collinearity problems (Yang et al. 2005). Sandels et al. (2015) presented a data analysis approach for conducting day-ahead predictions of electricity consumed by appliance, ventilation, and cooling equipment in an office building floor. From the experimental results using the developed regression

models, it is found that the most significant predictor for the applicant load is occupancy ratio which derives from occupancy sensor. Virote and Neves-Silva (2012) produced reliable prediction for building energy use through integrating the stochastic occupant behavioral model with energy consumption model. Wang and Ding (2015) proposed an occupancy-based energy consumption prediction models. As an effort to improve the accuracy of the prediction results, the prediction model used a time-varying indoor occupancy rate which is obtained by using Monte Carlo and Markov chain methods.

For the ANN models, it operates training procedures with historical data and then predicts building energy use. This approach has a high applicability when solving non-linear and complex problems (Jovanović et al. 2015). However, it has a potential problem with the reliability and accuracy of the prediction results since it depends on the obtained training data (González and Zamarreño 2005). Kwok et al. (2011) proposed a multi-layer perceptron model for building energy use prediction using the power consumption of primary air-handling units (PAU) as an alternative to occupancy data to mimic occupants' presence in a building. Yezioro et al. (2008) constructed an ANN prediction model which uses the occupancy schedule as one of the input variables. In the optimized ANN model for building energy forecasting

suggested by Li et al. (2015), the opening schedules of a library were used to represent the hourly occupancy of each reading room.

2.4 Summary

Until recently, demand-side management (DSM) programs have been widely adopted to achieve energy saving in commercial and residential sectors. This is due to the significant portion of the final energy consumption in building sector. The DSM programs have two different purposes: energy efficiency and demand response. In order to implement the effective DSM programs in buildings, its planning framework should include the following six steps: objective setting, initial site inspection, alternative generation, energy saving estimation, selection of the most viable alternative, M&V process.

Among various DSM programs in buildings, much attention has been given to HVAC control strategies. This is significant because HVAC systems account for more than half of the total energy consumed in buildings. In particular, this has been more emphasized due to its high energy saving potential. In the extensive literature, the energy-efficient control strategies of HVAC systems have been proposed in two aspects. HVAC scheduling

techniques include the adjustment of global temperature control and on/off state of HVAC systems. HVAC controller algorithms correspond to the operating environments for HVAC control (e.g., SBC, RBC, MPC).

Building energy use prediction is important to reduce energy consumption during the operation phase of buildings because the knowledge of energy use can help to optimize the operation of energy-consuming equipment. In the extensive literature, various influential factors have been addressed to improve the prediction accuracy. In particular, recent researchers have paid attention to occupancy because occupants in buildings interact with energy-using equipment and devices. Also, much effort has been made on two prediction approaches: thermodynamic modeling, statistical and artificial neural network. Since each approach has its own advantages and disadvantages, its usage should be dependent of the purpose of building energy use prediction.

Chapter 3. Conceptual Framework for Energy Performance Evaluation

This chapter presents a conceptual framework for evaluating energy saving from HVAC scheduling techniques in multi-zone buildings. First, a decomposition approach for energy saving estimation is proposed. After data collection from case buildings, energy performance evaluation methods are described to identify representative end-user groups and predict baseline/post-retrofit energy consumption in multi-zone buildings.

3.1 Decomposition Approach for Energy Saving Estimation

Once HVAC scheduling alternatives are selected, evaluating their performance is necessary to establish optimal control strategies. This is because each alternative can produce different energy saving potentials depending on temporal and weather condition. The prevailing method for quantifying energy saving can be described as follow (Kim et al. 2016).

$$TS = BE - PE \qquad \text{(Eq. 3-1)}$$

where TS: the total amount of energy saving from HVAC scheduling techniques; BE: baseline energy use that is energy use in absence of any HVAC scheduling techniques; PE: post-retrofit energy use that is energy use under controlled condition by HVAC scheduling techniques. However, since the existing method adopts baseline and post-retrofit energy use investigated at a building level, it can underestimate the total amount of energy saving from HVAC scheduling techniques unless occupancy status and various end-user groups are addressed during its aggregation process. For example, when adjusting HVAC temperature setpoint produces energy saving of 15 kWh during occupied hours but not during unoccupied hours, the total amount of energy saving is 15 kWh (see Fig. 3-1-a). However, without consideration of occupancy status, the HVAC control alternative creates energy saving of 10 kWh. Also, considering that multi-zone buildings have different end-user groups, such aggregation problem occurs (see Fig. 3-1-b). After aggregating the amount of energy saving per end-user group, the total amount is 50 kWh that is higher than the energy saving of 40 kWh obtained by Eq. 3-1. Therefore, in order to address these aggregation problems, this research improves the existing estimation method as follows.

$$TS = \sum_{k=1}^{n} \{(BEO_k - PEO_k) + (BEU_k - PEU_k)\} \qquad \text{(Eq. 3-2)}$$

where BEO_k: baseline energy use for end-user group k during occupied hours; PEO_k: post-retrofit energy use for end-user group k during occupied hours; BEU_k: baseline energy use for end-user group k during unoccupied hours; PEO_k: post-retrofit energy use for end-user group k during unoccupied hours.

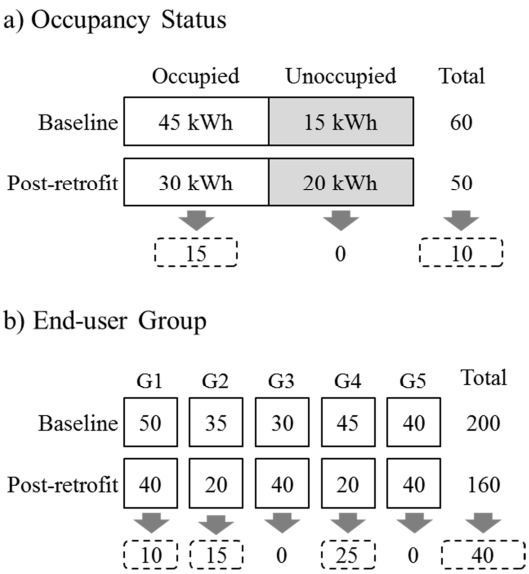


Figure 3-1. Aggregation Problems with Energy Saving Estimation

3.2 Data Collection and Preprocessing

Data is collected from seven dormitory buildings of a university in Seoul, South Korea, during the periods of November 1, 2014 to February 28, 2015. These buildings consist of 250 single rooms and 1125 double rooms, used for

residence purpose (see Fig. 3-2). All the rooms have two types of real-time measuring systems to collect data on energy use and occupancy status. First, smart metering systems measure the hourly electrical energy consumed in each room. The energy use data includes electrical loads incurred by under-floor electric heating systems (a max power rating of 4 kW), mini-refrigerators, lights and personal devices. Second, card entry systems provide a record of the changes in occupancy status of each room for the given periods. Table 3-1 represents the overview of the case buildings.

Figure 3-2. Dormitory Buildings of a University in Seoul, South Korea

Table 3-1. Description of Case Buildings

Building characteristics	Case buildings
Construction year	2010
Building function	Residential
Number of floors	7 or 8
Room size	250 single rooms, 1175 double rooms
Occupants	Graduate and undergraduate student
Heating system	Radiant floor heating with individual control, electric
Available periods for heating	January to March, October to December

Additionally, after the data collection, some rooms were excluded from analysis due to the incomprehensibility of energy use and occupancy status by system malfunction. Thus, the total number of rooms is 1097 for November 2014, 1036 in December 2014, 1067 in January 2015, and 1016 in February 2015, respectively (see Table 3-2).

Table 3-2. Number of Available Rooms for Analysis

Period	Room size		Total
	Single	Double	
November, 2014	193	904	1097
December, 2014	176	859	1036
January, 2015	173	894	1067
February, 2015	171	845	1016

3.3 Energy Performance Evaluation Methods

In order to estimate energy saving from HVAC scheduling techniques in the case buildings, this research proposes energy performance evaluation methods depending on the purpose of its usage. First, clustering analysis using *k*-means algorithm is introduced to find representative end-user groups in the buildings. Second, artificial neural network (ANN) and *k*-nearest neighbor (KNN) are used to predict baseline energy consumption for end-user groups. Third, simulation-based approach is adopted to predict post-retrofit energy consumption for end-user groups.

3.3.1 *k*-means Algorithm

In order to investigate representative end-user groups in the case buildings, clustering analysis is performed using energy use data collected at 24 hourly intervals. The clustering analysis is the process of finding similarities between objects and categorizing these objects into meaningful groups (Han et al. 2012). The similarity is calculated using distance measures such as Euclidean, Manhattan, Minkowski and Supremum distance. Among these distance measures, this research adopts Euclidean distance due to its simplicity and applicability (Panapakidis et al. 2014; Zhou et al. 2017). If p =

(p_1, p_2, p_3,..., p_n) and q = (q_1, q_2, q_3,…, q_n) are two objects, Euclidean distance is defined as

$$dist(p,q) = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \qquad \text{(Eq. 3-3)}$$

In the above equation, objects p and q should have non negative values. Based on the distance value, clustering algorithms such as *k*-means and agglomerative hierarchical clustering assigns objects to groups with the closest centroid or link the closest object (see Fig. 3-3). In this research, k-means algorithm is adopted as a cluster algorithm due to its higher computational efficiency for large dataset than agglomerative hierarchical clustering (Steinbach et al. 2000; Kaur and Kaur 2013).

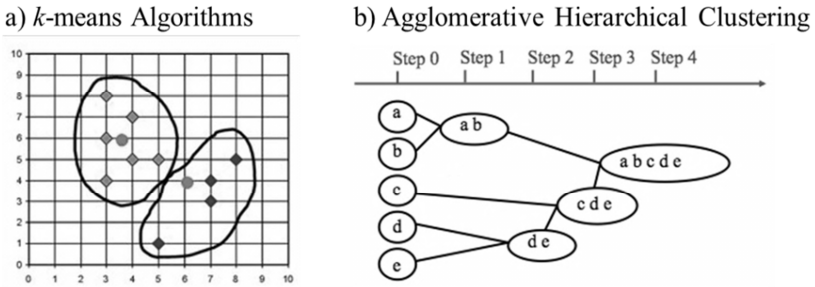


Figure 3-3. *k*-means Algorithms and Agglomerative Hierarchical Clustering

The k-means algorithm is one of partitioning clustering methods and categorizes a dataset with multiple objects into k clusters (Han et al. 2012). In k-means clustering, an objective function is employed to achieve high intracluster similarity and low intercluster similarity. More specifically, given that the difference between an object p and the centroid c_i of a cluster C_i is measured by the Euclidean distance, the quality of the cluster can be evaluated as follows.

$$E = \sum_{i=1}^{k} \sum_{p \in C_i} dist(p, c_i)^2 \qquad \text{(Eq. 3-4)}$$

where E: the sum of the squared error for all objects in the dataset; p: is the point in space representing a given object; and c_i: the centroid of cluster C_i. This objective function attempts to facilitate the resulting k clusters as compact and as separate as possible. Additionally, since the number of clusters cannot be known in given datasets, it is difficult to determine the best number of clusters. To overcome this difficulty, this research adopts Davies-Bouldin Index (DBI) as clustering evaluation criteria which is the mean value of a ratio of inter-cluster and intra-cluster distances (Davies and Bouldin 1979). The values of DBI can be calculated by the following equation:

$$DBI = \frac{1}{k}\sum_{i=1}^{k} max_{j \neq i}\left\{\frac{\bar{d}_i + \bar{d}_j}{d_{ij}}\right\} \quad \text{(Eq. 3-5)}$$

where k: the number of clusters; d_i: the average distance between all objects in the ith cluster and the centroid of the ith cluster; d_j: the average distance between all objects in the jth cluster; and d_{ij}: the distance between the centroids of the ith and j^{th} clusters. The minimum value of DBI corresponds to good clusters and is regarded as an optimal clustering solution.

3.3.2 Artificial Neural Network and *k*-nearest Neighbor

In order to calculate baseline energy use for end-user groups in the case buildings, this research adopts artificial neural network (ANN) because it can provide information about future energy use through training historical thermal behaviors of each group. The ANN has a computational structure which mimics a biological neural system of human brain (Schalkoff et al. 1997). In general, the ANN consists of a large collection of neurons, which are linked with one another. Each individual neuron obtains multiple input values from other connected neurons to produce a single output value. According to this physical scheme, ANN learns and generalizes the relationships in the given datasets, and then extrapolates results for new

datasets. Due to such capability, ANN has been successfully applied to solve pattern recognition, classification and forecasting problem.

Fig. 3-4 shows the structure of a typical three-layer feed forward neural network. The network consists of three types of layers in which the neurons are placed. The first layer, called input layer, obtains inputs from outside (e.g., hi. The second one is the output layer, which produce the results evaluated by the network. Lastly, a hidden layer exist between the input and output layer. It should be noted that each neuron of a given layer is connected to other neurons of a previous layer by a weighted links. For a three-layer network, the mathematical function is defined as

$$Y = f\left(b_0 + \sum_{j=1}^{k} h\left(\varphi_j + \sum_{i=1}^{m} p_i w_{ij}\right) b_j\right) \qquad \text{(Eq. 3-6)}$$

where Y: the network outputs; $f(\cdot)$: nonlinear transfer function; p_i: the network inputs; b_0: the output bias; b_j: the weight values from hidden layer to output layer; φ_j: the hidden layer biases; w_{ij}: the weights from input layer to hidden layer; $h(\cdot)$: hidden layer activation function.

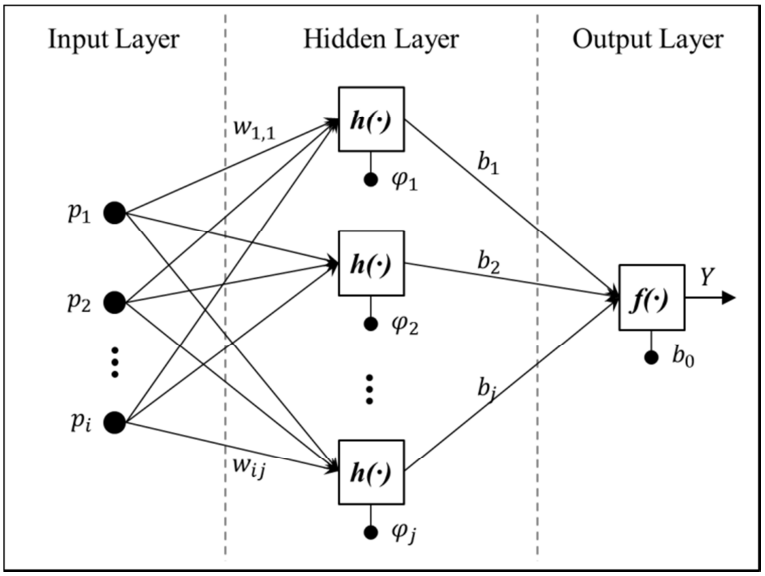


Figure 3-4. Structure of a three-layer feed forward neural network

In order to improve the network performance, the weight and bias parameters are optimize using the backpropagation algorithm, which finds the minimum of the mean-squared error between the network output and the actual value using the gradient performance function (Han et al. 2012). The combination of weights and biases that minimize the error function is regarded as an optimal solution of the learning problem. This algorithm runs with the following steps. First, the network is initialized with randomly selected weights and biases. Second, the gradient of the error function is calculated and used to improve the initial weights and biases. Third, the network training using the backpropagation algorithm is repeated, until the gradient of the error function reach to the specified threshold.

Additionally, In the process of constructing a ANN prediction model, the collected historical data will be used to adjust the weight and bias parameters of the ANN models. If all historical data are employed for model construction, it is convenient to mimic building thermal behaviors by optimizing the values of these parameters with a global solution (Fan et al. 2014). On the other hand, this leads to an increase in training time and over-fitting problem (Yun et al. 2012; Mustafaraj et al. 2011; Fan et al. 2014). As a consequence, the network will show poor performance in predicting building energy use. In order to overcome these problems, this research selects and uses an appropriate set of historical data by *k*-nearest neighbor. The *k*-nearest neighbor (KNN) searches for *k* similar historical datasets that are close to a given test dataset (Han et al. 2012). In this context, the closeness is calculated using distance measures such a Euclidean and Manhattan distance. Based on the distance value, the *k* corresponding closest datasets are obtained from the given historical dataset (see Fig. 3-5). In the KNN algorithm, the basic search process can be summarized as follow. The first step is to determine the number of the closest neighbors (*k* variables). Second, the closeness between the given test dataset and the historical datasets is calculated using distance measures. Third, *k*-minimum distance neighbors are selected. Importantly, to find the best number of the *k* variable, several experiments need to be conducted by adjusting the number of similar datasets, the results of which then need to be evaluated.

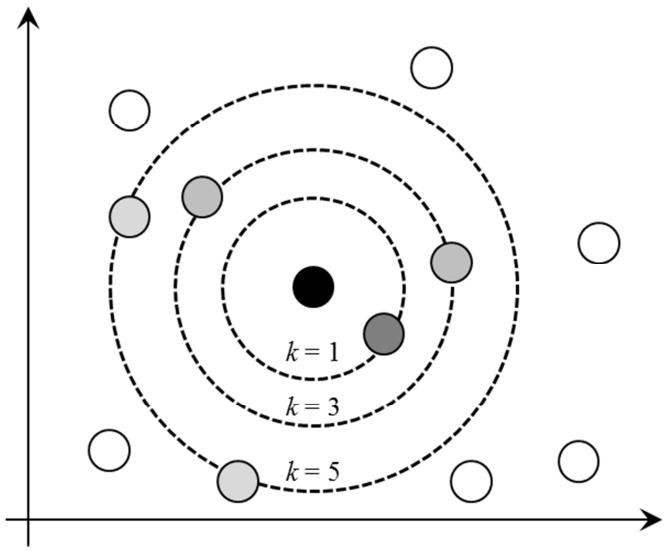


Figure 3-5. *k* corresponding closest datasets using KNN algorithm

3.3.3 Simulation-based Prediction

In order to predict post-retrofit energy use for end-user groups in the case buildings, simulation-based approaches are used due to its ability to elaborate thermal behaviors previously unobserved conditions. In fact, since the collected data does not include information about energy use under all types of controlled conditions by HVAC control, other prediction approaches have limitations in predicting post-retrofit energy use in the case buildings.

In the simulation-based approaches, a thermodynamic model is developed using simulation tools. According to the extensive literature on

energy use prediction, the major simulation tools are DOE-2, eQuest, EnergyPlus and Simulink (see Fig. 3-6). The DOE-2 helps elaborate the thermal behavior of spaces in a building as follow. First, this tool calculates loads through addressing external (e.g., solar gain) and internal loads (e.g., equipment loads, people loads, lighting loads). Second, based on the resulting loads, the simulation engine attempts to satisfy space loads with the predetermined HVAC systems.

The eQuest enables all functionalities of the DOE-2 and provides another functionality to compare specific input parameters, called Energy-Efficiency Measures. Additionally, compared to DOE-2, this simulation tool has advantages in terms of enhanced geometric representations, a newly developed HVAC system concept and additional HVAC components and features.

The EnergyPlus provides more accurate predictions of temperatures in spaces using an integrated approach (loads and systems simulation). The loads are calculated depending on ASHRAE's preferred heat-balanced-based approach. Since an EnergyPlus simulation is mainly performed using input from text files and thus leads to an increase in its execution periods, a plugin tool allows modeling the geometry of a building within the SketchUp interface.

The Simulink-based simulation tool predicts energy consumption using the graphical programming language. The graphical approach helps understand the complex interaction between the different parts of the thermal model using blocks with different properties. Also, since this tool can be used with Matlab functions, it supports the comprehensive evaluation of energy saving measures specified by users.

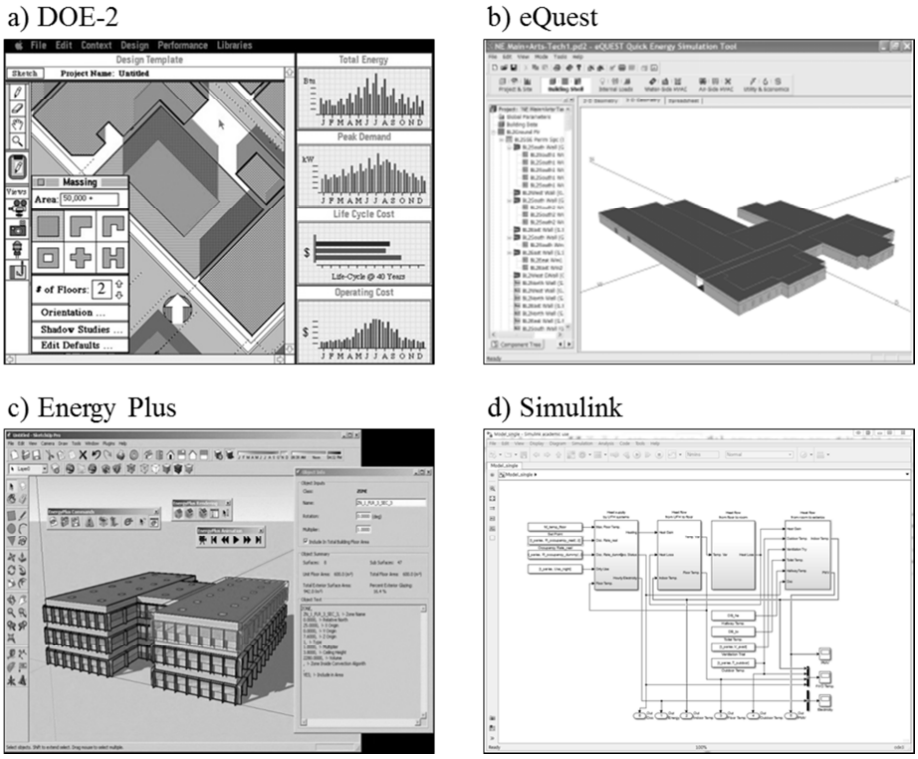


Figure 3-6. Major Simulation Tools for Energy Use Prediction

3.4 Summary

The prevailing method for quantifying energy saving from HVAC scheduling techniques would be to subtract baseline energy use from post-retrofit energy use. However, since the existing method has problems in aggregating energy saving achieved by end-user groups during occupied and unoccupied hours, it can underestimate the total amount of energy saving from HVAC control. Therefore, to address the aggregation problems, this research proposed the decomposition approach to energy saving estimation.

After collecting data from seven dormitory buildings of a university in Seoul, South Korea, energy performance evaluation methods were selected depending on the purpose of its usage. First, in order to identify representative end-user groups in the case buildings, clustering analysis is carried out using *k*-means algorithms. During the identification process, Davies-Bouldin Index (DBI) are used to determine the best number of end-user groups. Second, artificial neural network (ANN) is adopted to predict baseline energy use for end-user groups in the case buildings. Additionally, to improve the accuracy of ANN prediction model, an appropriate set of historical data is selected using *k*-nearest neighbor. Third, simulation-based approaches are employed to predict post-retrofit energy use for end-user groups in the case buildings.

Chapter 4. End-use Group Identification in Multi-zone Buildings

This chapter presents an exploratory analysis of representative end-user groups in multi-zone buildings. The study focuses primarily on quantifying the amount of energy consumed on a daily and hourly basis across all the identified groups. Then, the effect of temporal and weather variables on the percentage of total rooms by end-user group is investigated.

4.1 Issues in End-user Group Identification

When establishing control strategies in buildings, end-user group identification can contribute to further energy saving without compromising occupants' thermal comfort due to the following reasons. First, once representative end-user groups in buildings are identified, facility managers are able to personalize the operation of energy-consuming equipment depending on their energy use patterns. For example, university buildings require different levels of HVAC scheduling because various energy use patterns exist depending on the function of the rooms (e.g., administration, research, lecture and seminar) (Mossolly et al. 2009). If all rooms are

conditioned at the same level of operation periods, this cannot ensure occupants' thermal comfort. Second, after evaluating the energy efficiency for end-user groups, it is possible to select appropriate technology alternatives that can maximize energy saving from control strategies. In particular, considering that occupants have different energy use patterns depending on loading conditions (e.g., physical characteristics of buildings, season), the identification process can provide implications for energy efficiency and technology alternatives in a certain condition.

To date, many researchers have investigated representative end-user groups for the purpose of demand-side management in households (Räsänen et al. 2008; Sütterlin 2011; Ozawa et al. 2016; Zhou et al. 2017; Abreu et al. 2016; Gouveia and Seixas 2016; Abreua et al. 2012) and non-residential buildings (Chicco 2012; Wu and Zhao 2015). Field survey was a typical approach to classify end-users into similar groups and understand their energy use behaviors (Räsänen et al. 2008; Sütterlin 2011). Recently, with the increasing penetration of sensing and measurement technology such as smart meters in building energy management systems (BEMS), a substantial amount of studies analyzed load shapes for end-user groups using high resolution data on energy use (Ozawa et al. 2016; Zhou et al. 2017; Abreu et al. 2016; Gouveia and Seixas 2016). Several studies also compared the amount of daily electrical energy consumption to evaluate the energy efficiency for end-user

groups (Ozawa et al. 2016; Miller et al. 2015). Further, there were attempts to investigate the effect of building characteristics (Gouveia and Seixas 2016), climate zone (Kwac et al. 2014), day of the week (Abreua et al. 2012; Miller et al. 2015), month of the year (Abreua et al. 2012), household occupant (Gouveia and seixas 2016) and outdoor temperature (Abreua et al. 2012) on the distribution of energy use profiles in a household. Unfortunately, despite the previous achievements, two main problems still exist throughout much of the literature. First, the quantity of daily energy consumption cannot be an indicator to evaluate the energy efficiency of end-user groups. This is because occupancy period may cause a variation in daily energy consumption among end-user groups. For example, if groups A and B stay longer in their rooms than group C, it can be expected that the former two groups consume more energy on a daily basis. In this case, quantifying the amount of hourly energy consumption for end-user groups will be better to understand their energy efficiency. Further, considering that there are evidences about energy overconsumption in occupied and unoccupied buildings, it is necessary to investigate such quantities depending on occupancy status. Second, understanding how weather conditions affect the distribution of end-user groups in buildings is still limited. In a rare study (Abreua et al. 2012), prevalent daily energy use profiles of a household (one end-user group) were explored depending on outdoor temperature. However, little is known

regarding the distribution of daily profiles in buildings (various end-user groups) and its variation by weather condition.

As an effort to address these problems, this research evaluates the amount of hourly energy use for end-user groups in buildings. Also, we analyze how spatial, temporal and weather conditions affect the distribution of daily energy use patterns for end-user groups in buildings.

4.2 Identification Methods

4.2.1. Data Reduction and Transformation

Clustering analysis for identifying representative end-user groups has two main concerns. The first one is the sparsity of the available data in high dimensional spaces. In general, energy use time-series has high dimensional data. For example, if energy use data is collected with the 30 minute time interval, a time-series includes a set of 48 consecutive values. Such high dimensional time-series can make an adverse effect on its storage and clustering results (Ding et al. 2008). For these reasons, several studies on investigating representative energy use patterns have adopted data reduction techniques and observed its effect on clustering performance (see Table 4-1).

In this study, principal component analysis (PCA) is adopted as a data reduction technique. PCA converts time-series data into a set of feature vectors called principal components (Jolliffe 2002). The extracted features are linearly uncorrelated and its dimension is less or equal to the number of original variables. Most importantly, compared to other data reduction techniques, this has a wide applicability for identifying energy use pattern. Also, since no prior knowledge about data distribution is required, it takes relatively less time to extract features from original high dimensional data.

Table 4-1. Data Reduction and Transformation Techniques used in Related Works

Data Preprocessing Technique	Chicco et al. 2004	Kwac et al. 2014	Chicco et al. 2006	Rasanen et al. 2008	Miller et al. 2015	Carpaneto et al. 2006
a) Data Reduction						
- Principal Component Analysis	√	√	√			
- Sammon Maps			√			
- Curvilinear Component Analysis			√			
- Statistical Features				√		
- Symbolic Aggregate Approximation					√	
- Discrete Fourier Transform						√
b) Data Transformation						
- Min-max Normalization	√	√			√	
- Z-score				√		
- Sigmoid Normalization						√

The second concern refers to the different range of values for each variable. Basically, energy use time-series changes its values over time. For example, commercial buildings have an increasing tendency of energy consumption after 8 a.m., reach peak energy during the periods of 12-2 p.m., and rarely consume energy in the nighttime. In this situation, the variables with larger numeric values (e.g., energy consumption at 2 p.m.) can dominate the other attributes (e.g., energy consumption at 10 p.m.) when calculating the similarity between two time-series. Further, although they show the dissimilar trend in hourly energy use, they can be categorized into an identical group. To overcome these limitations, it is recommended that each variable is normalized using data transformation techniques such as min-max normalization, Z-score normalization, and sigmoid normalization (see Table 4-1). In this research, min-max normalization is used due to its wide applicability in the field of data mining. The normalized value of $v'_{i \cdot A}$ for variable A is calculated as follow.

$$v'_{i \cdot A} = \frac{v_{i \cdot A} - v_{min \cdot A}}{v_{max \cdot A} - v_{min \cdot A}} \left(v'_{max \cdot A} - v'_{min \cdot A} \right) + v'_{min \cdot A} \qquad \text{(Eq. 4-1)}$$

where $v_{i \cdot A}$: an existing value of variable *A*; $v'_{max \cdot A}$: the new maximum value of variable *A*; $v'_{min \cdot A}$: the new minimum value of variable *A*; $v_{max \cdot A}$: the

existing maximum value of variable A; and $v_{min \cdot A}$: the existing minimum value of variable A.

4.2.2. Identification Process

Step 1. Configuration of Data Structure: In order to explore how weather and temporal variables affect the behaviors of representative EUGs in multi-zone buildings, the collected data is organized as a dataset aligned by room and day (see Fig. 4-1). Each room has multiple sets of energy use time-series depending on the number of days for each month.

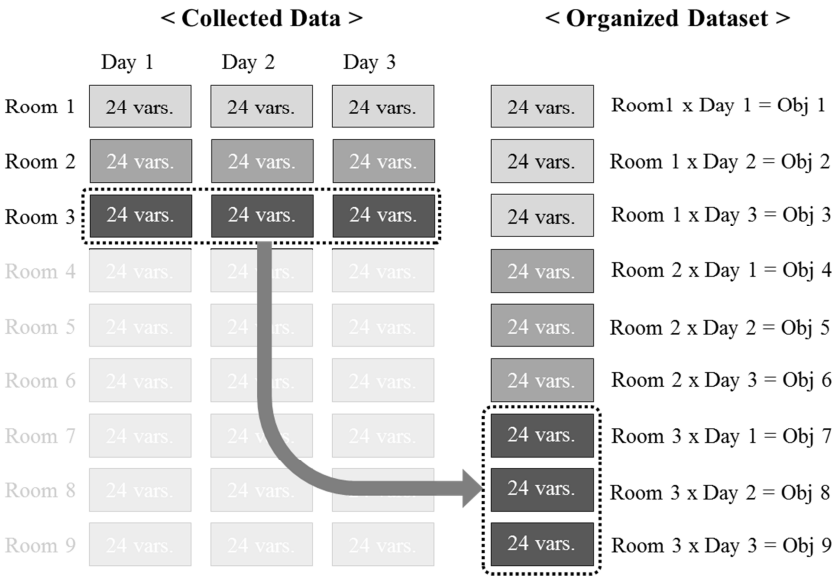


Figure 4-1.Dataset Organization by Room and Day

Step 2. Data Preprocessing: In order to improve the performance of clustering analysis, the original data is sequentially preprocessed in the following two aspects (see Fig. 4-2). First, min-max normalization maps all values of the original datasets in the range between 0 and 1. Second, PCA extracts *n* features from the normalized dataset. For the *n* variable, it is set to explain 86%, 88%, 90%, 92%, 94%, and 96% of the total variance to investigate its effect on clustering performance.

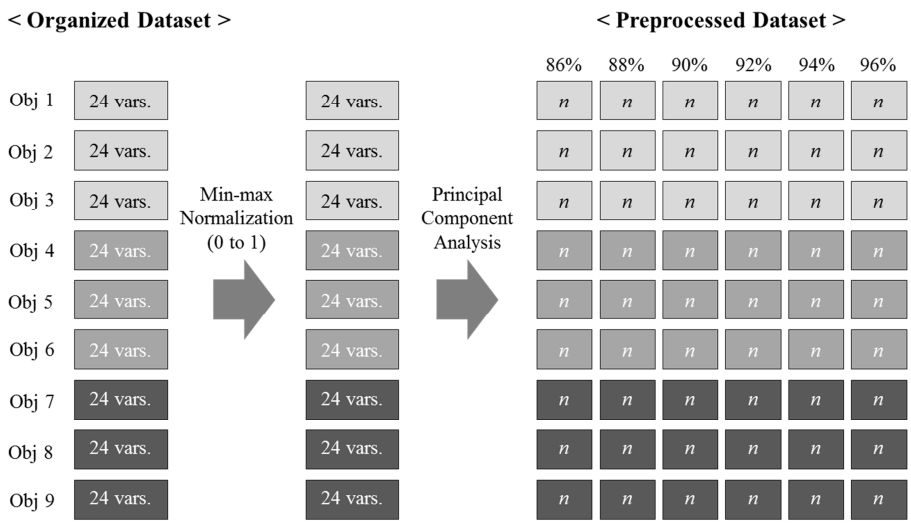


Figure 4-2. Preprocessed Datasets by Min-max Normalization and Principal Component Analysis

Step 3. Application of Clustering Algorithm: In order to identify representative EUGs in multi-zone buildings, *k*-means algorithm is applied to the preprocessed datasets (see Fig. 4-3). For the clustering analysis, energy use data collected with 24 hourly intervals is considered as input variables. Also, the *k* variable is set with a variation of its values from 2 to 100.

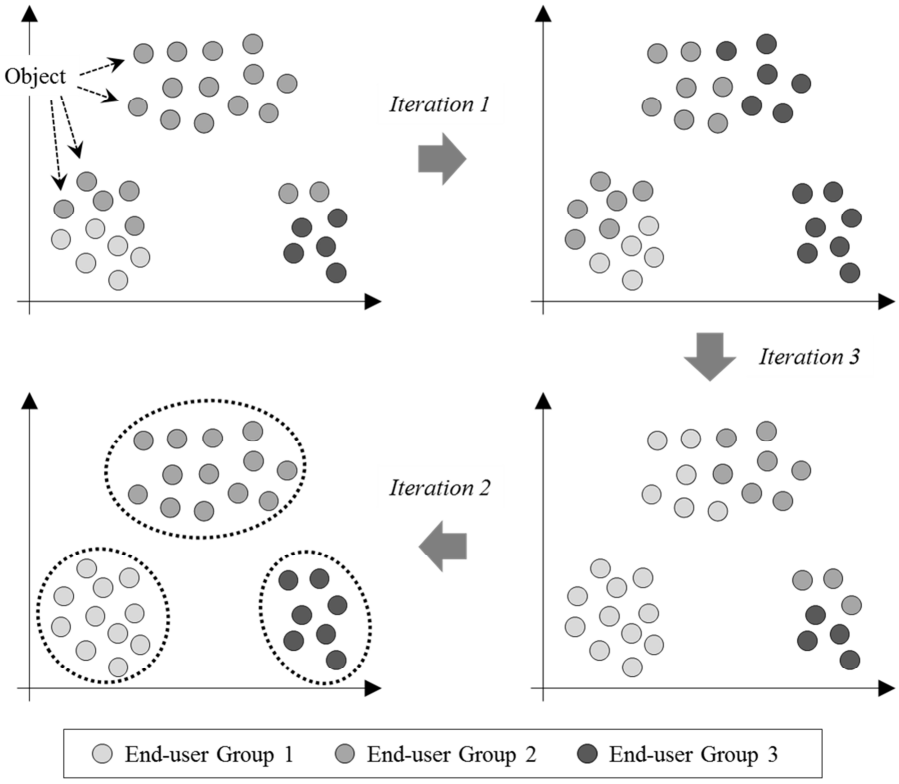


Figure 4-3.Recursive Search Process of *k*-means Algorithm

Step 4. Clustering Performance Assessment: In order to investigate the best number of representative end-user groups in the buildings, the value of DBI is used as a criterion for comparing clustering results. The lower values of DBI indicate higher discrimination between the identified end-user groups (see Fig. 4-4).

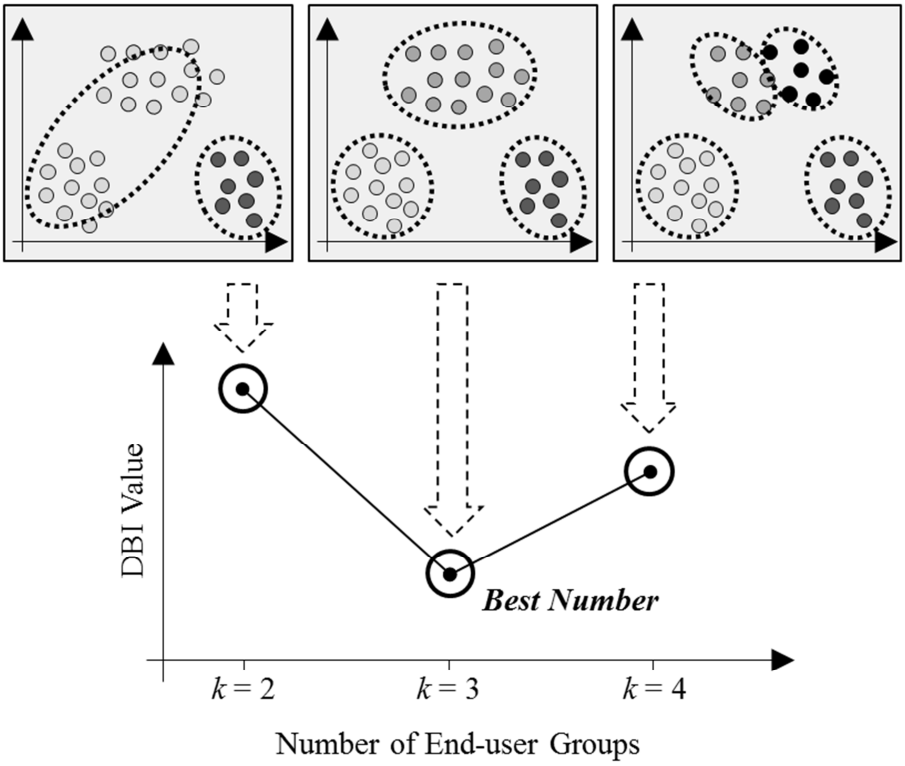


Figure 4-4.Best Number of Representative End-user Groups by Davies-Bouldin Index

4.3 Results and Discussions

This research conducted clustering analysis using *k*-means algorithm to identify representative end-user groups (EUGs) in the case buildings. Then, the amount of energy consumed by the identified EUGs was quantified on a daily and hourly basis. Lastly, the percentage of total rooms for EUGs was investigated in different weather and temporal contexts.

4.3.1 Representative End-user Groups

Fig. 4-5 represents the DBI values obtained for a number of cluster k variables from 2 to 100. Compared to the results of clustering experiments using original datasets, all the preprocessed datasets using PCA provided lower DBI values. Also, as the number of principal components decreases, lower DBI values were observed across almost the entire k variables. When evaluating the clustering performance by number of EUGs, smaller values of DBI occurred with an increase in the number of EUGs. Particularly, the lowest DBI value was 1.0675 at 10 EUGs resulted from the clustering experiment using PCA which explains 86% of the total variance in the original dataset. These results indicate that reducing data dimensionality is effective to improve the clustering performance in representative end-user

group identification. Further, considering that the minimum value of DBI correspond to the best solution with low variance within clusters and high variance between clusters, it can be concluded that the case buildings have 10 representative end-user groups during the given periods.

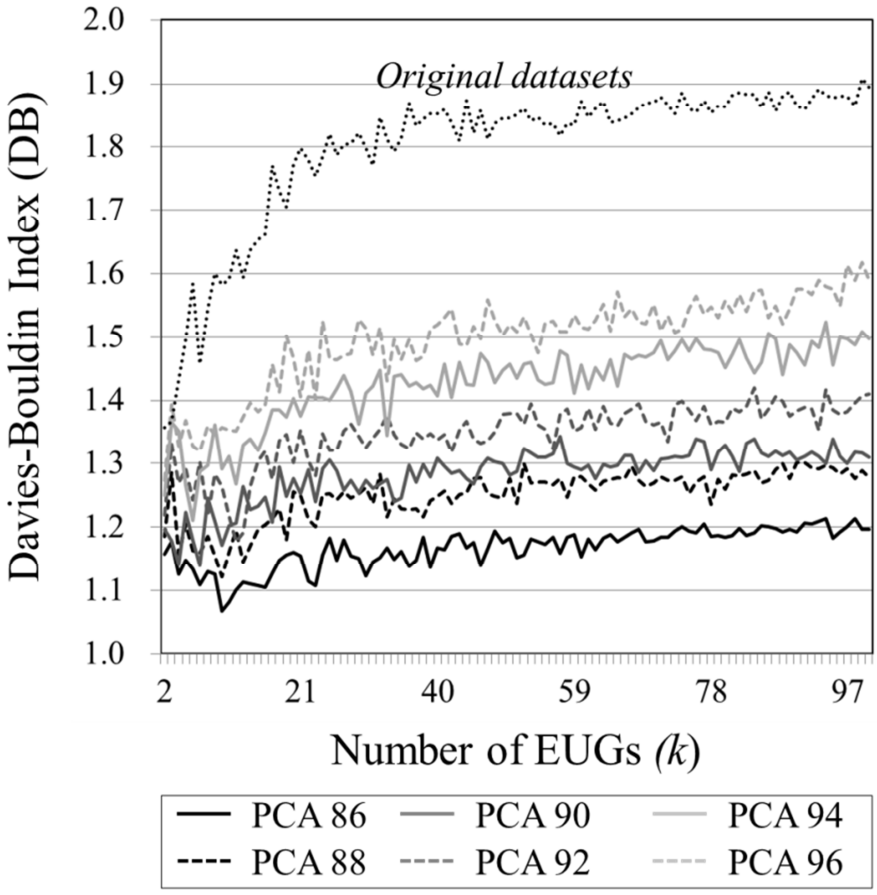


Figure 4-5. Comparison of Clustering Performance by Davies-Bouldin Index

As described in Fig. 4-6, the case buildings had 10 representative EUGs across all the given periods. When looking closely at the daily profiles of energy use and occupancy status for the 10 representative EUGs, they had different energy use behaviors as follow.

a) Daytime Peak (Group 4)*:* Group 4 generally stays indoors from 9 a.m. Also, it seems that energy consumption varies depending on occupancy status. In particular, this group has relatively high energy use in the daytime (2 to 4 p.m.).

b) Nighttime peak (Groups 2, 6, 9, 10): For these groups, it can be seen that a substantial amount of electrical energy is consumed during the occupied periods (12 to 9 a.m., 9 p.m. to 12 a.m). Especially, peak energy occurs in the nighttime.

c) Constant energy consumption (Groups 1, 3, 5, 7, 8): Although rooms are mainly occupied in the nighttime, these end-user groups tend to consume a certain amount of electrical energy regardless of occupancy status.

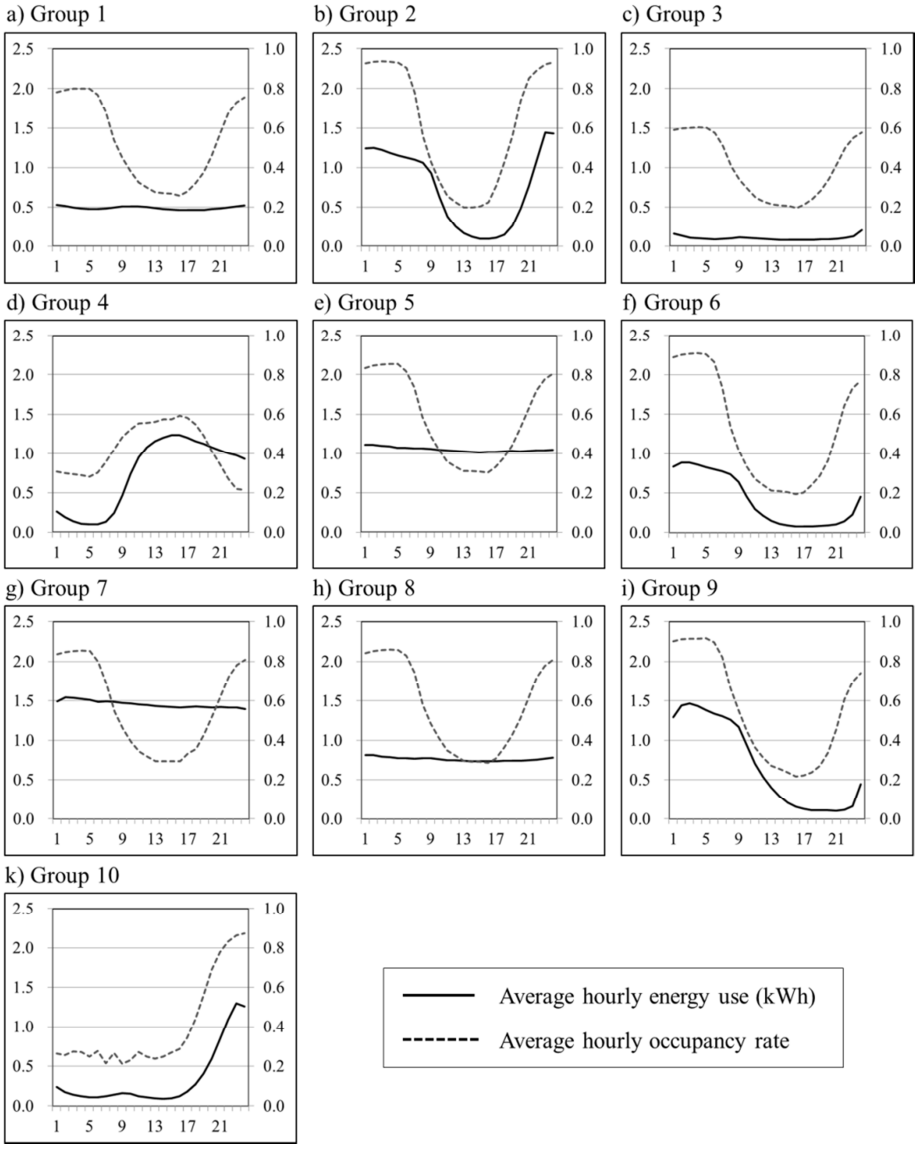


Figure 4-6. Representative Daily Profiles of Energy Consumption and Occupancy Rate (x-axis: time (hr); left y-axis: average hourly energy use (kWh); right y-axis: average hourly occupancy rate)

4.3.2 Energy Consumption by End-user Group

During the given periods, average daily energy use per room statistically differed among the EUGs (see Fig. 4-7). The EUGs 5, 7 and 8 spent more amount of electrical energy than other EUGs. Particularly, the EUG 7 consumed the highest amount of 35.1 kWh per room, followed by 25.2 kWh for the EUG 5 and 18.3 kWh for the EUG 8. In contrast, the EUG 3 had the lowest mean amount of electrical energy at 2.4 kWh per a day. This can be explained by the fact that a significant percentage of the daily energy consumption occurs during unoccupied hours. For example, as shown in Table 4-2, the EUGs 5 and 8 spend a comparable or lower amount of electrical energy in occupied rooms than the EUGs 2 and 9. However, while unoccupied, the EUGs 5 and 8 consume about 40% of daily energy use, which is higher than 20% for the EUGs 2 and 9.

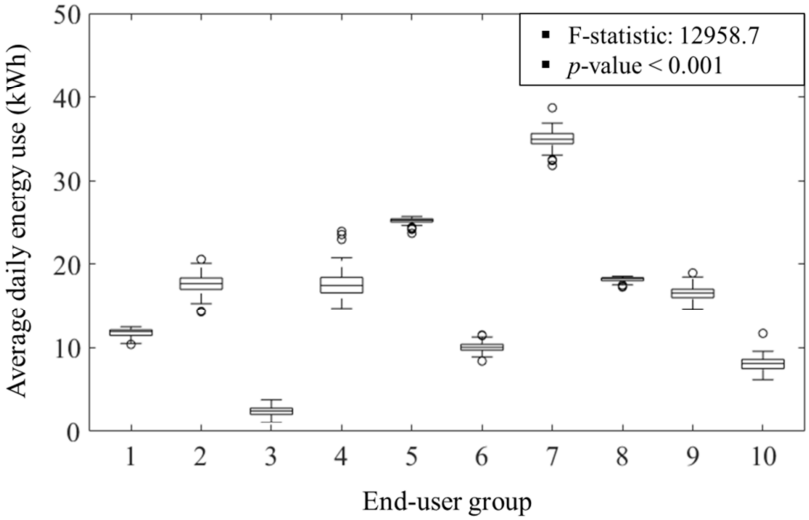


Figure 4-7. Average Daily Energy Consumption by End-user Group

Table 4-2. Average Daily Energy Use for Representative End-user Groups during the Given Periods

End-user Group	Average Daily Energy Use per Room (kWh)		
	Total	Occupied	Unoccupied
1	11.7	6.4	5.4
		(54%)	(46%)
2	17.7	14.1	3.6
		(79%)	(21%)
3	2.4	1.3	1.1
		(53%)	(47%)
4	17.8	8.3	9.6
		(46%)	(54%)
5	25.2	14.7	10.5
		(58%)	(42%)
6	9.9	7.1	2.7
		(72%)	(28%)
7	35.1	19.9	15.2
		(57%)	(43%)
8	18.3	10.6	7.7
		(58%)	(42%)
9	16.6	12.4	4.2
		(74%)	(26%)
10	8.1	5.3	2.8
		(66%)	(34%)

When evaluating the average energy use on an hourly basis, there were significant differences among the identified EUGs (see Figs. 4-8 and 4-9). The EUGs 5 and 7 consumed the most amount of electrical energy at 1.01 kWh and 1.4 kWh per occupied room, and 0.98 kWh and 1.29 kWh per unoccupied room (see Table 4-3). This can be caused by the fact that occupants tend to turn on HVAC systems at a high temperature setpoint all day. Another significant energy consumer was the EUGs 2 and 9 during occupied periods. They consumed electricity on average at 0.98 kWh and 0.96 kWh, respectively. This quantity can be explained by the underlying belief that occupants tend to feel thermally comfort in the indoor environment. For the EUGs 2 and 9, there might be a significant heating load during vacant periods because HVAC systems are generally turned off when occupants leave out their rooms. As a consequence, after occupants arrive, the substantial amount of electrical energy would be consumed by HVAC systems to recover their rooms at the acceptable thermal comfort level. Interestingly, the EUG 3 had little energy consumption regardless of occupancy status (occupied room: 0.10 kWh, unoccupied room: 0.08 kWh). This result can be explained for the following two reasons. First, in the light of the low occupancy rate for the EUG 3, dormitory rooms were empty all day (see Fig. 4-6). Second, there was no need for space heating due to a relatively high outdoor temperature (KEEI 2014).

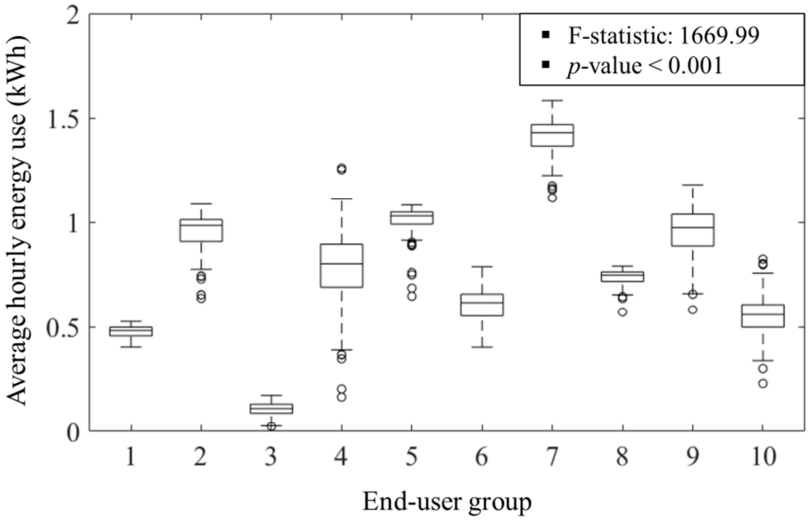


Figure 4-8. Average Hourly Energy Consumption per Occupied Room for End-user Groups

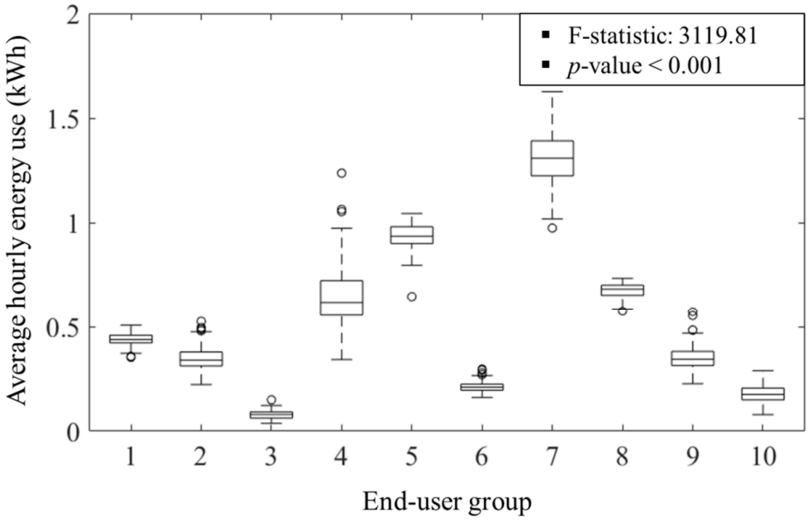


Figure 4-9. Average Hourly Energy Consumption per Unoccupied Room for End-user Groups

Table 4-3. Average Hourly Energy Use per Occupied and Unoccupied room for Representative End-user Groups

End-user Group	Average Hourly Energy Use per Room (kWh)	
	Occupied	Unoccupied
1	0.46	0.44
2	0.98	0.34
3	0.10	0.08
4	0.77	0.67
5	1.01	0.93
6	0.59	0.21
7	1.40	1.29
8	0.74	0.68
9	0.96	0.35
10	0.56	0.18

4.3.3 Percentage of Total Rooms by End-user Group

Fig. 4-10 shows a significant difference in the percentage of total rooms among the identified EUGs. Throughout the heating season, the EUG 8 on average was most prevalent at 21.7% of the total rooms. In contrast, the lowest percentage of total rooms is 1.9% for the EUG 4. Additionally, within the individual EUGs, the percentage of total rooms statistically varied depending on room size, floor level and exterior surface (see Table 4-4). The EUGs 1, 6 and 10 that consume less electrical energy on an hourly basis tend to live in single occupancy rooms, at middle floor and one exterior wall. On

the other hand, the EUGs 2, 5, 7, 8 and 9 with low energy efficiency during either occupied or unoccupied periods were more prevalent in double occupancy rooms, at ground and top floor and two exterior walls. These variations can be explained for two reasons. First, as the exposure to outdoor environment increases, more heating energy would be consumed by switching to a higher temperature setpoint. Second, larger living spaces have additional electronic equipment and devices due to the higher number of occupants. Further, from these results, it can be inferred that spatial characteristics have little effect on HVAC on/off switching during periods of non-occupancy. This is because there is not a consistent effect of spatial variables among some EUGs having similar load shape. For example, the EUGs 1, 5, 7 and 8 that leave on heaters and appliances during unoccupied periods were distinguishable by room size (EUG 1: single occupancy room; EUGs 5, 7 and 8: double occupancy room).

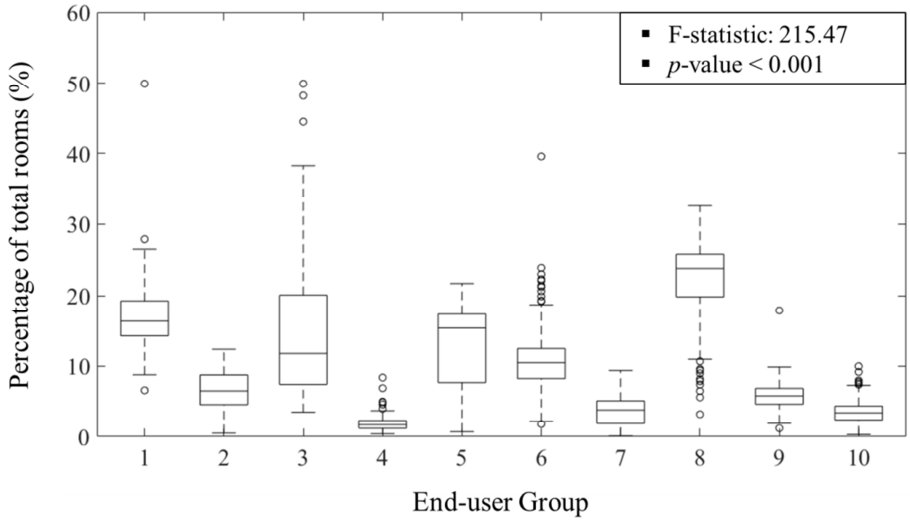


Figure 4-10. Percentage of Total Rooms by End-user Group

Table 4-4. Statistical Variations in Percentage of Total Rooms by Building Characteristics

Building Characteristics		Percentage of Total Rooms by Representative End-user Group										Chi-square
		1	2	3	4	5	6	7	8	9	10	
Room Size	Single	31	4	14	1	4	16	0	22	2	3	6212.67*
	Double	14	7	14	2	15	10	4	24	7	4	
Floor Level	Ground	15	5	9	2	16	11	6	31	3	2	1723.76*
	Middle	18	6	15	2	13	12	3	21	6	4	
	Top	13	9	13	2	18	9	6	21	7	3	
Exterior Surface	One	18	6	15	2	12	11	3	22	6	4	1403.61*
	Two	11	8	12	2	20	9	5	22	8	3	

*$p < 0.001$

When investigating how weather variables affect the percentage of total rooms by EUG, it can be seen that outdoor dry-bulb temperature is significantly related to its variation (see Table 4-5). For the EUGs 1, 3 and 6, there were positive correlation coefficients (see Fig. 4-11). This quantity represents that with an increase in outside dry-bulb temperature, these groups are more prevalent in the buildings. For example, the EUG 3 on average accounted for 9.8% of total rooms at sub-zero temperature but 19.1% over 0 ℃. In contrast, the percentage of total rooms for EUGs 2, 5, 7 and 8 decreases with higher outside dry-bulb temperature. For example, the EUG 8 was relatively prevalent at 25.2% of total rooms under 0 ℃ compared to 18.8% over 0 ℃. These variations can be understood because occupants have different energy use behaviors in response to weather conditions. For example, if occupants feel thermally comfort in a given environment, a small amount of energy will be consumed on an hourly basis due to non-use of heaters or low room temperature setpoint. As a consequence, low energy users such as EUGs 1, 3 and 6 will be prevalent in buildings. However, these results did not explain the difference in occupant's energy use behaviors while unoccupied (e.g., HVAC on/off switching) by outside dry-bulb temperature. Although the EUGs 1, 5, 7 and 8 have similar load shapes on a daily basis, they showed a different tendency for the percentage of total rooms by outdoor temperature.

Table 4-5. Correlation Coefficient between Weather Variables and Percentage of Total Rooms

End-user Group	Weather-related Variables			
	Outdoor Temperature	Wind Speed	Relative Humidity	Solar Radiation
1	0.478***	-0.005	0.232*	-0.074
2	-0.538***	0.120	-0.241**	0.174
3	0.701***	-0.052	0.190*	0.031
4	-0.146	0.122	-0.011	-0.125
5	-0.807***	0.033	-0.223*	0.035
6	0.609***	-0.108	0.132	-0.006
7	-0.774***	-0.001	-0.204*	0.033
8	-0.775***	0.032	-0.220*	-0.017
9	-0.143	-0.088	0.036	-0.170
10	0.259**	0.262**	0.081	-0.073

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

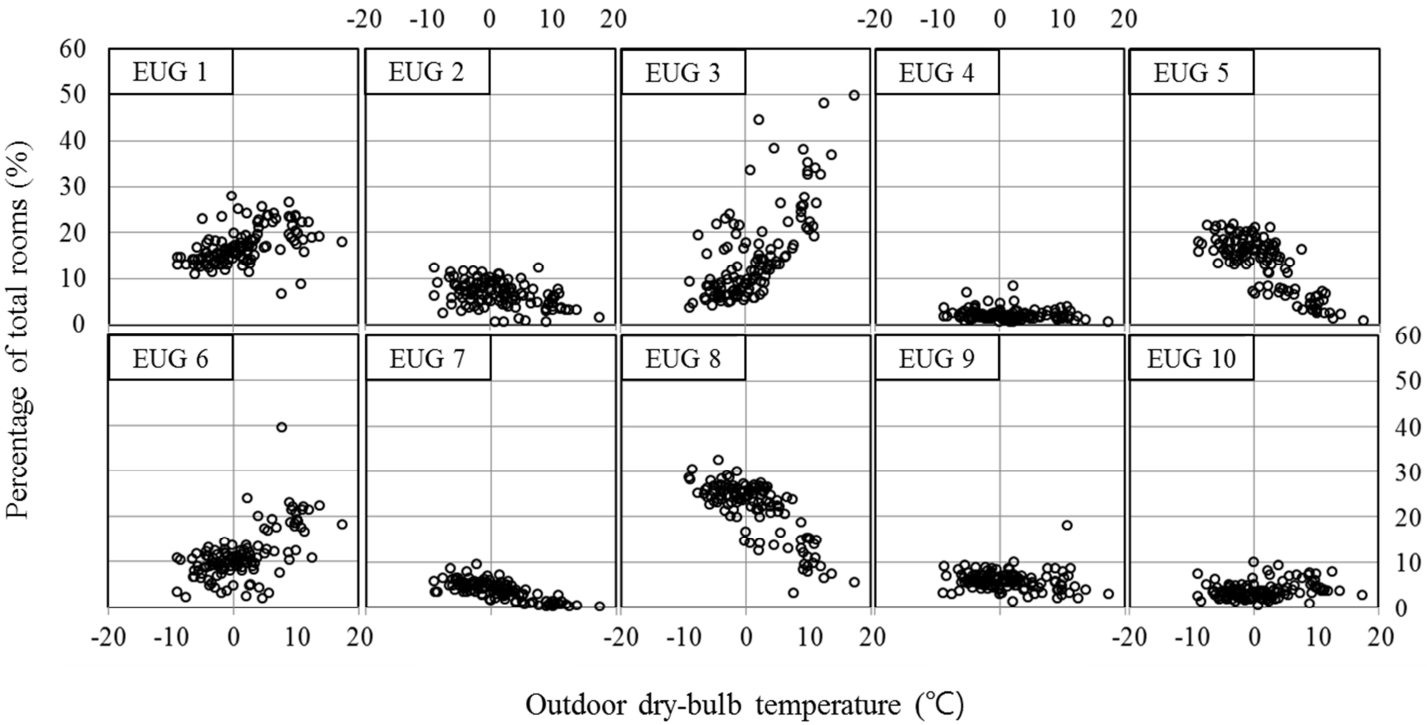


Figure 4-11. Percentage of Total Rooms by End-user Group and Outdoor Temperature

Table 4-6 describes the effect of temporal variables on the percentage of total rooms across the identified EUGs. Some EUGs had statistical variations in the percentage of total room by day of the week (see Fig. 4-12). The EUGs 2 and 6 were more prevalent on weekdays than weekends. Also, the EUGs 4 and 10 were weekend-dominant. These conflicting results may be due to occupants' weekly schedules. On weekdays, students generally leave out their rooms in the daytime to attend class or go to research offices. As a consequence, peak energy frequently occurs in the early morning or evening. In contrast, due to weekend leave for the students, dormitory rooms may have different energy use patterns during weekends. Additionally, as indicated in Fig. 4-13, course period made significant differences in the percentage of total rooms across almost all the EUGs. Compared to the fall semester, the EUGs 5, 7 and 8 accounted for a relatively high percentage of total rooms over winter semester. In contrast, the EUGs 1, 3, 6 and 10 were more common over fall semester than winter semester. These results can be expected because in Korea, the value of heating degree day (HDD) is higher in the winter semester than fall semester (KEEI 2014). As a consequence, there would be a change in the number of low and high energy users depending on course period.

Table 4-6. F-statistics of ANOVA for the Percentage of Total Rooms by Temporal Variables

End-user Group	Temporal Variables	
	Day of the Week	Course Period
1	0.0030	7.6069**
2	33.9871***	0.2353
3	2.1137	7.5538**
4	5.0431*	0.2788
5	0.8603	74.9361***
6	14.4270***	54.3741***
7	0.5263	40.9481***
8	0.3634	26.5345***
9	0.0047	0.3893
10	14.6737***	9.1158**

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

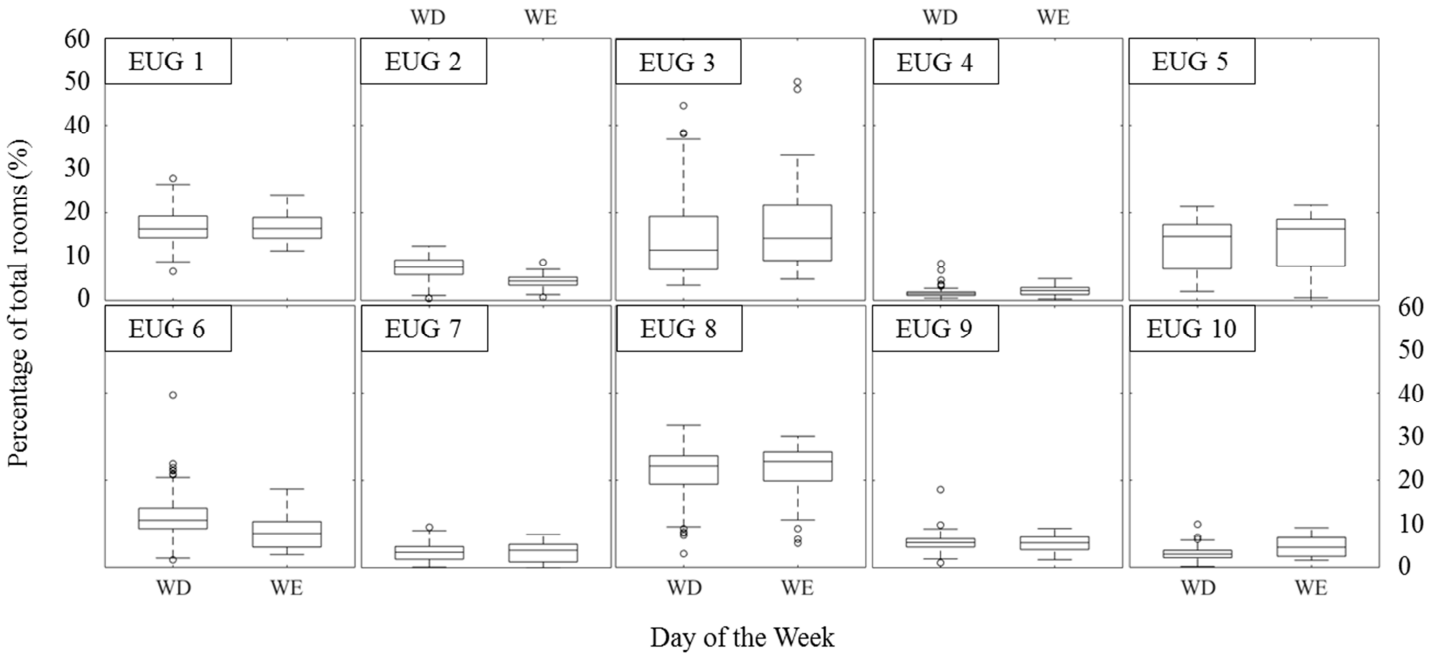


Figure 4-12. Percentage of Total Rooms by End-user Group and Day of the Week (WD: Weekdays, WE: Weekends)

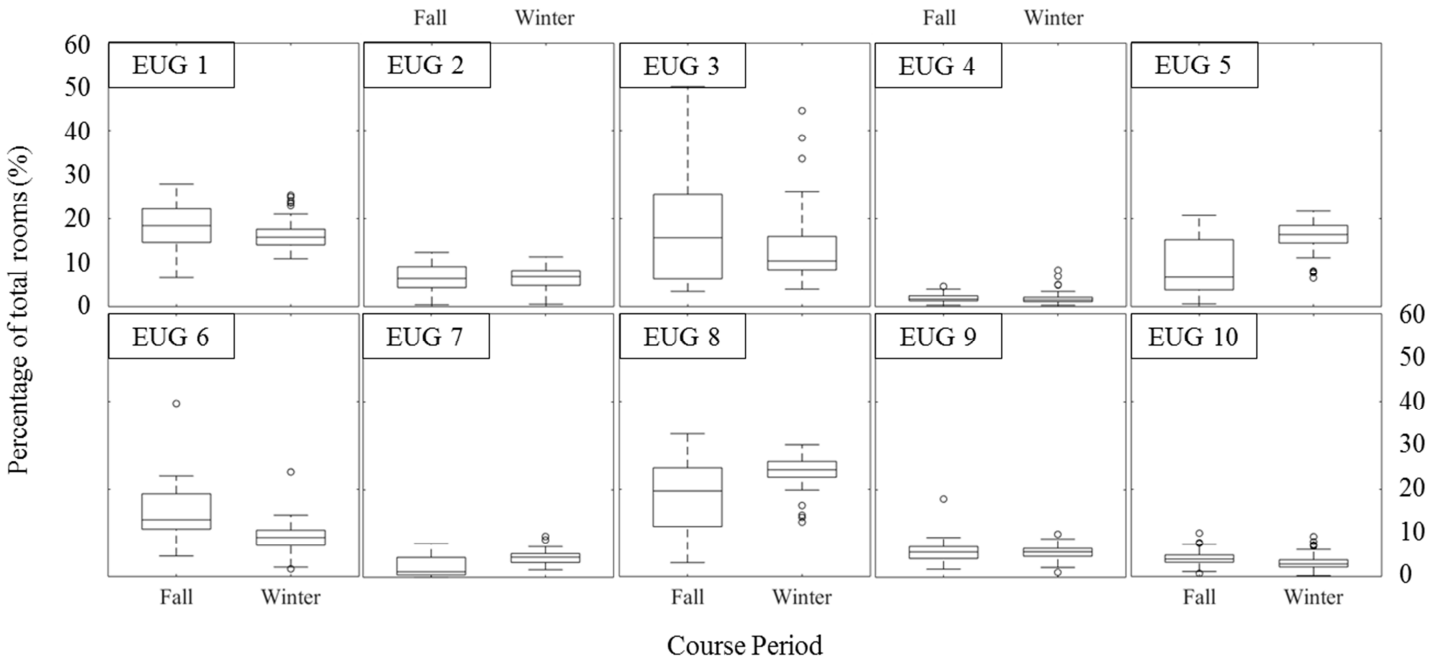


Figure 4-13. Variations in the Percentage of Total Rooms by Course Period

4.3.4 Discussions

In order to investigate the contextual behavior of representative end-user groups, this research conducted experiments using the data collected from the seven dormitory buildings. Although the dormitories are a single-purpose building for residence purpose, there were various daily profiles during the given periods. This indicates that identifying EUGs is a prerequisite process without exception of purpose and type of buildings.

When evaluating mean energy use per room on a daily basis, the EUG 7 consumed the most amount of electrical energy throughout the given periods, which was followed by the EUGs 5 and 8 (see Table 4-2). In particular, it was observed that they spend a significant percentage of daily energy while leaving out their rooms. From these results, it can be inferred that each room within the EUGs 5, 7 and 8 has energy saving potential from HVAC control during the periods of non-occupancy (e.g., interrupting the operation of HVAC systems, daytime setback strategy). Additionally, when investigating average hourly energy use per occupied and vacant room, the EUGs 2 and 9 consumed substantial amount of occupied energy (see Table 4-3). These results are important because it provides the following two implications. First, the EUGs 2 and 9 have energy saving potential while occupied through

HVAC control (e.g., temperature setpoint, pre-conditioning). Second, the EUGs 2 and 9 can use more energy with an increase in occupancy period.

Through investigating the behaviors of representative end-user groups in weather conditions, it is found that outdoor dry-bulb temperature significantly affects their proportion to the total number of rooms (see Table 4-5). Furthermore, it appears that most EUGs have a statistical variation in the number of rooms by day of the week and course period (see Table 4-6). These results are important because it provides a decision basis to establish optimal control strategies for HVAC systems in different contexts. For example, when outdoor dry-bulb temperature is in a range of -5 to -10℃, the EUGs 5 and 8 that consume significant amount of unoccupied energy account for 50% of total rooms. Based on this circumstance, interrupting the operation of HVAC systems during vacant hours can be an appropriate alternative to maximize energy saving in buildings. However, this alternative cannot be effective during warmer periods because the EUGs 5 and 8 are not prevalent in buildings.

4.4 Summary

As an effort to reduce energy consumption in buildings, it is highly recommended to control the operation of HVAC systems due to a significant energy saving potential with less effort. Based on the circumstance, considerable attention has been given to the identification process to find representative end-user group (EUGs) because it helps personalize the operation of HVAC systems depending on their energy use patterns. Further, this identification process allows selecting appropriate technology alternatives that can maximize energy saving potential in buildings. However, despite previous achievements, there has been little attempt to evaluate energy consumption for the EUGS and investigate their behaviors in different context. Therefore, in order to address this issue, this study conducted statistical tests to evaluate energy consumption for the EUGs on an hourly basis and investigate their contextual behavior. From the experimental results, the tree key findings are summarized as follows. First, the single-purpose buildings have various energy use patterns during the given periods. Second, there are opportunities to reduce energy consumption during occupied and unoccupied hours. Third, the behaviors of representative end-user groups statistically differ by temporal and weather context.

Chapter 5. Baseline Energy Use Prediction using Occupancy-related Characteristics

In order to predict energy use in a given context, this chapter introduces a data mining-based prediction model which addresses occupancy-related characteristics of representative end-user groups in multi-zone buildings. After constructing the prediction model, its performance is evaluated through comparing actual and predicted energy use on a daily basis.

5.1 Importance of Occupancy-related Characteristics in Building Energy Use Prediction

A substantial amount of studies have been conducted to investigate the effect of occupancy on the performance of building energy use prediction. This is caused by the fact that the presence of occupants within buildings provides significant implications on energy use. For example, occupants may adjust temperature setting point to improve their thermal comfort. As a consequence, this interaction will affect energy consumption for conditioning the indoor environment.

Despite the significant impact of occupancy on the prediction accuracy, two main problems still exist in the usage of occupancy data when predicting energy use in multi-zone buildings. First, diverse occupancy, which refers to the difference in occupancy status by temporal and spatial contexts in a building, exists among rooms. For example, as represented by Gul and Patidar (2015), university buildings have a complex occupancy status due to the various functions of the rooms such as administration, research, lecture, and seminar. Also, each of the rooms will show a variation in daily occupancy pattern among different time periods. However, in most studies (Neto and Fiorelli 2008; Yezioro et al. 2008; Li et al. 2015; Sandels et al. 2015; Virote and Neves-Silva 201; Wang and Ding 2015), occupancy diversity is eliminated by averaging the values of occupancy status at the building level, which may have contributed to the discrepancy between the actual and predicted energy use. Consequently, in order to minimize this discrepancy, different types of occupancy status need to be considered at the room level. Second, energy consumption could not be correlated with occupancy status. For example, a significant amount of energy is still consumed after some end-users have left their rooms, as they fail to switch off their equipment and devices (Anderson et al. 2015; Brown et al. 2010; Masoso and Grobler 2010). This inefficient behavior leads to non-correlation between energy use and occupancy status, rendering it difficult to ensure an improvement in the prediction accuracy. Nevertheless, to date, there has been little attention to

address this correlation issue. Although only Sandels et al. (2015) have used occupancy data after confirming a significant correlation between energy use and occupancy status, it is still unclear whether occupancy data contributes to the prediction accuracy when there is a weak correlation.

In an effort to address these problems, this research develops a data mining-based energy use prediction model focusing on occupancy-related characteristics of representative end-users in multi-zone buildings. For the proposed prediction model, three data mining techniques are employed since they facilitate to mimic the thermal behavior of buildings and investigate occupancy characteristics from the vast amount of historical data regarding energy use and occupancy.

5.2 Model Development

A building energy use prediction model is constructed using the three types of data mining techniques outlined in Section 3.3 This model is implemented in MATLAB environment with the Neural Network Toolbox, considering diverse occupancy and its correlation with energy consumption. Based on the data collected in Section 3.2, input variables that are used to construct the prediction model are selected. Then, in order to consider the

occupancy-related characteristics of end-users in multi-zone buildings, the data mining-based prediction model is developed which consists of four modules.

5.2.1 Input Variable Selection

Identifying significant determinants of building energy use is an important task because the prediction accuracy can be compromised by using input variables that have a weak relation to energy use. To date, various input variables have been employed to understand its impact on energy use prediction (see Table 5-1). In particular, the increasing concerns have been given to investigating the effect of occupancy on the prediction performance. This is caused by the fact that the presence of occupants provides significant implications on energy use. For example, occupants may adjust temperature settpoint to improve their thermal comfort. As a consequence, this interaction will affect energy consumption for conditioning the indoor thermal environment.

Table 5-1. Related Works on Building Energy Use Prediction and Input Variables

Input Variable	Neto and Fiorelli 2008	Yezioro et al. 2008	Li et al. 2009	Kwok et al. 2011	Azar and Menassa 2012	Edwards et al. 2012
Outdoor dry-bulb temperature	√	√	√	√		√
Relative humidity	√	√	√	√		
Wind speed				√		
Solar radiation/flux	√		√	√		√
Cloudness						
Rainfall				√		
Bright sunshine duration				√		
Day of the week						√
Hour of the day						√
Occupancy		√		√	√	
Occupant behavior					√	
Energy spent by equipment				√		
Energy use for previous time steps						√
Temperature setpoint		√			√	

(Table 5-1. Continued)

Input Variable	Yun et al. 2012	Sun et al. 2013	Jain et al. 2014	Monfet et al. 2014	Jovanović et al. 2015	Li et al. 2015
Outdoor dry-bulb temperature	√	√	√	√	√	√
Relative humidity	√	√		√	√	√
Wind speed	√				√	√
Solar radiation/flux	√	√	√		√	√
Cloudness		√				
Rainfall						
Bright sunshine duration						
Day of the week			√	√	√	
Hour of the day			√			
Occupancy	√	√				√
Occupant behavior						
Energy spent by equipment				√		
Energy use for previous time steps			√		√	
Temperature setpoint						

In this research, the proposed prediction model employs eight input variables depending on the purpose of its usage (see Table 5-2). The first four weather variables (i.e., outside dry-bulb temperature, wind speed, relative humidity, and solar radiation) are selected due to their high correlation to energy use. As an occupant-related characteristic, occupancy rate refers to the ratio of occupied rooms compared to the total number of rooms at a certain time. An occupancy rate value close to 1 indicates a higher possibility for occupants to be present in their rooms.

Table 5-2. Input Variables for Baseline Energy Use Prediction

Variables	Unit	Value
Outside dry-bulb temperature (OT)	℃	Continual
Wind speed (WS)	m/s	Continual
Relative humidity (RH)	%	Continual
Solar radiation (SR)	MJ/㎡	Continual
Occupancy rate (OR)	-	Continual

Additionally, in order to obtain information about occupancy rate, the following three date-related input variables are used since students show different occupancy status over time (see Table 5-3). The first input variable is the hour of the day, which has continual values ranged from 1 to 24. As shown in Fig. 5-1, there were statistical variations in average occupancy rate among different hours of the day. Second, the day of the week consists of weekdays

and the weekend. As shown in Fig. 5-2, lower occupancy rate is investigated during weekdays than weekends during the given periods. This difference can be expected since students living in dormitories tend to leave campus on weekends for their private life (e.g., visit to family or friends). Third, the course period is an indicator variable which denotes fall and winter semester. Fig. 5-3 shows that a statistical variation in average hourly occupancy rate exists between fall and winter semester. This difference stems from the fact that most students move out of their rooms over winter semester.

Table 5-3. Input Variables for Occupancy Prediction

Variables	Unit	Value
Hour of the day (HD)	hour	1 to 24
Day of the week (DW)	day	Weekday: 1, Weekend: 2
Course period (CP)	-	Fall: 1, Winter: 2

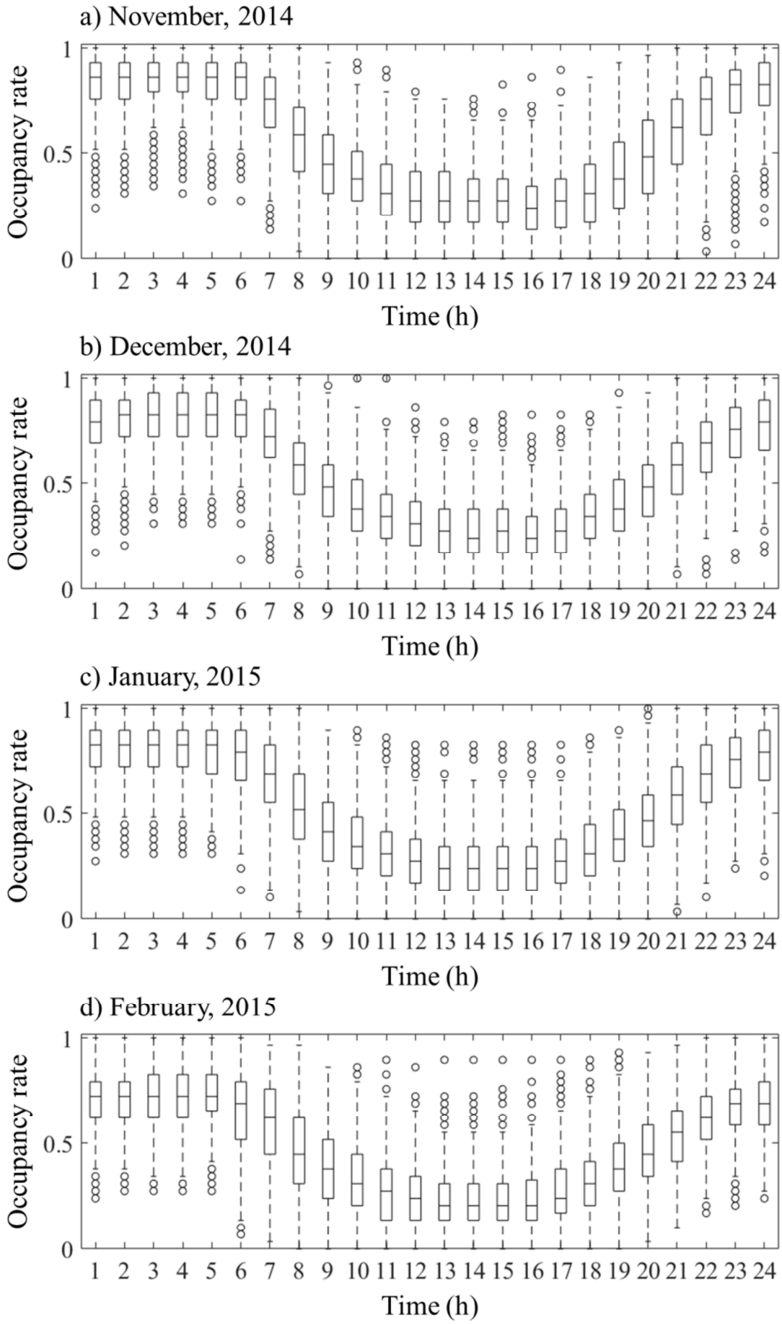


Figure 5-1. Average Hourly Occupancy Rate by Time of the Day

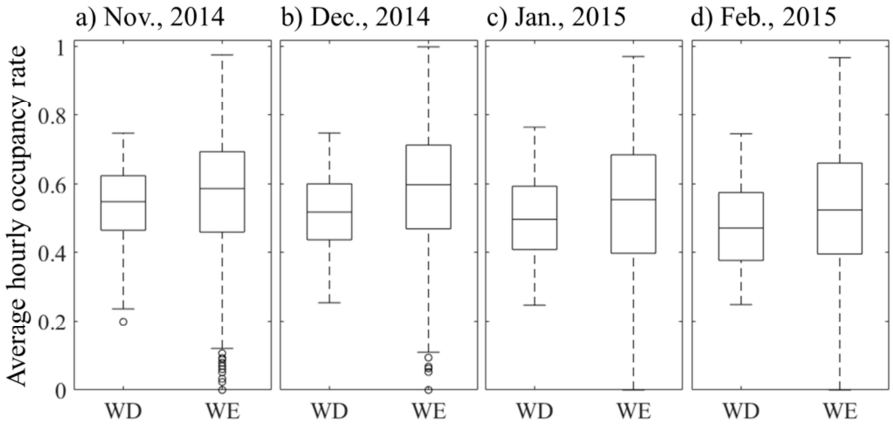


Figure 5-2. Average Hourly Occupancy Rate by Day of the Week (WD: Weekdays, WE: Weekends)

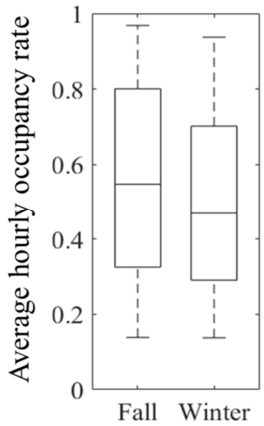


Figure 5-3. Average Hourly Occupancy Rate by Course Period

5.2.2 Structure of Data Mining-based Prediction Model

In order to examine how occupancy-related characteristics of end-user groups affect the accuracy of energy use prediction, a data mining-based prediction model is developed which consists of four modules named according to their role (see Fig. 5-4). As a beginning of predicting building energy use, the entry module collects historical data concerning input and output variable. Based on the historical datasets, the dataset selection module determines similar daily datasets to reduce training time and avoid over-fitting problem. Next, in an effort to investigate diverse occupancy in buildings, the cluster identification module draws representative daily profiles of energy use and occupancy status from the similar daily datasets. For the representative profiles, the prediction module then evaluates the correlation between energy use and occupancy status, and constructs prediction sub-models.

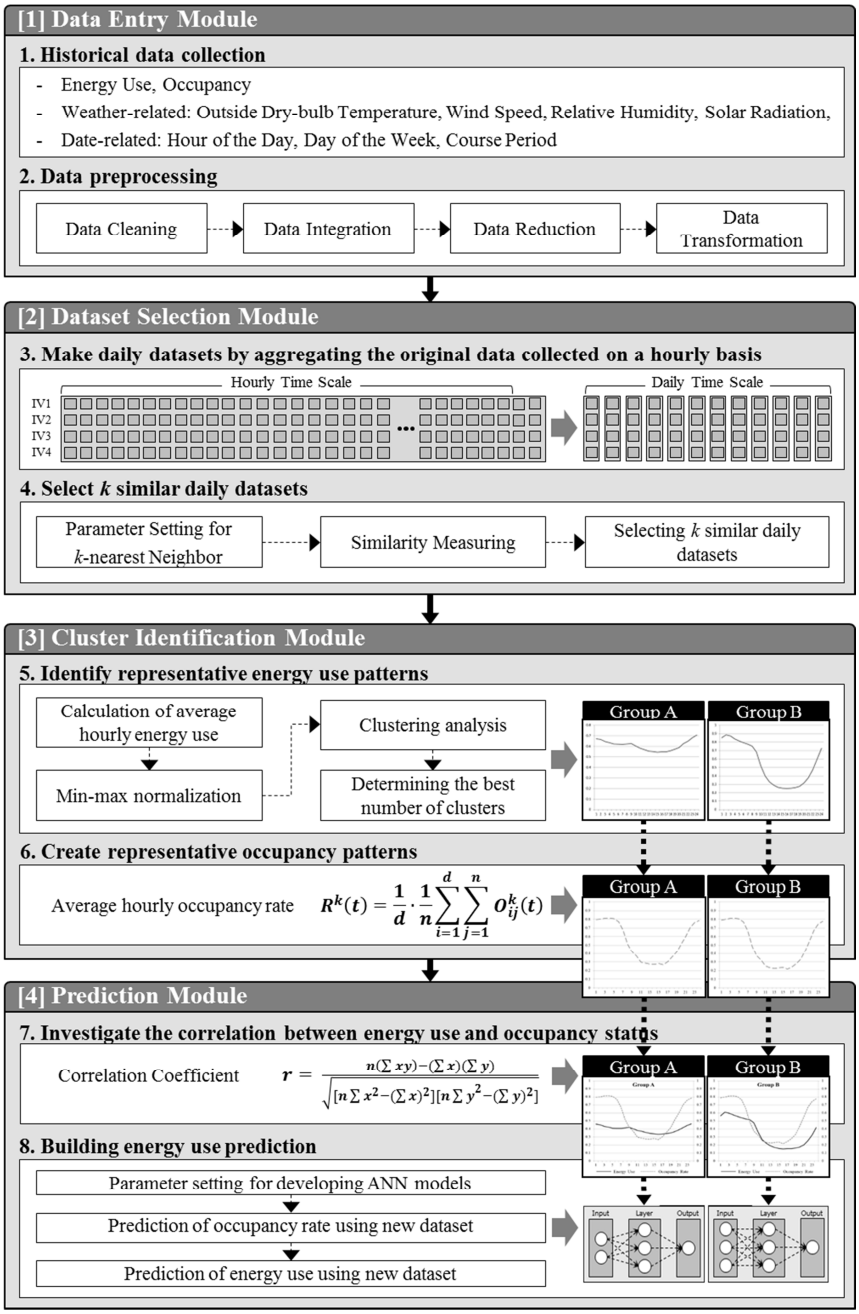


Figure 5-4. Main Structure of Data Mining-based Energy Use Prediction Model

a) Data Entry Model: The data entry module imports historical data related to the outside dry-bulb temperature, wind speed, relative humidity, solar radiation, hour of the day, day of the week, academic period, energy use, and occupancy rate. For the weather and occupancy-related variables, the historical data is collected every hour. The daily data for date-related variables is also obtained except for hour of the day. After the data collection, data preprocessing is carried out to improve the performance of building energy use prediction as follows. First, if a dataset contains missing and abnormal values during a certain period, this module does not make use of the remaining variables' values for building energy use prediction. The data collected from multiple sources is then combined to form a new dataset which includes the values of seven input variables and an output variable. Last, the preprocessed dataset is sent to the next module to investigate similar daily datasets for model development.

b) Dataset Selection Module: In order to address the problems incurred with a large amount of historical datasets, the dataset selection module determines *k* daily datasets to be used for model development. In this context, daily datasets are obtained by averaging the values of eight input variables imported from the data entry module. After constructing the daily datasets, the *k*-nearest neighbor algorithm searches for the *k* datasets that are most similar to the new daily dataset. In this process, similarity is determined by Euclidean

distance introduced in Eq. 3-1. Also, min-max normalization is used to minimize the scale difference among the input variables. After investigating *k* similar daily datasets, these outputs are sent to the next module to find representative daily profiles of energy use and occupancy status.

c) Cluster Identification Module: The cluster identification module has two functional roles for addressing occupancy-related characteristics of end-user groups. For the first role, this module finds representative daily profiles of energy use by clustering analysis. In order to perform this role, the *k*-means algorithm is applied to the similar daily datasets obtained in the dataset selection module. Clustering performance is then assessed to determine the best number of representative energy use patterns depending on the Davies-Bouldin Index (DBI). The second role involves making daily occupancy profiles. For the identified clusters, the average hourly occupancy rate is calculated from the following equation.

$$R^k(t) = \frac{1}{d} \cdot \frac{1}{n} \sum_{i=1}^{d} \sum_{j=1}^{n} O_{ij}^k(t) \qquad \text{(Eq. 5-1)}$$

where $R^k(t)$: average occupancy rate for the kth cluster at time t; d: the number of similar daily datasets; n: the number of rooms for the kth cluster; and $O_{ij}^k(t)$: occupancy state (0: vacancy or 1: presence) of the ith room for the kth cluster at time t of the jth similar dataset. After conducting these identification processes, representative daily profiles of energy use and occupancy status are drawn as outputs of this module and are exported to the next module.

d) Prediction Module: The prediction module provides information about the amount of energy that will be consumed in buildings for the next few days. In order to improve the accuracy of building energy use prediction, multiple prediction sub-models using ANN are constructed depending on the clusters identified in the cluster identification modules. Particularly, before training each of the ANN sub-models, the following two processes are required. First, the correlation between energy use and occupancy rate is examined by comparing hourly energy use with hourly occupancy rate. This process is important because occupancy could not significantly contribute to energy use under a situation of poor behaviors by the occupants. In order to conduct this process, the Pearson's correlation analysis (r) evaluates the relation between average hourly energy use and average occupancy rate for the groups. If these two variables are highly correlated, the occupancy rate is

used as one of the input variables. Second, if the groups have a high correlation between energy use and occupancy rate, their future occupancy rate is calculated using date-related input variables. This is significant because temporal context affect occupancy status. After training multiple prediction sub-models, the predicted building energy use is obtained by adding the results drawn from all the sub-models.

5.3 Model Validation

In order to evaluate the performance of the developed model, comparative experiments were conducted with other prediction models (see Table 5-4). The BN-ANN model uses the average values of occupancy rate drawn at the building level regardless of its correlation with energy use. For the BC-ANN model, occupancy rate is adopted as an input variable only if the correlation efficient is higher than 0.5, which is a threshold for determining significant correlation (Suomalainen et al. 2015). In contrast, RN-ANN accounts for the average values of occupancy rate investigated at the room level, which are used as an input variable regardless of the correlation coefficient. However, in the RC-ANN model, the occupancy rate is used as an input variable when investigating its high correlation with energy use.

Table 5-4. Description of Different Prediction Models

Model	Occupancy-related Characteristics	
	Occupancy Diversity among Different Rooms[a]	Correlation between Energy Use and Occupancy Rate
BN-ANN	X	X
BC-ANN	X	O
RN-ANN	O	X
RC-ANN	O	O

[a]For the identified clusters which show similar energy use patterns in buildings, representative daily profiles of occupancy rate are investigated at the room level and used as an input variable of each prediction sub-model.

Across all the prediction models, a parameter setting was performed as follows (see Table 5-5). Given a test dataset, 10 similar daily datasets were selected to find the number of rooms for each group. In the prediction module, the similar daily datasets were split into 80% for training and 20% for validation. Also, each ANN sub-model was constructed with 10 hidden neurons. The accuracy of the building energy use prediction was assessed using the coefficient of variation of the root mean squared error (CV-RMSE). For this performance index, the CV-RMSE value is given by combining $RMSE$ and $\bar{Y}_i$ as follows:

$$CV - RMSE = \frac{RMSE}{\bar{Y}_n} \times 100\% \qquad \text{(Eq. 5-2)}$$

$$RMSE = \sqrt{\frac{\sum_i^n \left(Y_i - \check{Y}_i\right)^2}{n}} \quad \text{(Eq. 5-3)}$$

where $RMSE$: root mean squared error; $\bar{Y}_n$: average value of actual energy use during the prediction period *n*; Y_i: actual energy use at time *i*; and $\check{Y}_i$: predicted energy use at time *i*. Also, since similar datasets are randomly divided into training and validation datasets, the network training and validation process were performed 10 times to find the best CV-RMSE values.

Table 5-5. Main Parameters of ANN Models

Parameter	Value
Number of similar daily datasets	10
Clustering algorithm	*k*-means algorithm
Network type	Feed forward neural network
Number of hidden layers	10
Number of nodes in hidden layer	10
Number of epochs	500
Minimum gradient of performance	1e-07
Maximum number of validation checks	50

With the experimental design, the effect of occupancy-related characteristics is examined from the perspective of one-day-ahead prediction to ensure the validity of the proposed model across a continuous time series of

several days. In the next section, I discuss the prediction results and suggest an improvement for the developed model.

5.3.1 Experimental Results

Experiments were conducted using four test datasets collected on a) November 12, 2014, b) December 10, 2014, c) January 19, 2015, and d) February 7, 2015. These test datasets list the different values for eight input variables to provide a basis to validate the results of one-day-ahead prediction. For each test dataset, 10 similar daily datasets were drawn depending on the average values of seven input variables (see Table 5-6). After selecting similar daily datasets, the representative daily profiles of energy use and occupancy status were identified. Across all given periods, the case buildings had ten end-user groups which show different percentage of rooms (see Table 5-7).

Table 5-6. Average Values of Input Variables for One-day-ahead Prediction

Test Dataset	Input Variable						
	OT	WS	RH	SR	HD	DW	CP
a) November 12, 2014	6.9000	5.7208	56.5833	0.3912	-	1	1
b) December 10, 2014	1.2292	2.0667	54.8750	0.1371	-	2	1
c) January 19, 2015	0.3292	3.2500	71.3333	0.3133	-	1	2
d) February 7, 2015	1.4625	2.3667	64.6667	0.2583	-	2	2

Note: OT = Outdoor Temperature (℃), WS = Wind Speed (m/s), RH = Relative Humidity (%), SR = Solar Radiation (MJ/㎡), DW = Day of the Week (weekday: 1, weekend: 2), CP = Course Period (fall: 1, winter: 2).

Table 5-7. Percentage of Total Rooms by End-user Group and Test Dataset

Test Dataset	End-user Group									
	1	2	3	4	5	6	7	8	9	10
a) November 12, 2014	19	4	38	1	3	19	1	8	2	5
b) December 10, 2014	12	11	6	2	17	12	6	25	5	4
c) January 19, 2015	23	7	7	1	15	8	5	24	5	2
d) February 7, 2015	17	5	7	1	17	10	4	30	7	2

Additionally, correlation analysis was conducted to determine the usage of occupancy rate as an input variable of BC-ANN and RC-ANN models. As shown in Table 5-8, occupancy rate is significantly correlated with energy use at the building level on December 10, 2014, January 19, 2015, and February 7, 2015; it was therefore used as an input variable of BC-ANN models. In contrast, since the correlation coefficient seems to be weak on November 12, 2014, a BC-ANN model did not account for occupancy rate as an input variable. Observing the experiment results of correlation analysis at the room level, the group 2s, 4s, 6s, 9s, and 10s show a significant correlation between energy use and occupancy rate throughout all the given periods, whereas there is a weak correlation in the case of the group 1s, 3s, 5s, 7s, and 8s.

Table 5-8. Correlation between Energy Use and Occupancy Status for One-day-ahead Prediction

Test Dataset	Building Level	End-user Group									
		1	2	3	4	5	6	7	8	9	10
a) Nov. 12, 2014	0.865	0.303	0.659	0.213	0.549	0.405	0.789	0.315	0.248	0.665	0.765
b) Dec. 10, 2014	0.381	0.471	0.817	0.329	0.873	0.368	0.610	0.398	0.356	0.899	0.866
c) Jan. 19, 2015	0.648	0.237	0.723	0.269	0.648	0.389	0.698	0.268	0.464	0.671	0.879
d) Feb. 7, 2015	0.594	0.403	0.815	0.246	0.798	0.261	0.834	0.416	0.324	0.863	0.824

When comparing the best CV-RMSE values for the prediction model, it is observed that ANN models considering the correlation between energy use and occupancy generally provide high performance in building energy use prediction (see Fig. 5-5). Except for the experiment using the data collected on February 7, 2015, the BC-ANN model produced lower CV-RMSE values than the BN-ANN model (Nov. 12, 2014: 8.0% compared to 8.3%; Dec. 10, 2014: 8.4% compared to 8.8%; Jan. 19, 2015: 5.7% compared to 6.0%). Also, the RC-ANN models provided higher accuracy of building energy use prediction than the RN-ANN models across all the given periods (Nov. 12, 2014: 5.6% compared to 6.5%; Dec. 10, 2014: 5.7% compared to 6.5%; Jan. 19, 2015: 4.6% compared to 6.4%; Feb. 7, 2015: 4.7% compared to 6.6%). When examining the effect of occupancy diversity on building energy use prediction, higher performance is generally found in the RC-ANN models. Across all the cases, the RC-ANN models produced lower CV-RMSE values than the BN-ANN and BC-ANN models (Nov. 12, 2014: 5.6% compared to 8.3% and 8.0%; Dec. 10, 2014: 5.7% compared to 8.8% and 8.4%; Jan. 19, 2015: 4.6% compared to 6.0% and 5.7%; Feb. 7, 2015: 4.7% compared to 5.2% and 6.0%). However, RN-ANN models rarely result in better prediction accuracy than both BN-ANN and BC-ANN models.

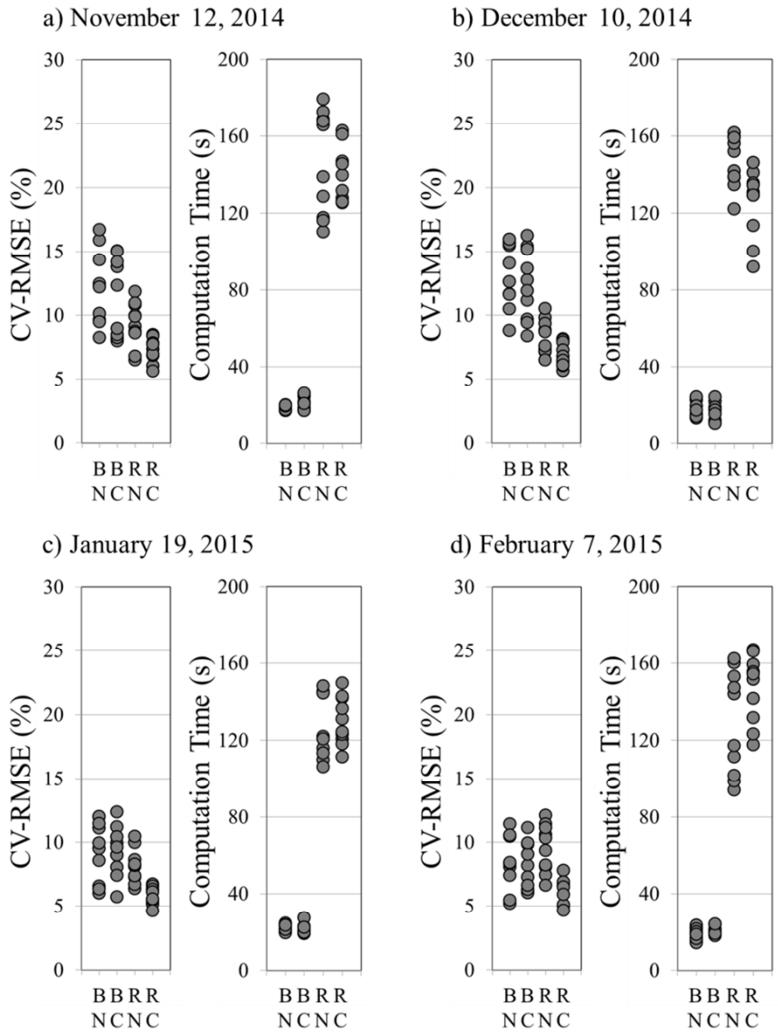


Figure 5-5. CV-RMSE and Computation Time for One-day-ahead Prediction

In addition, since the 10 similar datasets might not be optimal to construct the proposed RC-ANN models, sensitivity analysis was performed using 1 to 30 similar datasets to investigate how the number of similar daily datasets influences the prediction accuracy and training time. As shown in Fig.

5-6, CV-RMSE shows a consistent performance trend. As the number of similar daily datasets increases, the prediction accuracy tends to decrease across all the given periods. In contrast, training time does not significantly differ according to the number of similar daily datasets.

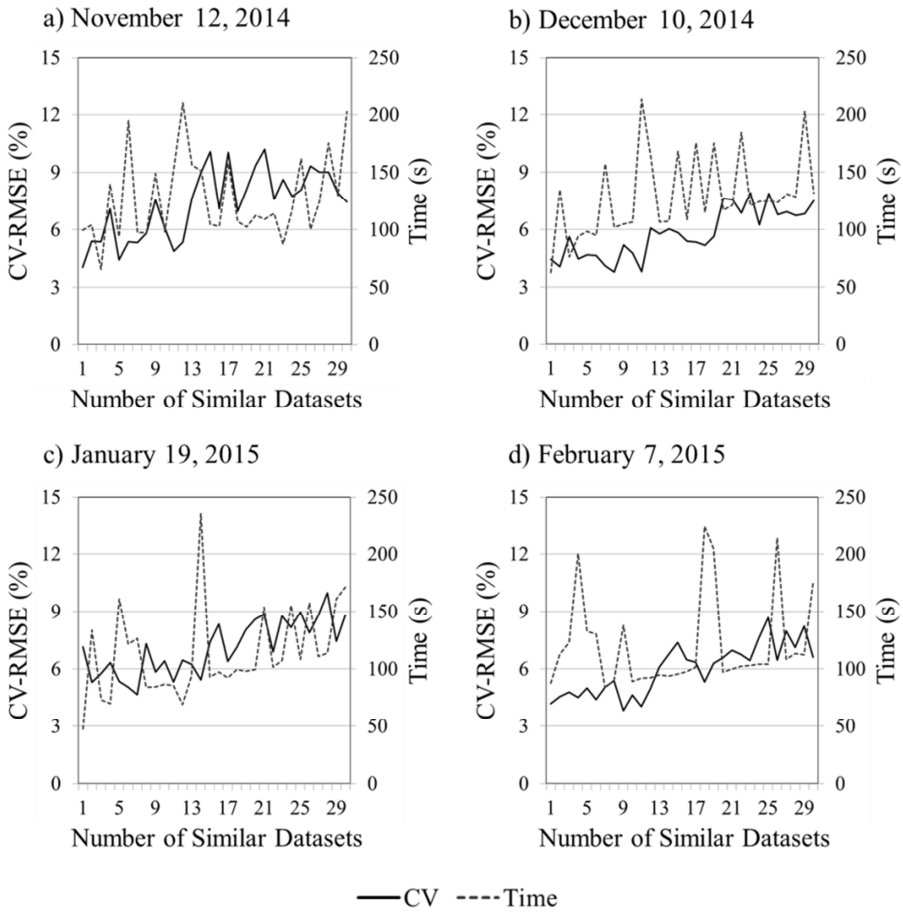


Figure 5-6. Performance of One-day-ahead Prediction by Number of Similar Daily Datasets

5.3.2 Discussions

In most studies on building energy use prediction (Kwok et al. 2011; Yezioro et al. 2008; Li et al. 2015; Sandels et al. 2015; Virote and Neves-Silva 2012; Wang and Ding 2015; Azar and Menassa 2012), the underlying belief is that occupancy is one of the major determinants of building energy use and significantly contributes to the prediction accuracy. This can be explained by the fact that occupants interact with energy-using items and thus consume energy during occupied hours. However, such contributions of occupancy data can be diminished under a situation of occupancy diversity and its non-correlation with energy use. Therefore, comparative experiments were performed in this research to examine the effect of the occupancy-related characteristics on building energy use prediction.

Fig. 5-5 compares the results of one-day-ahead energy use prediction depending on the values of CV-RMSE. Considering that a smaller CV-RMSE indicates better performance, it is observed that the proposed RC-ANN models provide more reliable accuracy within the acceptable tolerance (CV-RMSE, 25%) than the BN-ANN, BC-ANN, and RN-ANN models (ASHRAE 2002). Furthermore, although a small gap in CV-RMSE values is observed among the prediction models, this is significant because the RC-ANN models

show a relatively low distribution of CV-RMSE values regardless of the random selection of training and validation datasets. Therefore, it can be said that the proposed model produces more improved results for energy use prediction than the other prediction models.

More specifically, the improved accuracy of the one-day-ahead prediction is observed in the BC-ANN and RC-ANN models, which consider the correlation between energy use and occupancy status. Although they do not account for occupancy rate as an input variable, the CV-RMSE values are lower than those for the BN-ANN and RN-ANN models (e.g., one-day-ahead prediction on November 15, 2014). These improvements can be expected since occupancy status is not significantly correlated with energy use during the given periods and thus could have a detrimental effect on the prediction accuracy. In this context, the non-correlation could have resulted from poor occupant behaviors while the room was unoccupied. Through the intuitive assessment of the daily profiles shown in Fig. 5-5, it was observed that the groups with non-correlation consume a significant amount of electrical energy in unoccupied rooms, since occupants do not switch off the heating systems before leaving. Additionally, it appears that occupancy diversity affects the performance of one-day-ahead prediction. Compared to the BN-ANN and BC-ANN models, the RC-ANN models, that have multiple prediction sub-models, have the lowest CV-RMSE values. These results can be expected

since the occupancy data used in BN-ANN and BC-ANN models is simplified, although the case buildings have different types of daily occupancy profiles. Consequently, the use of simplified occupancy data undermines the performance of building energy use prediction. However, in contrast, the time taken to construct the network of RC-ANN models is longer than that for the BN-ANN and BC-ANN models (see Fig. 5-5). This is because the multiple sub-models should be individually trained and validated according to the number of representative energy use patterns. To summarize, these experimental results indicate that investigating the correlation between energy use and occupancy status is an essential prerequisite for using occupancy data. Furthermore, in order to improve the prediction accuracy, occupancy diversity should be considered while network training.

Through sensitivity analysis, it is found that changing the number of similar daily datasets has an impact on the prediction accuracy. In most cases of one-day-ahead prediction, RC-ANN models show lower prediction accuracy as the number of similar datasets increase. As shown in Fig 5-6, the best CV-RMSE value is obtained when the number of similar daily datasets is less than 10 across all the prediction cases. In terms of training time, a distinct tendency is not observed, regardless of the number of similar daily datasets. Interestingly, these results do not concur with the opinions expressed in many previous studies (Yun et al. 2012; Mustafaraj et al. 2011; Fan et al. 2014). In

general, the optimal parameters for ANN models are obtained with a large number of training datasets because it is possible to capture all of the useful information to find the optimum training dataset. Also, it is commonly recognized that the computation process with large training datasets takes is time-consuming. However, since similar daily datasets for model development were investigated and adopted in this research, it may not be necessary to use a substantial amount of training datasets. This gap in the literature can also be due to the low possibility of using the daily datasets that are most similar for network training when using large datasets. In this context, it would be difficult to update the gradient of the network performance in successive iterations, so the network training was terminated earlier than suggested in previous studies.

Utilizing the recent technical advances in real-time measuring systems, the proposed model facilitates both one-day-ahead prediction for building energy use. This helps recognize daily peak demand and daily energy consumption during the prediction periods. In particular, it is possible to obtain more detailed information about hourly energy consumption according to occupancy status for similar rooms. These improvements imply that daily operations of HVAC systems can be planned a priori depending on energy use patterns (e.g., pre-heating before use at room level).

5.4 Summary

With continuous efforts being made globally to enhance the reduction of building energy consumption, energy use prediction is an essential prerequisite to optimize the operation of energy-using equipment. To date, a number of building energy use prediction models have been proposed using various factors including weather, building physical characteristics, equipment, and occupant-related characteristics. Among these factors, considerable attention has been paid to occupant-related characteristics due to their significant impact on building energy use. In particular, recent studies have employed occupancy status as a significant determinant of building energy use. While utilizing occupancy status as an input variable contributes to improving the prediction accuracy, two problems that arise with the use of occupancy data were rarely addressed in the literature. In order to address the discrepancies between studies, this research developed a data mining-based energy use prediction model that considers diverse occupancy and its correlation with energy consumption in multi-zone buildings.

In order to evaluate the performance of the developed prediction model, comparative experiments for one-day-ahead prediction were conducted. From the experimental results, the three key findings are summarized as follows.

First, the use of occupancy rate as an input variable does not always ensure the improvement in prediction accuracy. An occupancy rate that is weekly correlated with energy use creates an adverse effect on prediction accuracy. Second, enhanced accuracy can be achieved by considering occupancy diversity in buildings. Third, the proposed prediction model will have a high accuracy when using fewer similar daily datasets.

Chapter 6. Post-retrofit Energy Use Prediction using Thermodynamic Modeling

This chapter establishes a thermodynamic model which facilitates to investigate baseline energy use under controlled conditions by HVAC scheduling techniques. First, this research introduces three basic requirements for a thermodynamic modeling. Second, based on the requirements, a thermodynamic model is constructed which consists of heater, floor and indoor environment modules. Lastly, the developed model is validated by comparing actual measurement and simulation results.

6.1 Basic Requirements for Thermodynamic Modeling

Until recently, despite the potential benefits and technical progress of thermodynamic models, limitations have been widely discussed due to significant discrepancies between actual and predicted energy use (Scofield 2009; de Wilde 2014). This is important because thermodynamic models affect the performance of design alternatives and control strategies. Accordingly, to elaborate thermodynamics, it is necessary to address the following three requirements while its development (Maile et al. 2017).

a) Input Data: As shown in Fig. 6-1, the basis input data includes building geometry, internal loads, HVAC systems and components, weather data, operating strategies and schedules, and model parameters. Based on the input data, any thermodynamic model can minimize the differences between an actual building constructed depending on design documents and a thermodynamic model, and thus produce accurate performance. For example, if weather data provides information about various weather parameters (e.g., outdoor dry-bulb temperature, relative humidity) collected around the buildings, it helps improve the prediction accuracy for external loads influenced by weather.

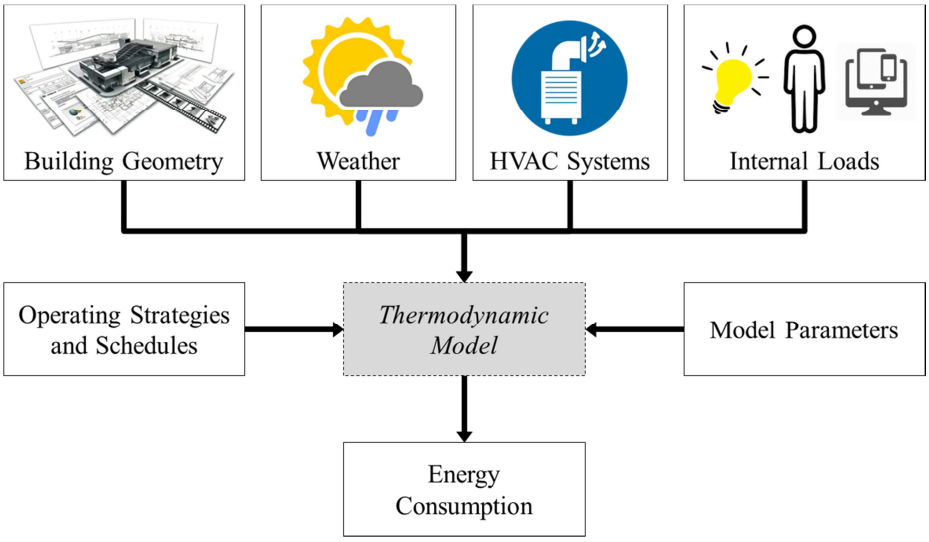


Figure 6-1. General Data Flow of Thermodynamic Model (Maile et al. 2007)

b) Assumption in Thermodynamic Modeling: Since thermodynamic models are based on assumptions for the input data on weather and internal loads, dynamic and complex interrelations can be simplified and managed. Accordingly, users are required to recognize these assumptions and determine whether they are reasonable for the purpose of thermodynamic modeling. For example, most thermodynamic models assume that all spaces in office buildings are occupied during periods of 9 a.m. to 6 p.m. This assumption becomes less acceptable when predicting energy performance on weekends.

c) Life-cycle Usage: Thermodynamic models are useful in any phase of the building's life, so that their usage is not limited to design only. However, if they do not reflect the flexibility of model parameters, their performance may be limited. For example, in reality, control mechanisms vary depending on occupancy status. Additionally, the performance of HVAC systems becomes deteriorated with the progress of time. Thus, more detail is needed to construct thermodynamic models with an improved performance.

6.2 Model Development

In order to predict post-retrofit energy use for end-user groups, a thermodynamic model is developed in Simulink environment. Although

energy simulation programs such as Energy Plus and DOE-2 have been widely used to predict energy consumption and thermal comfort, they have limitations of elaborating thermodynamics in different contexts due to the absence of various weather and climatic data. Their usage is also limited because occupancy diversity among end-user groups cannot be addressed during thermodynamic modeling.

For developing the thermodynamic model, mathematical equations are introduced to calculate heat transfer and thermal comfort in a room. Also, based on the mathematical approaches, a thermodynamic model is developed which consists of three modules.

6.2.1 Heat Transfer Calculations

The thermodynamic state of buildings varies depending on temperature variables. As shown in Fig. 6-2, the average temperature of a room also evolves with the following five elements of heat transfer (Fazenda et al. 2016): *heat exchanges* through surfaces such as walls, roofs, doors, floors, windows and shade; *air exchanges* by HVAC system ventilation supply, natural ventilation, inter-zonal air-flow, infiltration and exfiltration; *solar gains* represented by the rate of solar radiation on the building exterior surface, and

transmitted through windows; *internal gain* generated by occupants, electrical appliances, lights, computers, etc.; *heat generation* by HVAC systems. However, although all the combined elements produce dynamic thermal environment in a room, this research excludes the solar gains and internal gain from heat transfer calculations due to its relatively less impact on energy consumption during heating seasons.

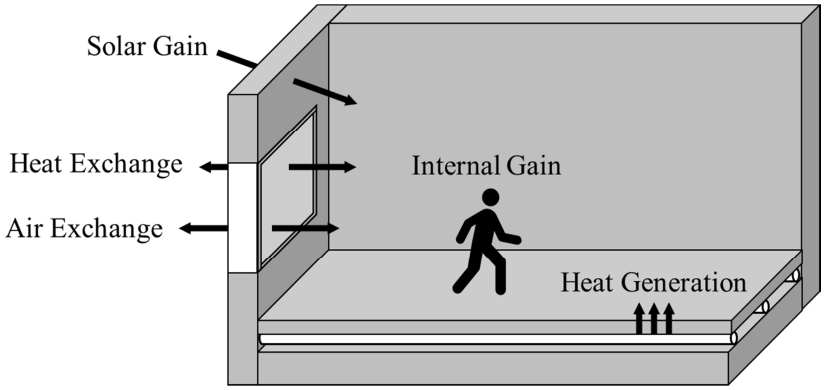


Figure 6-2. Main Elements of Heat Transfer in Rooms

a) Heat Generation

For this research, heat generation by HVAC systems is considered as a major contributor to thermodynamics in each room. This can be expected because Korea has high values of heating degree days (HDD) during winter months (KEEI 2016). The space heating is incurred by under-floor electric heating systems (UHG) which are the prevalent HVAC systems in Korea (see Fig. 6-3). The heat gain from the heater is presented in the following equation.

$$Q_{hc} = q_{hc} \times l_{hc} \times e_{hc} \quad \text{(Eq. 6-1)}$$

where Q_{hc}: heat gain from under-floor electric heating systems (W); q_{hc}: heat flow density of electric heating cables (W/m); l_{hc}: length of electric heating cables (m); e_{hc}: efficiency of electric heating cables.

Figure 6-3. Under-floor Electric Heating Systems installed in Buildings

b) Heat Exchange

In order to elaborate thermodynamics in rooms, additional effort is given to heat exchange through windows, exterior walls, toilets, entrance doors, roofs and ground. As shown in Fig. 6-4, they provide a heat flow path or thermal bridge for heat exchange by conduction. Additionally, this research does not address heat interactions between adjacent rooms due to a low difference in indoor dry-bulb temperatures. As mentioned earlier, heat transfer is taken place with a variation in dry-bulb temperature. While the surrounding

environment of rooms mostly has a significant difference in the average temperature, there seems to be little difference between adjacent rooms. Thus, this research made an assumption about no heat exchange through internal walls and slabs.

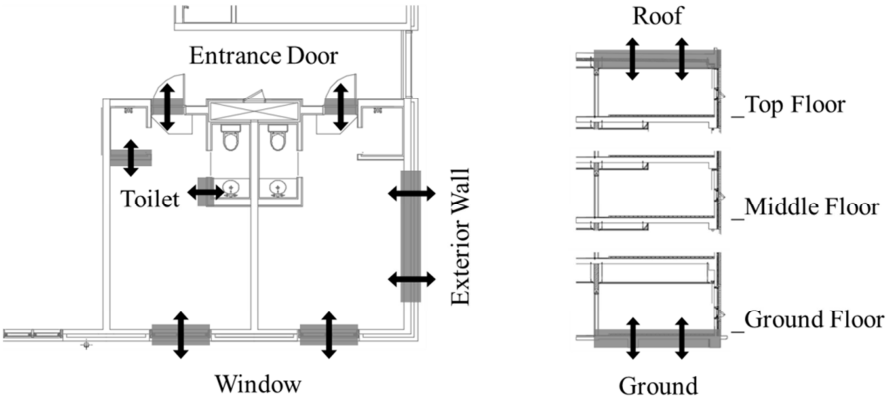


Figure 6-4. Heat Exchange through Interior and Exterior Surfaces

The heat exchange through wall, toilet, roof and ground is defined using the following respective equations.

$$Q_w = \frac{k_w \times A_w \times (t_i - t_o)}{T_w} \qquad \text{(Eq. 6-2)}$$

where Q_w: heat exchange through walls (W); k_w: thermal conductivity of walls (W/m.℃); A_w: area of walls (m^2); t_i: indoor dry-bulb temperature (℃); t_o: outdoor dry-bulb temperature (℃); T_w: thickness of walls (m^2).

$$Q_t = \frac{k_t \times A_t \times (t_i - t_t)}{T_t} \qquad \text{(Eq. 6-3)}$$

where Q_t: heat exchange through toilets (W); k_t: thermal conductivity of toilets (W/m.℃); A_t: area of toilets (m^2); t_i: indoor dry-bulb temperature (℃); t_t: outdoor dry-bulb temperature (℃); T_t: thickness of toilets (m^2).

$$Q_r = \frac{k_r \times A_r \times (t_i - t_o)}{T_r} \qquad \text{(Eq. 6-4)}$$

where Q_r: heat exchange through roofs (W); k_r: thermal conductivity of roofs (W/m.℃); A_r: area of roofs (m^2); t_i: indoor dry-bulb temperature (℃); t_o: outdoor dry-bulb temperature (℃); T_r: thickness of roofs (m^2).

$$Q_g = \frac{k_g \times A_g \times (t_i - t_o)}{T_g} \qquad \text{(Eq. 6-5)}$$

where Q_g : heat exchange through grounds (W); k_g : thermal conductivity of grounds (W/m.℃); A_g: area of grounds (m^2); t_i: indoor dry-bulb temperature (℃); t_o: outdoor dry-bulb temperature (℃); T_g: thickness of grounds (m^2).

The heat exchange through window and entrance door is calculated as follow.

$$Q_g = \frac{A_s \times (t_i - t_o)}{R_s} \qquad \text{(Eq. 6-6)}$$

where Q_w: heat exchange through glass (W); A_w: area of glass (m^2); t_i: indoor dry-bulb temperature (℃); t_o: outdoor dry-bulb temperature (℃); R_w: thermal residence of glass (m^2.℃/W).

$$Q_e = \frac{A_e \times (t_i - t_h)}{R_e} \qquad \text{(Eq. 6-7)}$$

where Q_e: heat exchange through entrance doors (W); A_e: area of entrance doors (m^2); t_i: indoor dry-bulb temperature (℃); t_h: dry-bulb

temperature of hallway (℃); R_w: thermal residence of entrance doors (m^2.℃/W).

c) Air Exchange

Each room could induce outdoor air by occupant behaviors such as opening and closing a window, which make thermal convection around the window. Also, natural infiltrations will produce heat exchange. In this research, the following two assumptions are set to calculate heat loss from the air exchange: constant rate of ventilation by occupant behaviors; no natural infiltration. If r_v is a ventilation rate, the ventilation loss is defined as

$$Q_v = 0.33 \times r_v \times V_{room} \times (t_i - t_o) \qquad \text{(Eq. 6-8)}$$

where Q_v: ventilation loss by window opening (W); V_{room}: Volume of room (m^3); t_i: indoor dry-bulb temperature (℃); t_o: outdoor dry-bulb temperature (℃).

6.2.2 PMV Calculation

To date, many researchers have tried to address occupants' thermal comfort to establish more efficient HVAC control strategies. This is important because the primary aim of HVAC systems is to ensure the thermal comfort of a building's occupants. In the extensive literature, Franger's predicted mean vote (PMV) index is the most commonly used as a metric for measuring occupants' thermal comfort (Franger 1970). According to ASHRAE thermal sensation scale, the level of thermal comfort ranges from -3 to +3, indicating "cold" sensation to "hot" sensation, respectively. For the calculation of the PMV index, two types of parameters are necessary: environment-related parameters (e.g., air temperature, mean radiant temperature, air velocity,) and occupant-related parameters (e.g., clothing resistance, activity level). Additionally, simplified approaches to the PMV index has been developed by Rohles (1971) and Buratti et al. (2013). Their models are based on the same equation but require different coefficient values.

For this study, the simplified model proposed by Buratti et al. (2013) is used for the PMV calculation because the Franger's PMV index has a complex computation process and all these data are not always available. Also, since the Rohles' model was referred to sedentary activity and to clothing

thermal insulation of 0.6 m^2K/W (clo). In the Buratti's model, the PMV is expressed as a function of T and P_v:

$$PMV_{Rohles} = aT + bP_v - c \qquad \text{(Eq. 6-9)}$$

where T: indoor dry-bulb temperature (℃); P_v: pressure of water vapor in the indoor environment (kPa). The a, b, and c are experimental coefficients (see Table 6-1).

Table 6-1.Rohles coefficients a, b, and c

clo	Gender	Coefficient		
		a	b	c
0.25-0.50	Male	0.2630	0.3027	6.8066
	Female	0.2658	0.1072	6.7232
	Both	0.2803	0.1717	7.1383
0.51-1.00	Male	0.1162	-0.1338	2.2011
	Female	0.2424	0.0614	5.5869
	Both	0.1383	0.0269	3.0190
1.01-1.65	Male	0.150	-0.1668	2.5121
	Female	0.1494	-0.1056	2.6408
	Both	0.1478	-0.1371	2.5239

6.2.3 Structure of Thermodynamic Model

In order to elaborate dynamic thermal environment in a given context, a thermodynamic model is developed which includes three modules named according to their role (see Fig. 6-5). As a first step to predict the energy performance in a room, the controller module investigates the current state of indoor thermal environment and then operates HVAC systems with predetermined controller settings. Next, based on the signal from controller module, the heater module consumes energy for space heating. Lastly, after calculating heat transfer in a room, the thermal behavior module predicts energy consumption and thermal comfort.

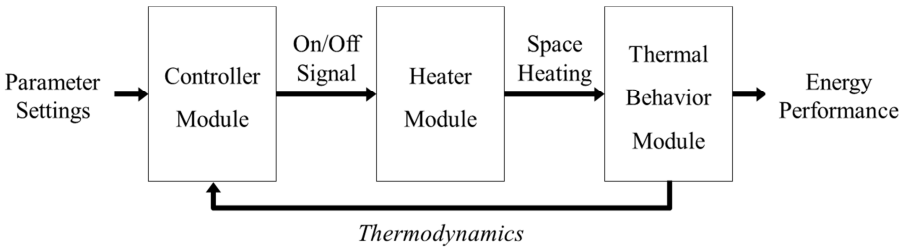


Figure 6-5. Main Structure of Thermodynamic Model

a) Controller Module

The controller module sends out signals about the operation of HVAC systems in a room. For this, the basic input data about building geometry,

weather, HVAC systems and occupancy status is collected in the following two ways. First, the static data on building geometry and HVAC systems, which has fixed values regardless of time, is obtained from design documents. Second, the dynamic data on weather and occupancy status, which changes its values with the progress of time, should be collected on a minutely basis. This is important because the actual thermodynamics of rooms occur at a frequency of smaller periods than hours. Table 6-2 shows the details of static and dynamic data.

Table 6-2. Static and Dynamic Data for Thermodynamic Modeling

Data	Variables
Building	• Physical Characteristics: Room Size, Floor Level, Exterior Surfaces
	• Insulation Performance of Room: Outside and Inside Wall, Window, Entrance Door
HVAC Systems	• Length of Electric Heating Cable
	• Power Output of Electric Heating Cable
	• Efficiency of Under-floor Electric Systems
Internal Gain	• Type of Energy-consuming Items: Lights, Fridge, Computer
	• Power Output of Energy-consuming Items
	• Frequency in Use of Energy-consuming Items
Weather	• Outdoor Dry-Bulb Temperature
	• Relative Humidity
Occupant-related Characteristics	• Occupancy Status

After the data collection, control strategies and model parameters are set to predict energy performance of a room. More specifically, establishing control strategies is to determine HVAC scheduling alternatives (e.g., temperature setpoint) and controller algorithms (e.g., schedule-based HVAC control). For the model parameter settings, users input the values of variables that are used for heat transfer calculation and set simulation time to predict energy performance.

Lastly, based on the preliminary investigation and planning, simulations are conducted to determine whether HVAC systems should be operated in the current state of floor temperature and occupancy (see Fig. 6-6). For example, if a room does not reach to the predetermined level of floor temperature, the HVAC systems still remain operating to improve thermal comfort conditions. In addition, the operation of HVAC systems is dependent on occupancy status. As a consequence of these processes, a signal about the operation of HVAC systems is sent to the next module to determine heat generation from under-floors.

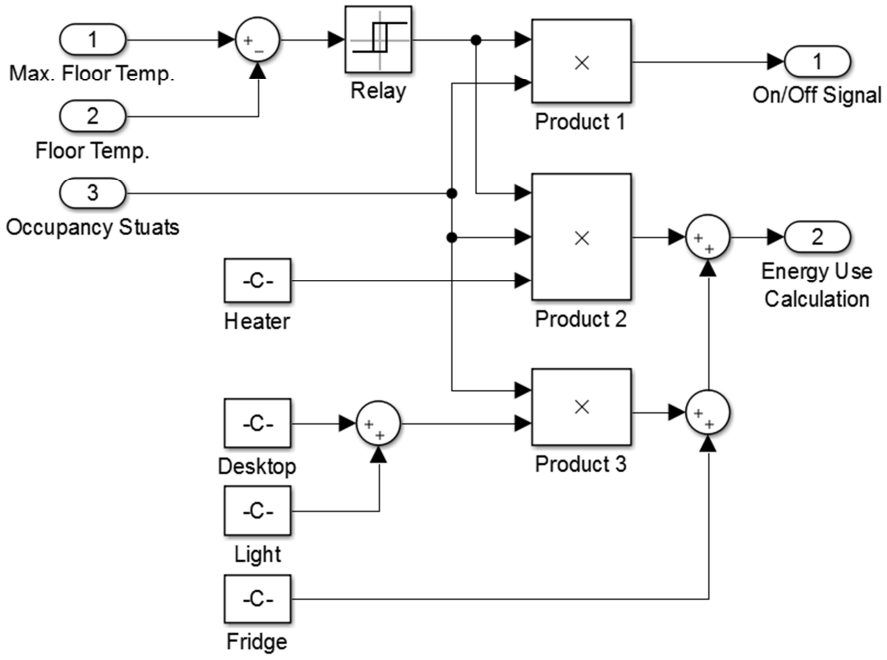


Figure 6-6. Block Diagram of Controller Module in Simulink Environment

b) Heater Module

In order to condition rooms within an acceptable range of thermal comfort, the heater module transfers heat generated by under-floor heating systems to indoor environment as follows (see Fig. 6-7). First, after receiving actuation signals from the controller module, the heater implements heat generation using Eq. 6-1. In this process, the efficiency of electric heating cables should be addressed for responding to the performance degradation during its life cycle. Next, in order to investigate a current temperature of floors, its thermal storage is calculated through comparing current heat gain

from the HVAC system and previous heat loss from floor to indoor environment. This is mathematically defined as follow.

$$t_{f.c} = \frac{(Q_{hc.c} - Q_{l.i.p})}{(T_f \times A_f \times D_c \times S_c)} + t_{f.p} \qquad \text{(Eq. 6-9)}$$

where $t_{f.c}$: current floor temperature (℃); $Q_{hc.c}$: current heat gain from under-floor electric heating systems (W); $Q_{l.i.p}$: previous heat loss from floor to indoor environment (W); T_f: thickness of floor (m); A_f: area of floor (m^2); D_c: density of mortar (kg/m^3); S_c: specific heat of cement (J/kg.℃); $t_{f.p}$: previous floor temperature (℃). After the calculation process for current floor temperature, the quantity of heat transfer from a heated floor to indoor environment is investigated by the following simplified equation, proposed by Holman (2002).

$$Q_{l.i.c} = 1.52 \times A_f \times (t_{f.c} - t_{i.c})^{3/4} \qquad \text{(Eq. 6-10)}$$

where $Q_{l.i.c}$: current heat loss from floor to indoor environment (W); A_f: area of floor (m^2); $t_{f.c}$: current floor temperature (℃); $t_{i.c}$: current indoor temperature (℃).

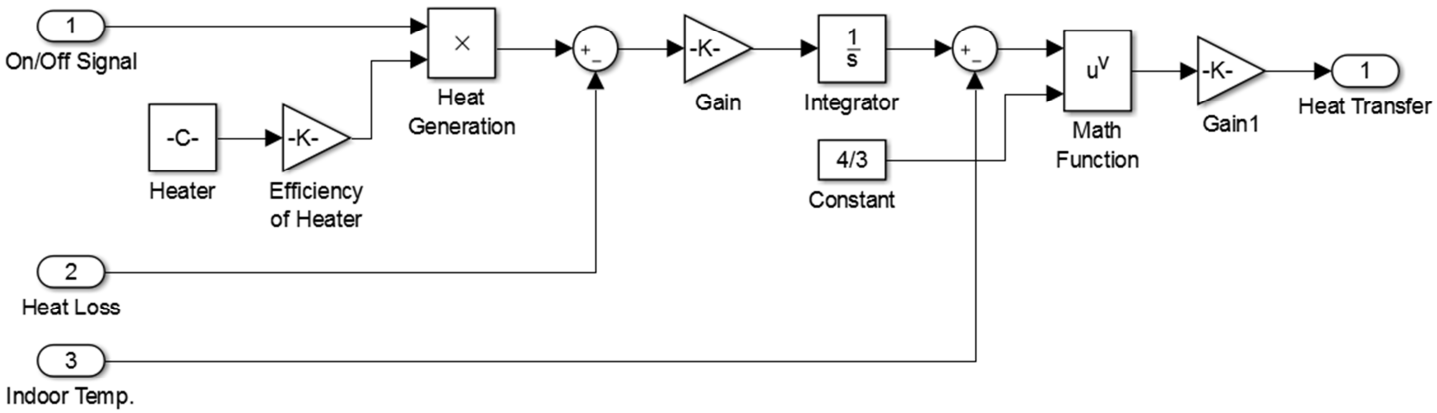


Figure 6-7. Block Diagram of Heater Module in Simulink Environment

c) Thermal Behavior Module

The thermal behavior module provides information about indoor dry-bulb temperature and predicted mean vote on a minutely basis (see Fig. 6-8). In order to predict such energy performance, the thermal storage of a room is investigated through comparing current heat gain and previous heat loss. More specifically, the heat loss includes air exchange by window opening and heat transfer through exterior surfaces (e.g., walls, windows) and interior thermal paths (e.g., toilets, entrance doors). Thus, the overall heat loss $Q_{o.l}$ is defined as follows.

$$Q_{o.l} = Q_v + Q_w + Q_g + Q_t + Q_e \qquad \text{(Eq. 6-11)}$$

Additionally, since indoor furniture such as desk, bed and wardrobe have thermal mass to store heat energy, a current indoor temperature can be simplified as τ times the rate of overall heat loss (Kennedy et al. 2009). This can be calculated by the following equations.

$$t_{i.c} = \frac{(Q_{l.i.c} - Q_{o.l})}{\tau \times 3600 \times Q_{o.l}} \qquad \text{(Eq. 6-12)}$$

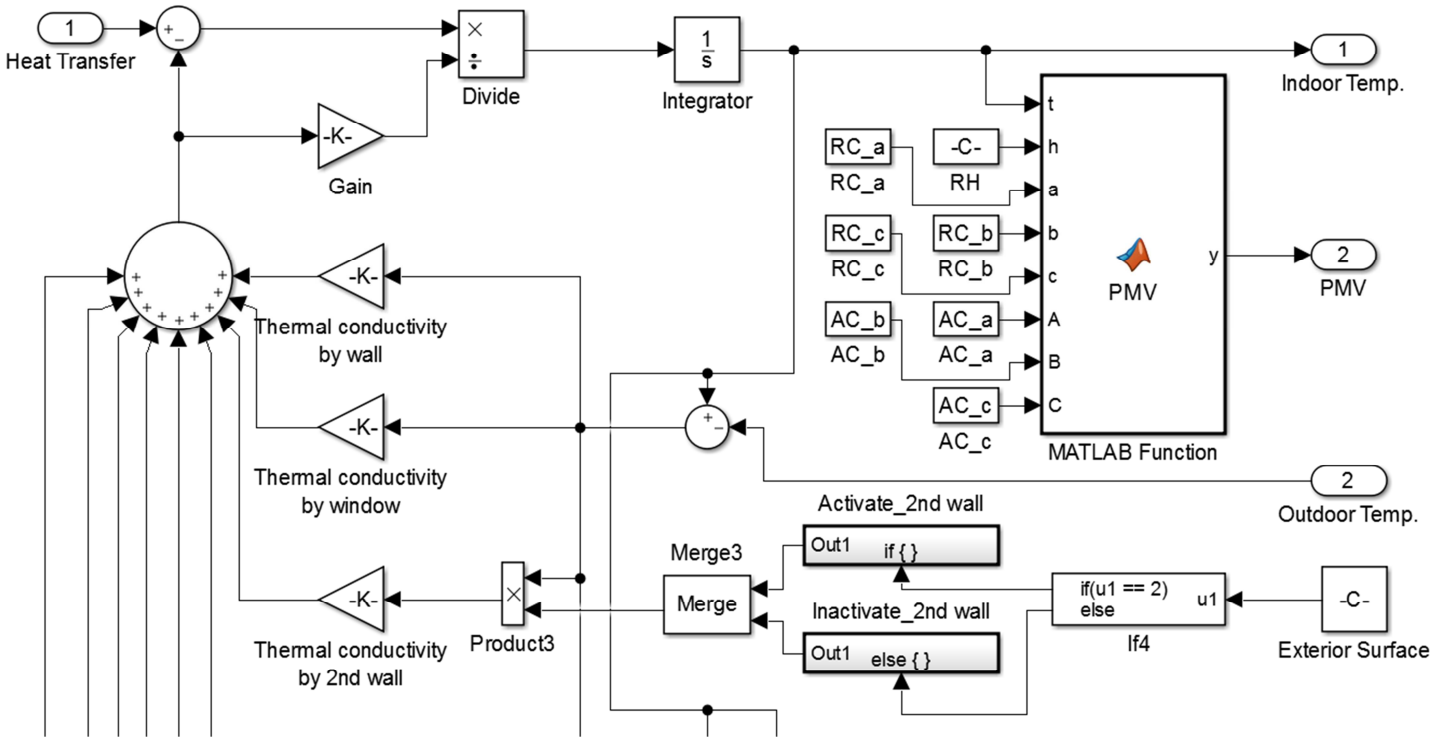
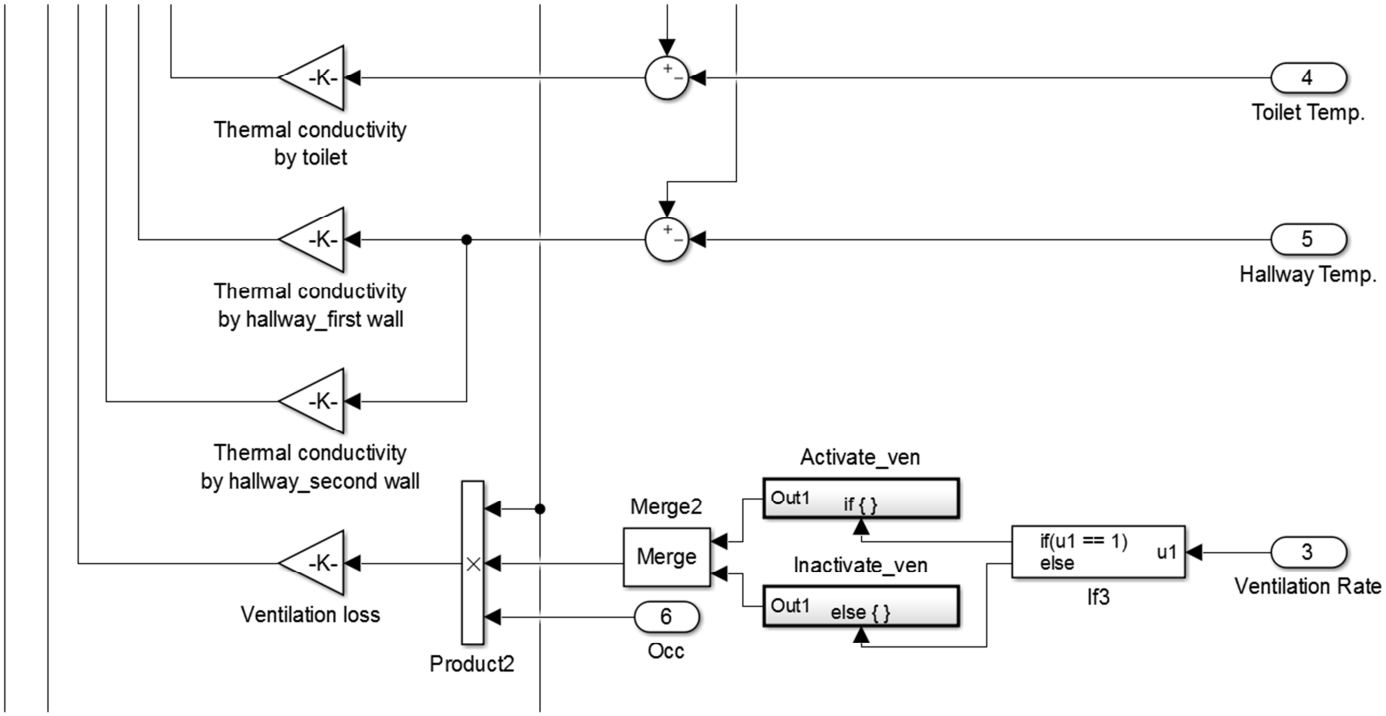
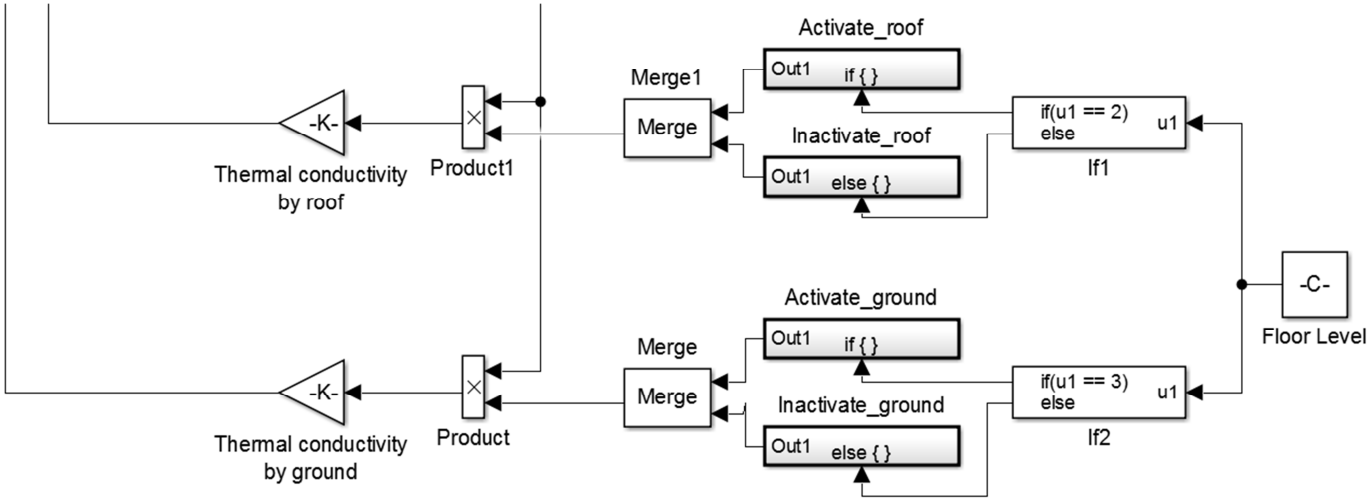


Figure 6-8. Block Diagram of Thermal Behavior Module in Simulink Environment



(Figure 6-8. Continued)



(Figure 6-8. Continued)

6.3 Model Validation

In order to validate the developed thermodynamic model, this research selected a single and a double room which is located on middle floor of the case buildings and has one exterior surface (see Fig. 6-9). For modeling the rooms, the static input data on physical properties, insulation performance and HVAC systems was collected from design documents (see Appendix A). The dynamic data on occupancy status was collected from card entry systems which provide a record of its variation by room.

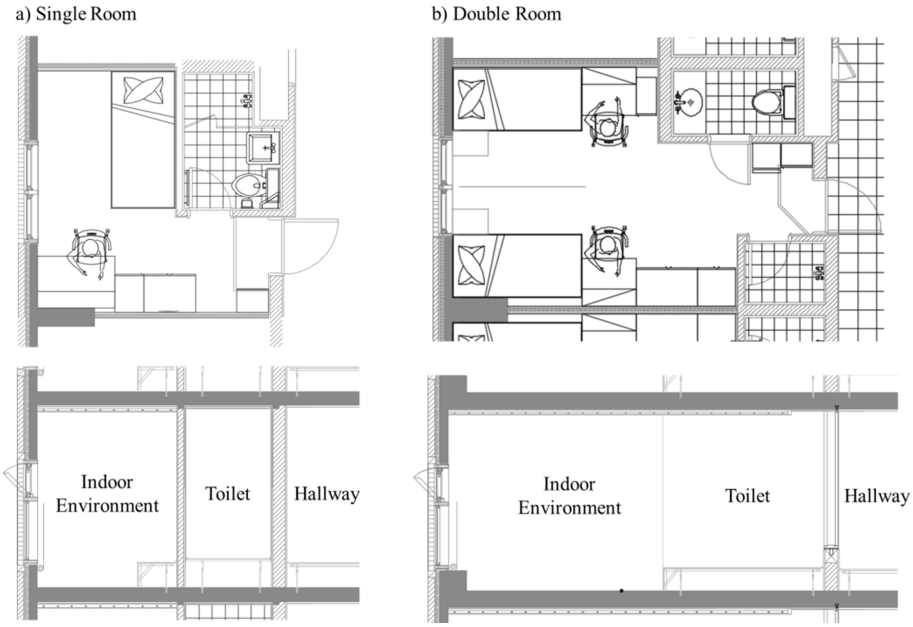


Figure 6-9. Plane and Sectional Plan of Single and Double Room

Additional effort was given to model parameter settings as follows. First, the efficiency of electric heating cables was set as 95%, which is provided by product suppliers. Second, energy-consuming items except for fridge were employed depending on occupancy status. Third, the thermal time constant τ was 9.87 hours for the single room, and 10.25 for the double room, obtained from two field experiments (see Fig. 6-10). Four, ventilation by window opening was assumed at 0.5 per hour. Five, since the dormitories are used for residence purpose, it was assumed that occupants have the clo-value of 0.25-050.

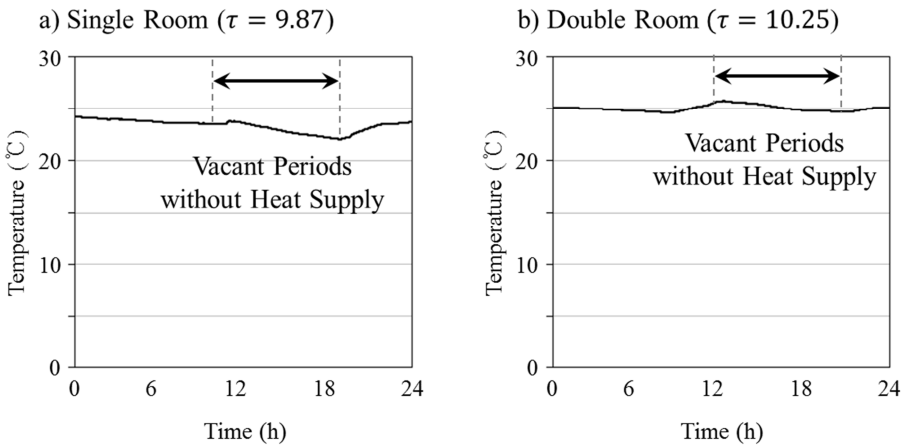


Figure 6-10. A Decrease in Indoor Dry-bulb Temperature during Vacant Periods without Space Heating

With the experimental design, comparative experiments were conducted to ensure the validity of the proposed model. As a perform index, this research

adopts the coefficient of variation of the root mean squared error (CV-RMSE), introduced in Section 5.3. Although the developed model produces two outputs including energy use and predicted mean vote, there is a limitation to compare the predicted and actual PMV values due to a low reliability in results of field survey for thermal comfort. In the next section, the simulation results are discussed and an improvement for the developed model is suggested.

6.3.1 Results

Simulation experiments were conducted using two test datasets collected on February 21 and 22, 2017. These test datasets list different values for weather variables to provide a basis to validate the performance of the developed thermodynamic model. Additionally, as shown in Fig. 6-11, the rooms were conditioned with different control strategies during the periods. In the first test dataset, under-floor electric heating systems were operated at a temperature setpoint of 50℃ while occupied. The second test dataset was composed of implementing space heating regardless of occupancy status at a temperature setpoint of 45℃. Lastly, the rooms had different occupancy patterns during the periods.

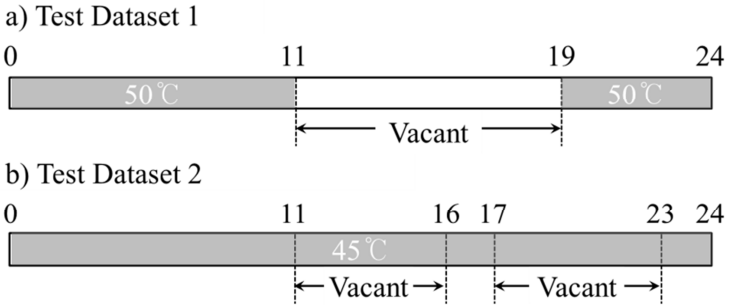


Figure 6-11. Different Control Strategies of Under-floor Electric Heating System in Rooms (Note: V = Vacant)

When simulating thermodynamics of the single room using the first test dataset, the developed model produced the value of CV-RMSE at 21.6 %. On a daily basis, the simulated energy consumption was 14.1 kWh, which was higher than the actual energy consumption of 13.8 kWh. Looking closely at the trend in actual and simulated hourly energy consumption, they seem similar with the progress of time (see Fig. 6-12-a). Also, the thermodynamic model had similar behaviors of indoor dry-bulb temperature compared to the actual measurements.

Similarly, the simulation results using the second test dataset show that the thermodynamic model produced the value of CV-RMSE at 20.2 %. Compared to the amount of actual daily energy use, the simulated energy use was lower at 14.5 kWh versus 14.7 kWh. Also, investigating the energy use on an hourly basis, there is a similar trend between actual measurement and

simulation results (see Fig. 6-12-b). Lastly, there were little differences between actual and simulated indoor dry-bulb temperature in the double room.

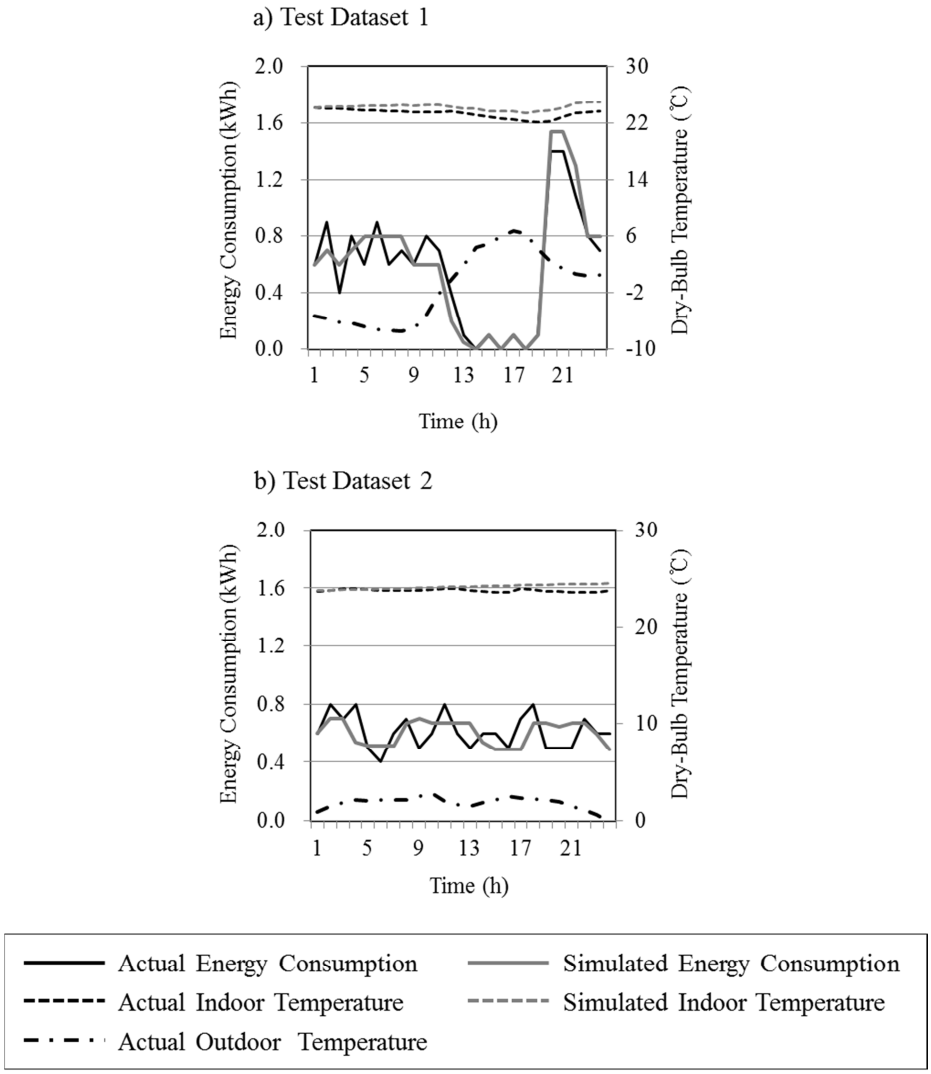


Figure 6-12. Simulation Results using Two Test Datasets

6.3.2 Discussions

In the extensive literature, energy simulation programs have been widely used to investigate the effect of design alternative and control strategies on energy consumption. However, due to the limitations in elaborating different thermal behaviors by end-user group, this research constructed a thermodynamic model which facilitates to predict energy performance in given contexts.

Through simulation experiments using the two test datasets, it is found that the developed model provides reliable accuracy within the acceptable tolerance (CV-RMSE, 25%). Furthermore, similar behaviors of energy use and indoor temperature are observed among actual measurements and simulation results. From these findings, it can be seen that the developed model is useful to elaborate different thermal behaviors by end-user groups.

For the developed model, additional efforts could be to evaluate the simulated PMV in comparison of the actual thermal comfort. In fact, this is important because thermal comfort is one of the major concerns when establishing design alternatives and control strategies in buildings. As thermal environmental quality increases in buildings, occupants tend to maintain

healthy lifestyle and maximize their productivity. Therefore, field survey will provide meaningful information in the following two aspects. First, investigating occupants' activity and clothing in a room will contribute to the improved prediction accuracy of PMV in a thermodynamic model. Second, the data on occupants' thermal comfort will provide a basis to evaluate the simulated PMV.

6.4 Summary

To date, a number of thermodynamic models have been adopted to evaluate the performance of design alternatives and control strategies. For this research, thermal behaviors of a room were elaborated in MATLAB Simulink environment to predict baseline energy use under controlled conditions by HVAC systems. Although many researchers have widely used energy simulation programs, there are limitations in elaborating thermodynamics in different contexts due to the absence of various weather and climatic data. In addition, their usage is also limited because occupancy diversity among end-user groups cannot be addressed during thermodynamic modeling.

The developed thermodynamic model consists of three modules named according to their roles. The controller module aims to evaluate the current

state of indoor thermal environment and then sends out signals about whether HVAC systems should be operated for space heating. Next, based on the signals, the heater module generates heat to maintain occupants' thermal comfort in a room. Lastly, in the thermal behavior module, energy consumption and thermal comfort of a room are predicted after calculating heat transfer by heat generation, heat exchange and air exchange. After the model development, simulation experiments were conducted using two test datasets to validate the developed model. From the experimental results, it is observed that the developed model provides reliable accuracy within the acceptable tolerance. Additionally, similar behaviors of energy use and indoor temperature exit among actual measurements and simulation results.

Chapter 7. Energy Performance Simulation for Multi-zone Buildings

In this chapter, simulation experiments are conducted to investigate the effect of temporal and weather variables on energy saving from HVAC scheduling techniques in multi-zone buildings. For the case studies, the developed models are employed depending on their role in simulation environment. Most importantly, the comparative analysis of simulation results is performed to select optimal control strategies in different contexts.

7.1 Simulation Design and Process

As an effort to understand how temporal and weather variables affect energy saving from HVAC scheduling techniques in multi-zone buildings, this research conducts simulation experiments using the data collected in seven dormitory buildings of a university, Seoul, South Korea. As observed in Section 4.3, it appears that some end-user groups have energy overconsumption during the occupied and unoccupied hours, respectively, so that it is necessary to improve their energy efficiency through HVAC control throughout a day. Although peak energy is another contributor to the

overconsumption, it would have a limitation due to its low proportion to the total energy consumption in the buildings. For these reasons, global temperature control[2)] and on/off control by occupancy status[3)] are selected as HVAC scheduling alternatives to improve energy efficiency in the buildings. The former strategy can produce energy saving in both occupied and unoccupied rooms. However, if occupants turn off HVAC systems in person, there will be less energy saving during vacant periods. For the latter alternative, it is effective to achieve energy saving through interrupting unnecessary energy use in vacant rooms. Additionally, these control strategies are evaluated in different temporal and weather contexts to investigate their contextual effect on energy saving in multi-zone buildings.

Fig. 7-1 describes the energy performance evaluation process to quantify the amount of energy saving from the HVAC scheduling alternatives. First, input data collection and model parameter setting are performed. Second, representative end-user groups are identified in a given temporal and weather context. Third, the data mining-based prediction model produces the amount of baseline energy consumption for each end-user group. Fourth, the thermodynamic model calculates post-retrofit energy consumption for each end-user group, which is a desirable value caused by HVAC scheduling

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[2)] Global temperature control is to adjust temperature setpoint in all rooms.
[3)] On/off control by occupancy status provides space heating in occupied rooms.

alternatives in a given context. Lastly, the effect of temporal and weather variables on energy saving from HVAC scheduling alternatives is investigated by comparing the baseline energy consumption to the post-retrofit energy consumption at a building level. Most importantly, in order to improve the reliability of simulation results, this process is carried out 100 times because the data mining-based model produces different prediction results every iteration.

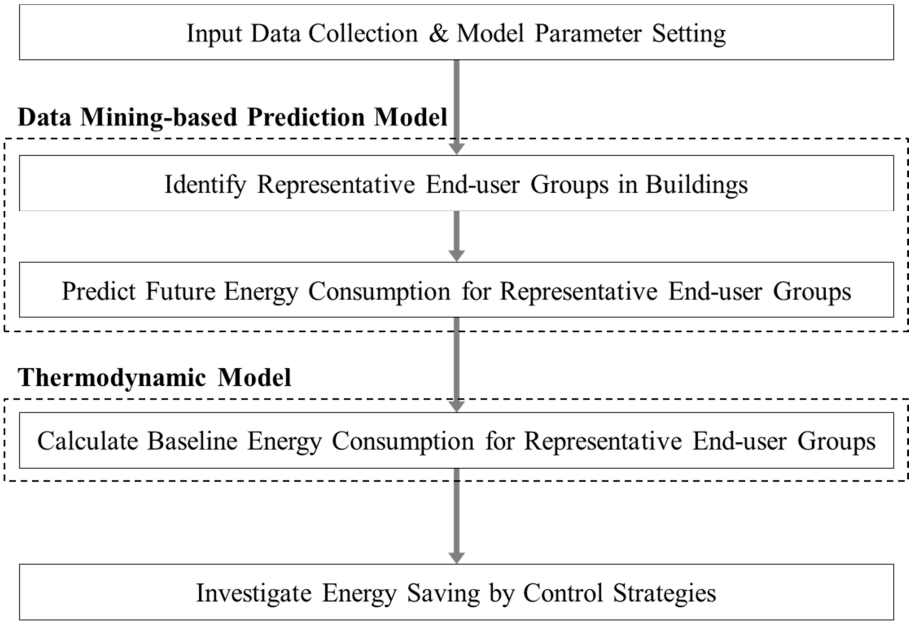


Figure 7-1. Simulation Process for Evaluating Energy Saving from HVAC Control Strategies in Multi-zone Buildings

7.2 Simulation Results by Outdoor Temperature

7.2.1 Overview of End-user Groups

In order to investigate how weather variables affect energy saving from HVAC scheduling techniques, simulation experiments were performed using four test datasets collected on a) November 3, 2014, b) November 13, 2014, c) February 8, 2015 and d) February 15, 2015 (see Table 7-1). These test datasets have the different values for the weather variables, but there are the same values for the temporal variables in the first two and the remaining test datasets. Based on the test datasets, representative EUGs were investigated with the number of their rooms (see Table 7-2). On November 3 and 13, 2014, there is a variation in the percentage of total rooms varies among the EUGs 1, 3, 6 and 8. As outdoor dry-bulb temperature decrease, the EUGs 1 and 8 are more prevalent at 27.9% and 14.5% of total rooms compared to 19.05 and 8.2%, respectively. In contrast, the percentage of total rooms by the EUGs 3 and 6 decreases with lower outdoor dry-bulb temperature (EUG 3: 38.0% compared to 16.5%; EUG 6: 18.5% compared to 13.5%). On February 8 and 15, 2015, the percentage of total rooms varies among the EUGs 3 and 8. When the outdoor dry-bulb temperature becomes higher, there is an increase in the percentage of total rooms by the EUG 3 (9.3% compared to 16.6%) but a decrease by EUG 8 (28.7% compared to 23.7%).

Table 7-1. Weather Variables by Test Dataset

Test Datasets	Weather Variables				Temporal Variables	
	OT	WS	RH	SR	DW	CP
a) November 3, 2014	9.2	3.3	38.0	0.5	1	1
b) November 13, 2014	-0.2	3.8	36.7	0.5	1	1
c) February 8, 2015	-9.2	5.4	34.1	0.5	2	2
d) February 15, 2015	7.6	3.0	64.1	0.4	2	2

Note: OT = Outdoor Temperature (℃), WS = Wind Speed (m/s), RH = Relative Humidity (%), SR = Solar Radiation (MJ/㎡), DW = Day of the Week (weekday: 1, weekend: 2), CP = Course Period (fall: 1, winter: 2)

Table 7-2. Percentage of Total Rooms by End-user Group and Test Dataset

Test Dataset	End-user Group									
	1	2	3	4	5	6	7	8	9	10
a) November 3, 2014	19.0	4.3	38.0	1.1	3.2	18.5	0.7	8.2	2.1	5.0
b) November 13, 2014	27.9	5.5	16.5	2.6	7.2	13.5	1.7	14.5	4.2	6.5
c) February 8, 2015	14.7	6.2	9.3	3.5	18.0	3.2	5.8	28.7	3.2	7.3
d) February 15, 2015	16.2	4.8	16.6	1.9	16.3	7.5	3.0	23.7	6.6	3.2

Fig. 7-2 represents the total amount of daily energy consumption in the case buildings. On February 8, 2015, the buildings consume the most amount of electrical energy at 17,186 kWh, whereas the lowest value of 6,758 kWh was spent on November 3, 2014. Looking closely at the daily energy use by occupancy status, it was found that the case buildings consume more than half of the electrical energy while occupants are present in their rooms across (November 3, 2014: 60.1% compared to 39.9%; November 13, 2014: 58.7% compared to 41.3%; February 8, 2015: 54.3% compared to 45.7%; February 8 15, 2015: 89.3% compared to 10.7%). As indicated in Fig. 7-2, when quantifying the energy consumption for representative EUGs, the EUG 8s are significant contributors to the daily energy spent in the case buildings (November 3, 2014: 18.3%; November 13, 2014: 21.3%; February 8, 2015: 31.5%; February 8 15, 2015: 28.3%). In particular, although the EUG 3s are not the most prevalent on November 3 and 13, 2014, they accounts for a considerable percentage of total energy use in the buildings (see Table 7-2). These results are caused by the fact that the EUG 8 consumes a substantial amount of electrical energy on a daily basis. Additionally, another consumer having a large percentage of total energy consumption is the EUG 1s on November 3 and 13, 2014, and the EUG 5s on February 8 and 15, 2015. This can be expected due to their high proportion and energy consumption during the periods (see Table 7-2).

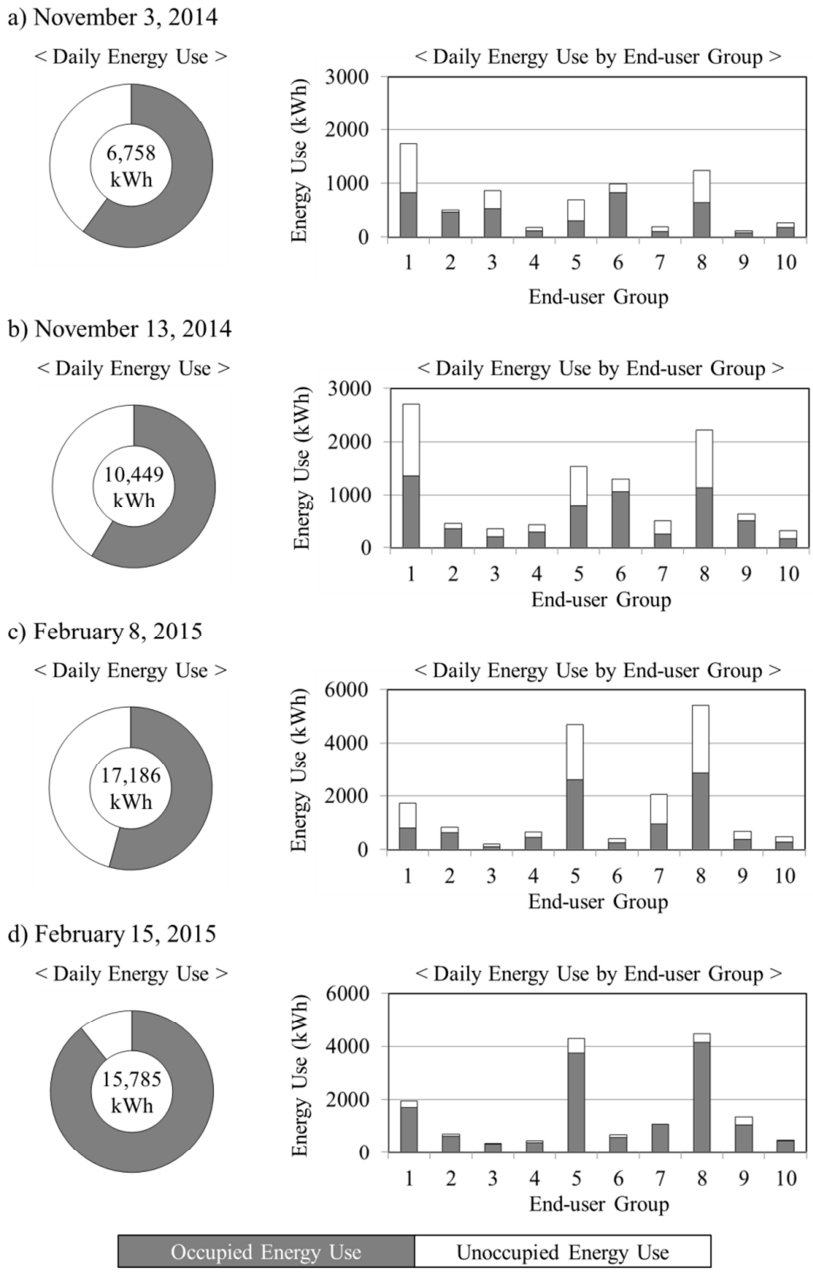


Figure 7-2. Daily Energy Consumption on November 3 and 13, 2014 and February 8 and 15, 2015

7.2.2 Energy Saving from HVAC Scheduling Alternatives

Fig. 7-3 represents a comparison of energy saving from global temperature control and on/off control of HVAC systems in the case buildings. During the given periods, there are statistical differences in energy saving among the control strategies (November 3, 2014: 1154.35). On November 3, 2014 and February 15, 2015, adjusting global temperature setpoint on average reduces 43.4 % and 58.6% of total energy consumption, which are higher than the energy saving of 28.7% and 39.1% from the on/off control. In contrast, on November 13, 2014 and February 9, 2015, interrupting the operation of HVAC systems in vacant rooms produced energy saving of 32.7% and 40.1% in the case buildings. This is more effective than the global temperature control, which resulted in 24.4% and 25.7%, respectively.

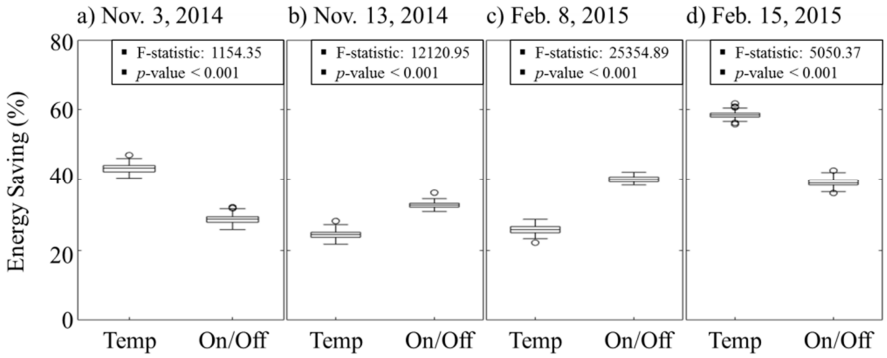


Figure 7-3. Energy Saving from Global Temperature and On/off Control

Looking closely at the energy saving by occupancy status, adjusting global temperature setpoint reduces the daily energy consumption in both occupied and unoccupied buildings except for February 8, 2015 (see Fig. 7-4). On November 3 and 13, 2014, more energy saving is achieved while occupants leave out their rooms at 24.4% and 21.7% compared to 22.7% and 6.5%, respectively. These results stem from the fact that HVAC systems consume less energy in the daytime due to relatively low heat loads compared to the nightime. As observed in Fig. 4-6, almost all the groups leave out their rooms in the daytime (9 a.m. to 6 p.m.). Thus, although the temperature setpoint is optimally adjusted throughout the given periods, there could be more energy saving in the vacant buildings. In contrast, on February 15, 2015, the temperature setpint control produces higher energy saving of 53.3% in the occupied buildings compared to 8.5% achieved during unoccupied periods. This can be expected because the case buildings rarely consume unoccupied energy although high energy saving potential exists in the day time. Additionally, across all the given periods, the on/off control of HVAC systems produces the energy saving only while occupants leave out their rooms (November 3, 2014: 32.1%; November 13, 2014: 36.2%; February 8, 2015: 42.7%; February 15, 2015: 41.6%). This is because interrupting the operation of HVAC systems is taken place in vacant buildings.

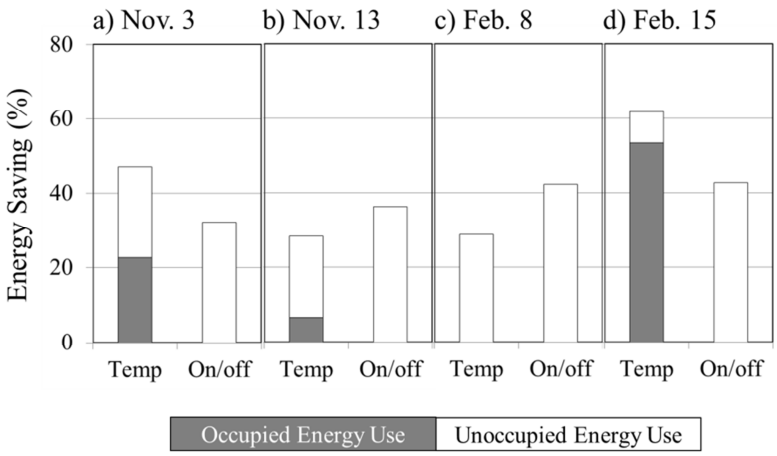


Figure 7-4. Energy Saving from Global Temperature and On/off Control in Occupied and Unoccupied Buildings

Figs. 7-5 and 7-6 show the percentage of energy saving from global temperature control by EUG. Across all the given periods, a major contributor to the energy saving is EUGs 5 and 8 (November 3, 2014: 8.5% and 14.3%; November 13, 2014: 9.7% and 10.3%; February 8, 2015: 11.6% and 10.9%; February 15, 2015: 21.7% and 19.5%) This would be expected considering that the EUGs 5 and 8 account for significant percentage of total energy use in the case buildings. It is also fitting that the amount of hourly energy use per room is high during both occupied and unoccupied hours.

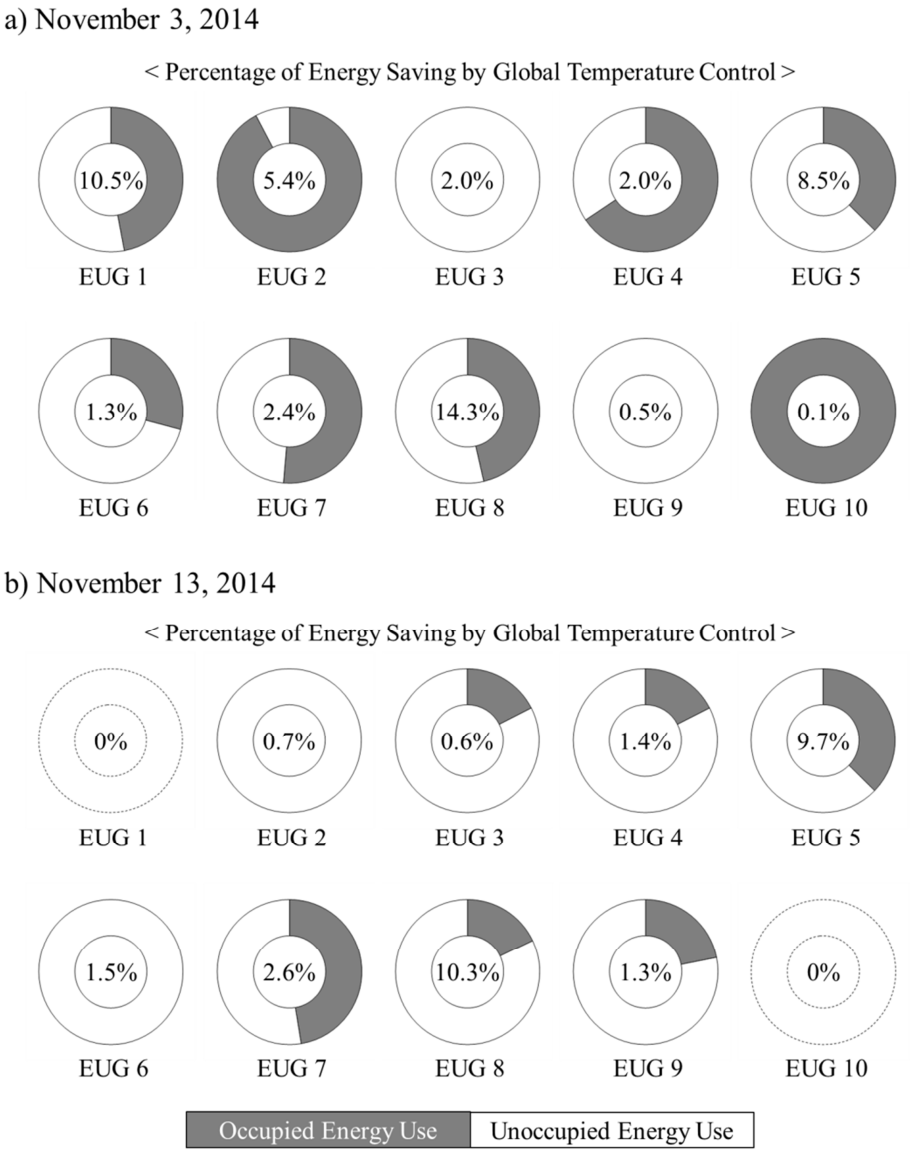
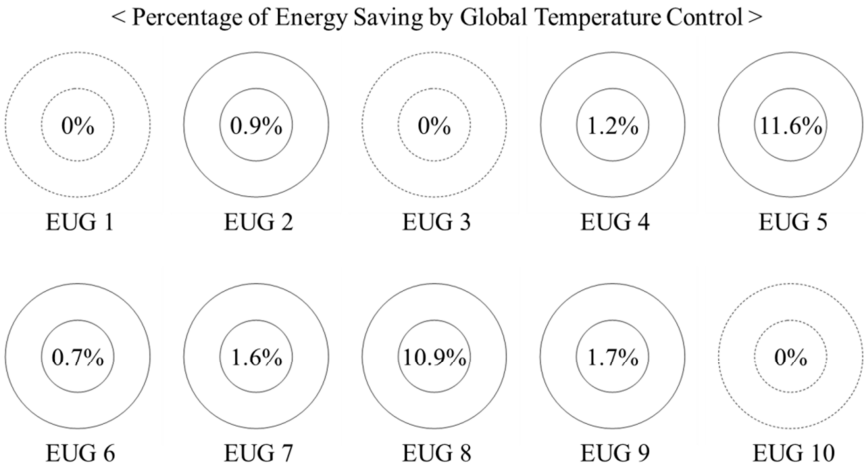


Figure 7-5. Percentage of Energy Saving from Global Temperature Control by End-user Group on a) November 3, 2014 and b) November 13, 2014

c) February 8, 2015



d) February 15, 2015

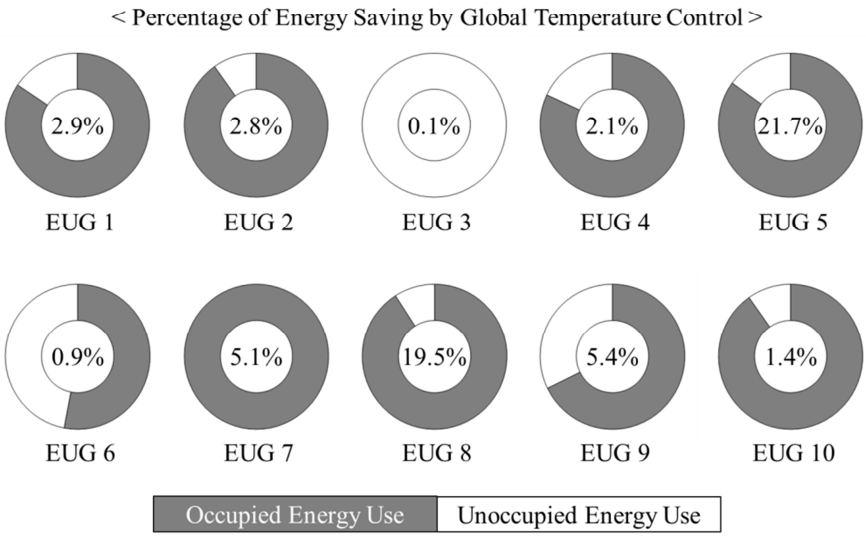


Figure 7-6. Percentage of Energy Saving from Global Temperature Control by End-user Group on c) February 8, 2015 and b) February 15, 2015

Table 7-3 describes the percentage of energy saving for EUGs achieved by interrupting the operation of HVAC systems in vacant rooms. Across all the given periods, the EUG 8s significantly contribute to a reduction in the total amount of energy consumption in the case buildings (November 3, 2014: 8.2%; November 13, 2014: 9.7%; February 8, 2015: 13.9%; February 15, 2015: 14.8%). Also, another significant contributor to the energy saving is EUG 1s on November 3 (11.9%) and 13 (11.3%), 2014, and EUG 5s on February 8 (11.6%) and 15 (12.9%), 2015. These results stem from the fact that they account for high percentage of daily energy spent in the occupied buildings.

Table 7-3. Percentage of Energy Saving from On/Off Control among End-user Groups

Test Dataset	End-user Group									
	1	2	3	4	5	6	7	8	9	10
a) November 3, 2014	11.9	0.3	2.0	0.8	5.3	1.0	1.4	8.2	0.5	0.8
b) November 13, 2014	11.3	1.1	0.7	0.4	7.4	1.3	2.2	9.7	1.2	0.9
c) February 8, 2015	4.8	1.0	0.2	1.2	11.6	0.7	6.2	13.9	1.7	0.9
d) February 15, 2015	5.6	0.8	0.5	1.2	12.9	0.8	3.8	14.8	1.6	0.7

7.3 Simulation Results by Course Period

7.3.1 Overview of End-user Groups

In order to understand the effect of temporal variables on energy saving from the HVAC scheduling techniques, the following test datasets were selected on a) November 18, 2014, d) February 25, 2015, b) December 16, 2014 and c) January 28, 2015 (see Table 7-4). The first two test datasets have the same values of 5.0 ℃ for outdoor dry-bulb temperature, but the different values for course period. The remaining test datasets have the same values of 4.2 ℃ for outdoor dry-bulb temperature, but the different values for course period. Table 7-5 represents the percentage of total rooms by EUG during the given periods. On November 18, 2014 and February 25, 2015, there is a difference in the number of total rooms by EUGs 1, 2, 5 and 6. Compared to the fall semester, the EUGs 2 and 5 are more prevalent in the winter semester (EUG 2: 6.6% versus 10.0%; EUG 5: 6.2% versus 12.1%). In contrast, the percentage of total rooms by EUGs 1 and 6 decreases in the winter semester (EUG 1: 21.9% compared to 16.7%; EUG 6: 17.2% compared to 11.5%). On December 16, 2014 and January 28, 2015, the EUG 1 has a change in the percentage of total rooms from 13.0% in the fall semester to 17.8% in the winter semester.

Table 7-4. Weather and Temporal Variables by Test Dataset

Test Datasets	Weather Variables				Temporal Variables	
	OT	WS	RH	SR	DW	CP
a) November 18, 2014	5.0	2.2	55.1	0.5	1	1
b) February 25, 2015	5.1	3.0	49.6	0.5	1	2
c) December 16, 2014	-4.2	4.9	64.2	0.4	1	1
d) January 28, 2015	-4.2	2.2	48.9	0.5	1	2

Note: OT = Outdoor Temperature (℃), WS = Wind Speed (m/s), RH = Relative Humidity (%), SR = Solar Radiation (MJ/㎡), DW = Day of the Week (weekday: 1, weekend: 2), CP = Course Period (fall: 1, winter: 2)

Table 7-5. Percentage of Total Rooms by End-user Group and Test Dataset

Test Dataset	End-user Group									
	1	2	3	4	5	6	7	8	9	10
a) November 18, 2014	21.9	6.6	13.6	1.9	6.2	17.2	1.3	22.5	5.0	3.7
b) February 25, 2015	16.7	10.0	13.1	1.2	12.1	11.5	2.6	23.5	6.4	3.0
c) December 16, 2014	13.0	9.7	5.8	3.3	16.3	10.8	5.3	25.6	5.9	4.3
d) January 28, 2015	17.8	8.0	8.5	1.3	17.9	8.6	4.5	26.6	4.3	2.5

Fig. 7-7 indicates the total amount of daily energy consumption during the given periods. On December 16, 2014, the case buildings spent the most amount of daily energy at 18,028 kWh. In contrast, the lowest amount of daily energy consumption is 10,944 kWh on November 18, 2014. When investigating the daily energy use by occupancy status, over 30% of electrical energy is consumed in the unoccupied buildings across all the given periods (November 18, 2014: 32.25; February 25, 2015: 46.3%; December 16, 2014: 42.9%; January 28, 2015: 47.3%). Looking closely at the daily energy use by EUG, the EUG 8s account for the most significant percentages of total energy use in the case buildings (November 18, 2014: 30.9%; February 23, 2015: 30.9%; December 16, 2014: 27.1%; January 28, 2015: 28.7%). These results are expected because the EUG 8s consume significant amount of electrical energy per occupied and unoccupied room. Also, this can be explained by the fact that they are the most prevalent across all the periods. Interestingly, although the EUG 5s are not always prevalent during the given periods, they are another consumer with higher percentage of the daily energy use in the buildings (November 18, 2014: 11.6%; February 25, 2015: 21.9%; December 16, 2014: 23.3%; January 28, 2015: 26.7%). These results can be supported by the fact that they consume significant amount of electrical energy regardless of occupancy status.

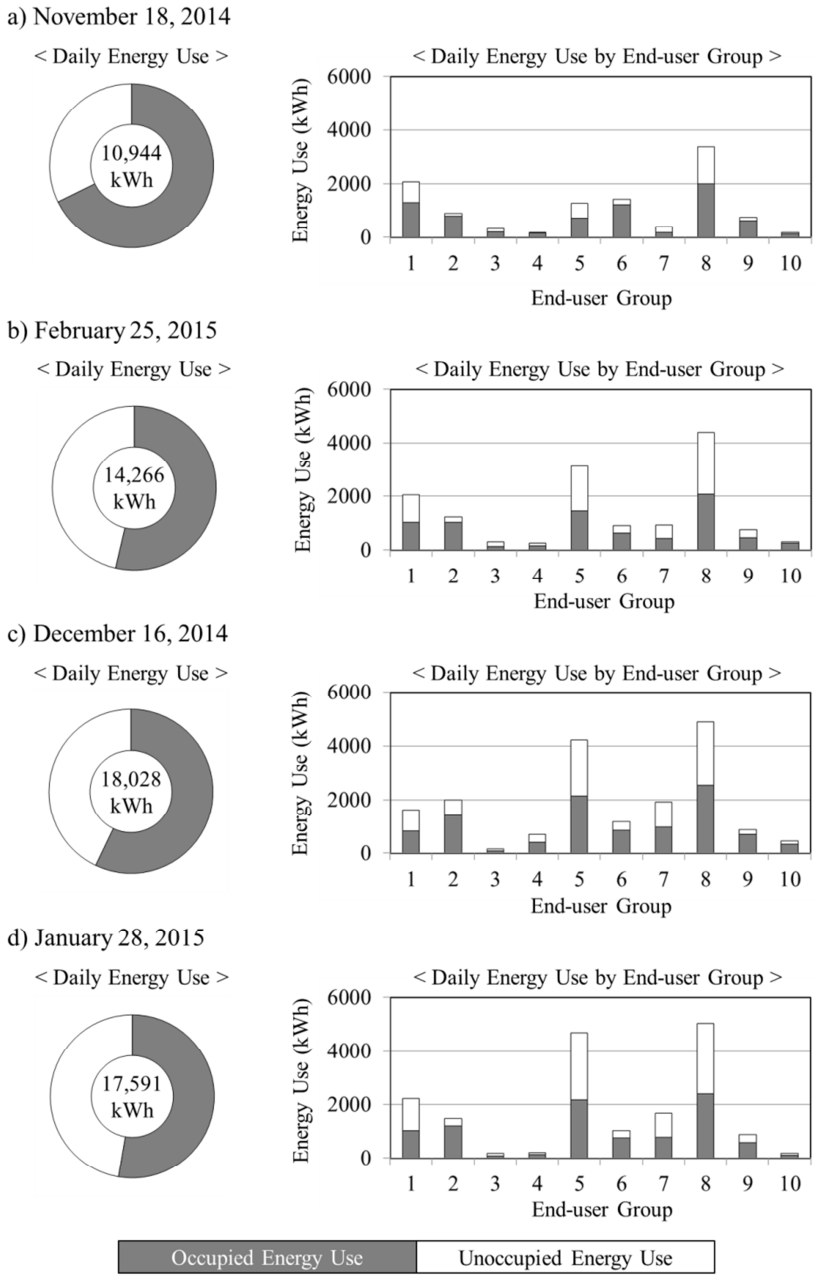


Figure 7-7. Daily Energy Consumption on November 18, 2014, February 25, 2015, December 16, 2014 and January 28, 2015

7.3.2 Energy Saving from HVAC Scheduling Alternatives

When comparing energy saving from global temperature control and on/off control of HVAC systems during the given periods, there are statistical variations among the control strategies (see Fig. 7-8). On November 18, 2014, December 16, 2014 and January 28, 2015, interrupting the operation of HVAC systems during unoccupied hours on average produces the energy saving of 35.4%, 36.8% and 41.3%, respectively. These quantities are higher than the energy saving from global temperature control of HVAC systems (November 18, 2014: 29.0%; December 16, 2014: 32.7%; January 28, 2015: 35.9%). In contrast, adjusting temperature setpoint on average reduces the more amount of daily energy use than on/off control on February 25, 2015 (43.9% compared to 38.6%).

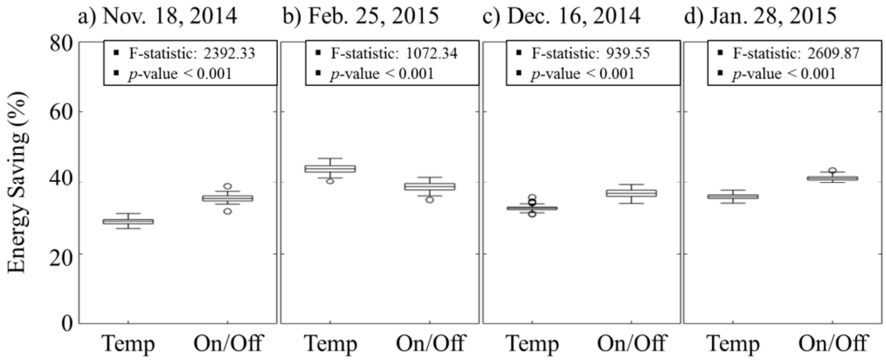


Figure 7-8 Energy Saving from Global Temperature and On/off Control

More specifically, when adjusting global temperature setpoint of HVAC systems in the case buildings, energy saving is achieved while occupied and unoccupied periods (see Fig. 7-9). Compared to the energy saving in vacant rooms, the less amount of occupied energy use is reduced across all the given periods (November 18, 2014: 11.0% versus 20.1%; February 25, 2015: 17.8% versus 29.2%; December 16, 2014: 5.9% versus 29.8%; January 28, 2015: 5.0% versus 32.7%). This is derived by the fact that buildings have relatively high heat loads in the nighttime compared to the daytime. Therefore, despite the change in global temperature setpoint in the case buildings, HVAC systems might be more frequently operated in the nighttime to maintain occupants' thermal comfort within its acceptable range. Additionally, the on/off control strategies contributes to the energy saving only in vacant buildings

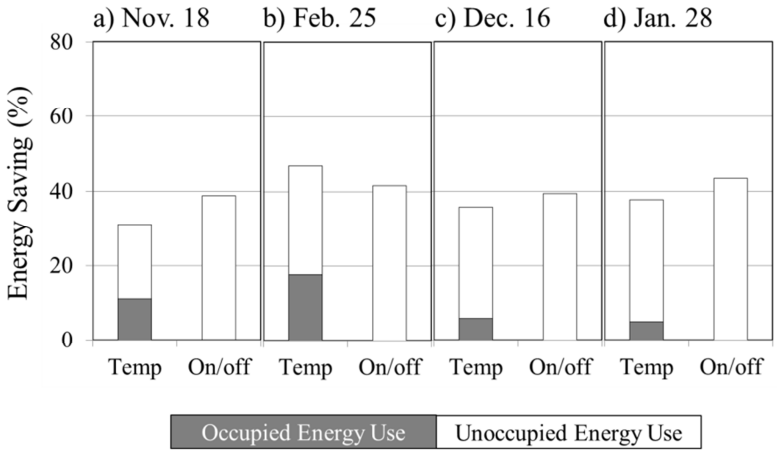


Figure 7-9. Energy Saving from Global Temperature and On/off Control in Occupied and Unoccupied Buildings

Figs. 7-10 and 7-11 indicate comparisons of the energy saving from global temperature control by EUG. Across all the given periods, a major contributor is the EUGs 5 and 8 across all the given periods (November 18, 2014: 7.3% and 14.5%; February 25, 2015: 14.4% and 14.0%; December 16, 2014: 11.8% and 7.5%; January 28, 2015: 16.0% and 14.6%, respectively). These results can be explained for the following two reasons. First, the EUGs 5 and 8 more significantly contribute to the total amount of daily energy spent during the given periods. Second, the average amount of hourly energy use while the EUGs 5 and 8 are occupied and unoccupied is significantly higher than the other EUGs. In contrast to the EUGs 5 and 8, energy saving is rarely achieved by the EUGs 1, 3, 4, 6 and 10 across all the given periods. In particular, although the EUGs 1, 3 and 6 are prevalent in the case buildings, they produce a very low percentage of energy saving from global temperature setpoint control. This can be expected because they exhibit low energy-consuming behaviors while occupied and/or unoccupied periods. For example, the EUG 6s generally tends to not only turn off HVAC systems before leaving out their rooms, but also spend low electrical energy in occupied rooms. For these reasons, although the global temperature setpoint of HVAC systems is adjusted during the given periods, the EUGs 1, 3 and 6 cannot contribute to a reduction in total energy consumption.

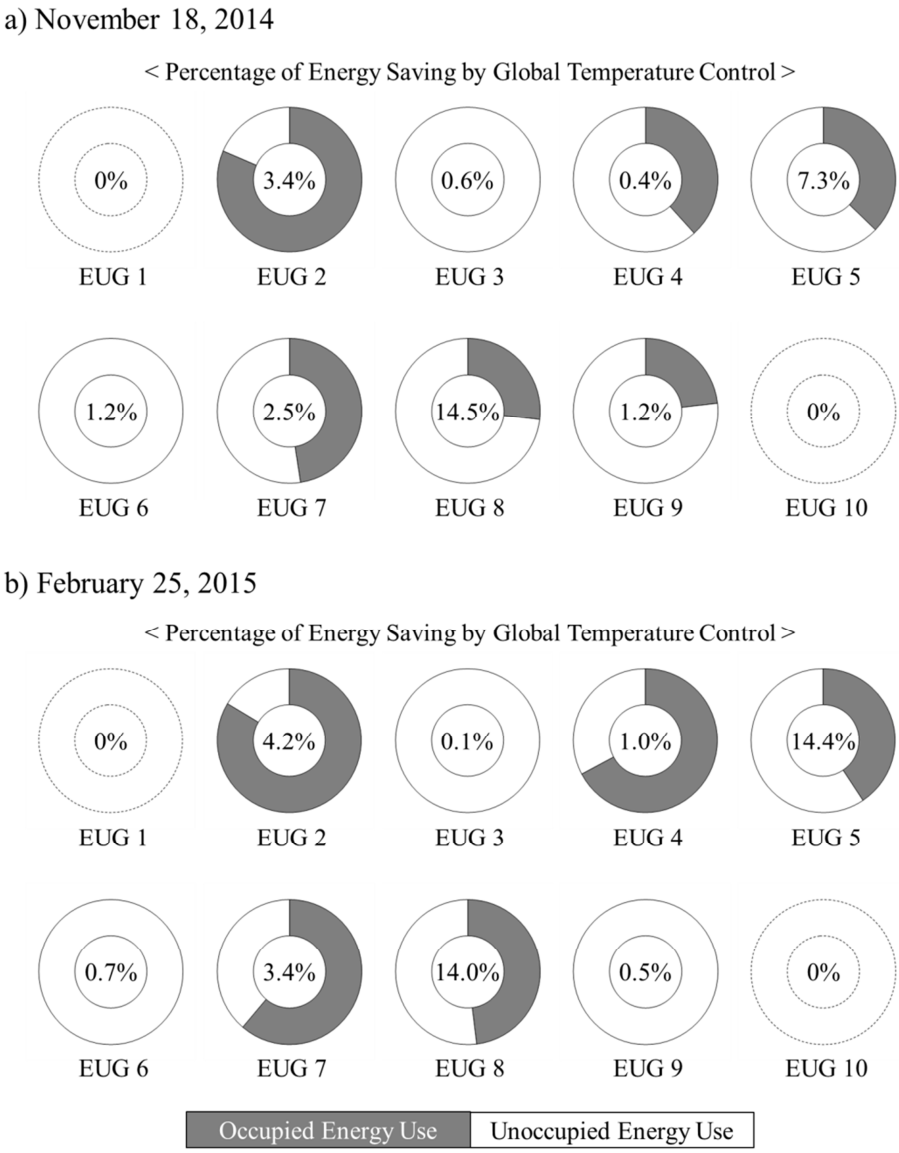
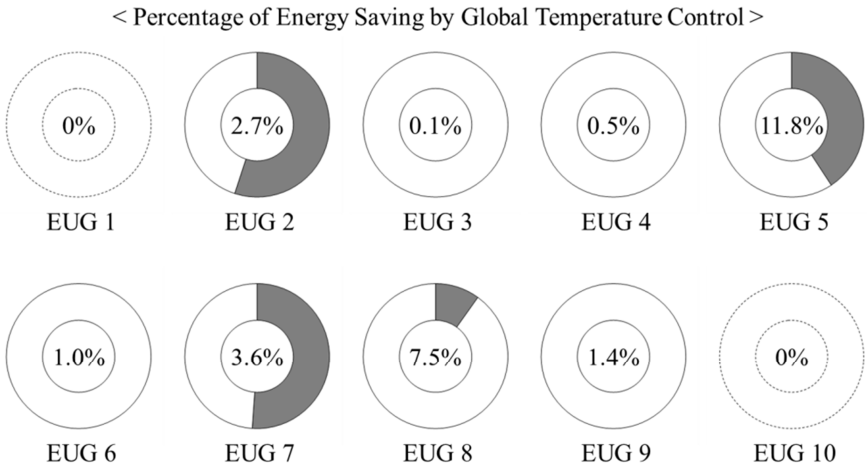


Figure 7-10. Percentage of Energy Saving from Global Temperature Control on a) November 18, 2014 and b) February 25, 2015

c) December 16, 2014



d) January 28, 2015

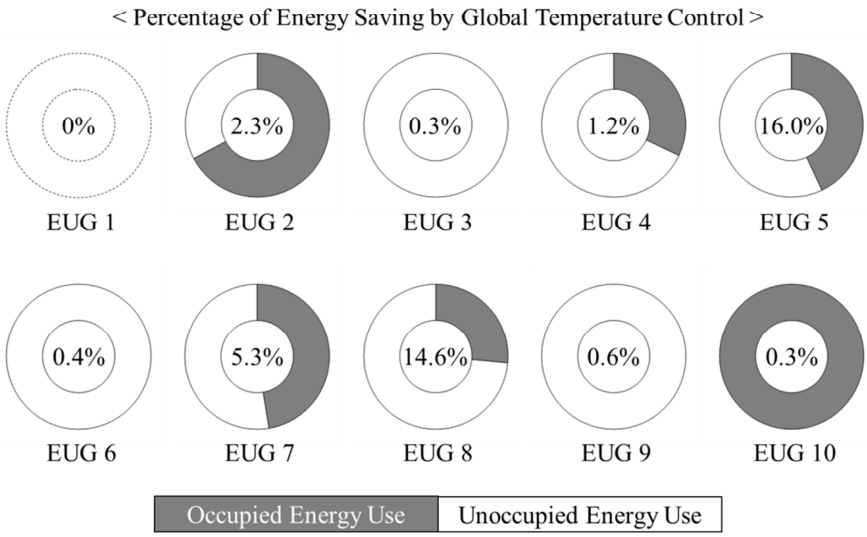


Figure 7-11. Percentage of Energy Saving from Global Temperature Control on c) December 16, 2014 and d) January 28, 2015

Table 7-6 shows a comparison of the percentage of energy saving from on/off control by EUG. The most significant contributor to the saving is the EUG 8s across all the given periods (November 18, 2014: 13.9%; February 25, 2015: 15.2%; December 16, 2014: 12.2%; January 28, 2015: 14.1%). Additionally, another significant contributor to the energy saving is the EUGs 1 and 5. On November 18, 2014, the EUG 1 reduces 8.8% of total energy consumption by interrupting the operation of HVAC systems while unoccupied. For the EUG 5s, there is a significant reduction in total energy consumption at 11.2% on February 25, 2015, 10.8% on December 16, 2014 and 13.6% on January 28, 2015. This would be expected because the EUGs 1, 5 and 8 account for a considerable percentage of total energy spent in the empty buildings.

Table 7-6. Percentage of Energy Saving from On/Off Control among End-user Group

Test Dataset	End-user Group									
	1	2	3	4	5	6	7	8	9	10
a) November 18, 2014	8.8	2.6	0.8	0.4	5.6	3.8	2.0	13.9	2.0	0.4
b) February 25, 2015	6.4	0.9	0.5	0.7	11.2	1.2	3.4	15.2	1.8	0.3
c) December 16, 2014	4.0	2.9	0.3	1.6	10.8	1.3	5.1	12.2	0.8	0.5
d) January 28, 2015	6.1	1.4	0.2	0.3	13.6	1.2	4.9	14.1	1.5	0.2

7.3 Discussions

In this research, the simulation experiments were conducted to investigate the effect of weather and temporal variables on energy saving from global temperature control and on/off control of HVAC systems in the case buildings. From the simulation results, it is observed that the global temperature control and on/off control of HVAC systems produce significant amount of energy saving in the case buildings. Across all the given periods, the buildings have the energy saving of 28.2-61.8% from adjusting the global temperature setpoint of HVAC systems. Also, it is found that interrupting the operation of HVAC systems in vacant rooms always reduces more than 30% of total energy consumption. These results imply that the case buildings exhibit the characteristics of low energy efficiency in the heating seasons.

Additionally, the simulation results show that the amount of energy saving from HVAC scheduling techniques varies depending on outdoor dry-bulb temperature and course period. These results can be explained by the fact that all the EUG has different percentages of total room by different weather and temporal variables (see Tables 7-2 and 7-5). This is important because energy saving from HVAC scheduling techniques is significantly related to the characteristics (e.g., energy use patterns, the number of rooms) of

representative EUGs. For example, interrupting the operation of HVAC systems in vacant rooms is effective for a EUG that consumes significant amount of electrical energy regardless of occupancy status. Further, if the EUG accounts for large percentage of the total rooms in the buildings, the effect of the control strategy would be improved. Additionally, these results indicate that establishing optimal control strategies is dependent on the given contexts. As outdoor dry-bulb temperature increases within the same course periods, the more amount of energy saving is achieved by adjusting the global temperature setpoint compared to the saving from on/off control. However, there is not always a consistency in optimal HVAC control strategies between different course periods. This is because optimal temperature setpoint for maintaining thermal comfort in rooms also varies depending on outside dry-bulb temperature. In general, the optimal setpoint has an important role in energy saving potential estimation due to its significant relationship with post-retrofit energy use in a given context. For example, as the temperature setpoint of HVAC systems decreases in winter season, a room consumes less energy for space heating and thus the control strategy produces more amount of energy saving.

Compared to the energy saving from interrupting the operation of HVAC systems while unoccupied hours, the global temperature control reduces electrical energy spent during both occupied and unoccupied hours (see Figs.

7-4 and 7-9). This is understandable because HVAC systems seem to be operated in vacant rooms of the EUGs 1, 5 and 8. Accordingly, adjusting a temperature setpoint of HVAC systems contributed to the reduction in both occupied and unoccupied energy consumption. Interestingly, except for February 15, 2015, most energy saving was achieved while occupants leave out their rooms. This result stems from the fact that HVAC systems consume less energy in the daytime due to relatively low heat loads compared to the nightime. As observed in Fig. 4-6, almost all the EUGs leave out their rooms in the daytime (9 a.m. to 6 p.m.). Therefore, although the temperature setpoint increases throughout a day, there could be more energy saving in vacant rooms. More specifically, when implementing the global temperature control in the buildings, it appears that the EUGs 5 and 8 are generally the most significant contributors to the total energy saving across all the given periods. (see Figs. 7-5, 7-6, 7-10 and 7-11). This can be expected because each of their rooms consumes a significant amount of electrical energy on both a daily and hourly basis (see Figs. 4-7, 4-8 and 4-9). In addition, since they account for a large proportion of total rooms, they achieved significant energy saving from the global temperature control of HVAC systems. In a rare case, although some EUGs are not prevalent in the case buildings, they significantly contribute to the total energy saving from the global temperature setpoint adjustment. This can be expected because they consume a significant amount of energy per occupied and unoccupied room.

In this research, as an effort to maintain occupants' thermal comfort within its acceptable rage, HVAC control strategies are personalized depending of EUG in multi-zone buildings. On the other hand, there might be concerns about the usability of the proposed control strategies because the advance technologies for smart meter, occupant detection and individual HVAC controllers should be equipped with building energy management systems (BEMS) such as those used in the case buildings. However, despite the difficulty, the proposed control strategies will most likely be used in BEMS since various attempts have previously been made to adopt such technologies in the field of building energy use management (Jain et al. 2014; Sandels et al. 2015; Virote and Neves-Silva 2012). In practice, the system air-conditioners which are individually installed and operated in each of rooms are widely adopted across Asia. Also, in a sensor-based approach, data from Internet of Things (IoT) devices such as sensors, cameras and RFIDs as well as smart meter, has been fed into a wide types of machine learning and deep learning algorithms to analyze the complex relationships of energy consumption with weather and spatiotemporal variables in buildings (Edwards et al. 2012; Zhao and Magoulès 2012; Jain et al. 2014). Additionally, considering the practical application of the proposed control strategies to other buildings, its usefulness would increase because more energy use patterns exist in office and manufacturing buildings.

7.4 Summary

This section conducted simulation experiments to investigate the quantity of HVAC scheduling techniques in different weather and temporal contexts. As alternatives to reduce energy consumption by HVAC systems, the global temperature setpoint adjustment and on/off control are considered because the case buildings have significant energy-consuming EUGs in both occupied and unoccupied buildings. From the simulation results, the three key findings are summarized as follow. First, the global temperature control and on/off control of HVAC systems, as HVAC scheduling techniques, produce significant amount of energy saving in the case buildings. This implies that the buildings exhibit characteristics of low energy efficiency in heating seasons. Second, establishing optimal control strategies is dependent on the given contexts. As outdoor dry-bulb temperature increases within the same course periods, the more amount of energy saving is achieved by adjusting the global temperature setpoint compared to the saving from on/off control. In contrast, there is not a consistency in optimal control strategies with a change in course periods because it affects the maximum temperature of HVAC systems. Third, the contribution of end-user groups to total energy saving in multi-zone buildings varies with a change in temporal and weather variables.

Chapter 8. Conclusions

This chapter summarizes the research results and explains contributions to the researchers and practitioners in the field of building demand-side management. Finally, limitations and recommendations are provided for the further practical uses of this research's outcomes in facility management companies.

8.1 Research Results

Demand-side management plays an important role to reduce energy consumption in the operation phase of buildings. Based on the circumstances, recent researchers have focused on control strategies for HVAC systems due to the significant energy saving potentials with relatively less effort. However, despite the previous achievements, establishing optimal control strategies in multi-zone buildings is difficult because the effect of HVAC scheduling techniques on energy saving varies depending on weather and temporal variables. Further, practical issues on thermal comfort for various end-users in multi-zone buildings are rarely addressed. For these reasons, this research investigated how weather and temporal variables affect energy saving from HVAC scheduling techniques in multi-zone buildings.

This research started with the following four studies: a) to identify representative end-user groups in multi-zone buildings; b) to develop a data mining-based prediction model for baseline energy consumption in multi-zone buildings; c) to create a thermodynamic model for post-retrofit energy use prediction in multi-zone buildings; d) to investigate the amount of energy saving from HVAC scheduling techniques in multi-zone buildings. A summary of the research results from the studies follows.

a) To identify representative end-user groups in multi-zone buildings: In this study, I conducted an exploratory analysis to investigate representative end-user groups in dormitory buildings of a university in Seoul, South Korea. Although the buildings are used for a residence purpose, 10 representative end-user groups were observed during the given periods. Also, after quantifying the amount of energy consumption on an hourly basis, it was found that some end-user groups have energy overconsumption per occupied and unoccupied room. Lastly, the distribution of representative end-user groups statistically varies by outdoor dry-bulb temperature, day of the week and course periods. These findings imply that there is significant energy saving potential through applying HVAC scheduling techniques during both occupied and vacant hours. Also, it can be expected that HVAC scheduling techniques provide different contributions to the energy saving depending on weather and temporal context.

b) To develop a data miming-based prediction model for baseline energy consumption in multi-zone buildings: This study developed a data mining-based prediction model which addresses occupancy-related characteristics of representative end-user groups in multi-zone buildings. After conducting comparative experiments using the developed model, the three key findings are provided as follow. First, the use of occupancy rate as an input variable does not always ensure the improvement in prediction accuracy. An occupancy rate that is weakly correlated with energy use creates an adverse effect on prediction accuracy. Second, enhanced accuracy can be achieved by considering occupancy diversity in multi-zone building. Third, the proposed prediction model will have a high accuracy when using fewer similar daily datasets.

c) To create a thermodynamic model for post-retrofit energy use prediction in multi-zone buildings: In this study, a thermodynamic model was constructed to predict the amount of energy spent under controlled conditions by HVAC scheduling techniques. Additionally, in order to validate the developed model, experiments were performed using the actual data collected from the case buildings. The experimental results show that the developed model provides reliable accuracy within the acceptable tolerance to predict post-retrofit energy use in rooms. In addition, similar behaviors of energy use and indoor temperature in rooms were elaborated by the thermodynamic

model. These results indicate that the developed model is useful to simulate thermal behaviors by weather and temporal context.

d) To investigate the amount of energy saving from HVAC scheduling techniques in multi-zone buildings: This study performed simulation experiments to improve our understanding of how weather and temporal variables affect energy saving from the global temperature and on/off control of HVAC systems in multi-zone buildings. The simulation results show that the control strategies provide significant energy savings (16.3-53.7%) in multi-zone buildings. Also, it was found that optimal control strategies are dependent on weather condition. As outdoor dry-bulb temperature decreases, interrupting the operation of HVAC systems while unoccupied produces more energy saving compared to adjusting the temperature setpoint of HVAC systems. However, there was not a meaningful relationship between temporal variables and optimal control strategies in multi-zone buildings.

8.2 Contributions

a) To identify representative end-user groups in multi-zone buildings: The contribution of this research is to improve our understanding of hourly energy consumption for representative end-user groups in multi-zone

buildings. Additionally, this research is significant because it present a first look at investigating how temporal and weather variables affect the distribution of end-user groups in multi-zone buildings. From a practical perspective, this research enables facility managers to investigate appropriate HVAC control alternatives depending on temporal and weather context.

b) To develop a data miming-based prediction model for baseline energy consumption in multi-zone buildings: The contribution of this research is its enhancement of the knowledge about the impact of occupancy-related characteristics on prediction accuracy in multi-zone buildings. Additionally, this research is significant because the developed model provides practical solutions to achieve acceptable prediction accuracy using minimal historical data.

c) To investigate* the *effect of weather and temporal variables on energy saving from HVAC scheduling techniques in multi-zone buildings: This research contributes to improving our understanding of how weather and temporal variables affect energy saving from HVAC scheduling alternatives in multi-zone buildings. This enables facility managers to establish optimal HVAC control strategies in a given temporal and weather contexts.

8.3 Future Research

While this work has expanded our understanding of the effect of temporal and weather variables on energy saving from HVAC scheduling techniques in multi-zone buildings, many improvement opportunities still remain as follow.

a) As a prerequisite process to select appropriate HVAC scheduling alternatives in multi-zone buildings, this research investigated representative end-user groups during the heating season. However, since occupants can have different energy use patterns depending on season, future research will include quantifying the amount of energy use for representative end-user groups during the cooling season and examining their distribution by temporal and weather context.

b) This research developed the ANN model to predict baseline energy consumption in multi-zone buildings. In fact, no attempt is made in this research to investigate optimal parameters for the proposed models and evaluate the performance of other network models; limitations in the prediction accuracy thus remain. In order to address this issue, sensitivity analysis about how the number of hidden layers and its nodes affect the

prediction performance should be performed in future research. Also, recurrent neural networks, where the output variable depends not only on the current input variables but also the previous input and output variable, could improve the prediction accuracy since building energy use has sequence-dependent feature.

c) A thermodynamic model should be elaborate to predict the amount of energy spent under controlled condition by HVAC scheduling alternatives. Since the developed model has assumptions for heat transfer calculation, additional effort could conduct field survey regarding occupants' activity and clothing in a room. Moreover, the improved performance of the thermodynamic model can be achieved by addressing the insulation performance of main thermal bridges (e.g., wall, window).

d) The energy performance simulation was conducted to establish optimal HVAC control strategies in multi-zone buildings. In reality, the planned control strategies can have deviations between actual and expected performance. Therefore, much effort should be made to measure and verify the planned control strategies in multi-zone buildings. Through identifying the determinants of the deviations, it will ensure the performance of the planned HVAC control strategies in multi-zone buildings.

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Appendices

Appendix A: Input Data for Thermodynamic Modeling

A-I. Physical Characteristic

Input Variables	Values
- Height of wall	2.690
- Height of window	1.600
- Height of door in hallway	2.100
- Length of roof in room	3.900
- Length of ground in room	3.900
- Length of toilet in single room	3.900
- Length of toilet in double room	5.715
- Length of hallway in single room	1.610
- Length of hallway in double room	1.580
- Length of door in hallway	0.900
- Width of wall	3.900
- Width of wall_2nd surface	6.000
- Width of window	1.600
- Width of roof in single room	3.900
- Width of roof in double room	6.000
- Width of ground in single room	3.900
- Width of ground in double room	6.000
- Thickness of concrete in wall	1.200
- Thickness of insulation in wall	0.065
- Thickness of air in wall	0.025
- Thickness of brick in wall	0.090
- Thickness of concrete in roof	0.210

(A-I. Continued)

Input Variables	Values
-Thickness of concrete in ground	0.210
-Thickness of insulation in ground	0.050
-Thickness of concrete in floor	0.078
- Thickness of concrete in toilet	0.090
- Thickness of concrete in hallway	0.190
- Thickness of door in hallway	0.040
- Thickness of indoor wall	0.135
- Area of floor in single room	9.360
- Area of floor in double room	17.014

A-II. Insulation Properties

Input Variables	Values
- Density of air	1.290
- Density of mortar	1800.0
- Specific heat of air	1005.0
- Specific heat of cement	920.9
- Thermal conductivity of concrete in walls	1.600
- Thermal conductivity of insulation in walls	0.028
- Thermal conductivity of brick in walls	0.470
- Thermal conductivity of air in walls	0.025
- Thermal conductivity of concrete in roof	1.600
- Thermal conductivity of insulation in roof	0.036
- Thermal conductivity of concrete in ground	1.600
- Thermal conductivity of insulation in ground	0.028
- Thermal conductivity of concrete in hallway	1.600
- Thermal conductivity of concrete in toilet	1.600

A-III. Under-floor Electric Heating Systems

Input Variables	Values
- Length of electric heating cable in single room	38
- Length of electric heating cable in double room	50
- Efficiency of electric heating cable	95
- Watt of electric heating cable	42

A-IV. Model Parameters

Input Variables	Values
- Rohles experimental coefficients of a	0.138
- Rohles experimental coefficients of b	0.027
- Rohles experimental coefficients of c	3.019
- Coefficient A of Antonie equation	8.071
- Coefficient B of Antonie equation	1730.6
- Coefficient C of Antonie equation	233.4
- Thermal time constant of single room	10.25
- Thermal time constant of double room	9.87
- Number of ventilation by window	1.5

Appendix B: Matlab Code for Energy Performance Evaluation

B-I. Similar Data Selection

```
load('Input_Data.mat');
In_total = [In_seasonal; In_temporal];

TDays = 119
NIn_seasonal = size(In_seasonal,1);
NIn_temporal = size(In_temporal,1);

RInteger = Day;
TIn_seasonal = In_seasonal(:,(24*RInteger)-23:24*RInteger);
TIn_temporal = In_temporal(:,(24*RInteger)-23:24*RInteger);

DTIn_seasonal = zeros(NIn_seasonal,TDays);
DTIn_temporal = zeros(NIn_temporal,TDays);
for i = 1:TDays;
	DTIn_seasonal(:,i) = mean(In_seasonal(:,(24*i)-23:24*i),2);
	DTIn_temporal(:,i) = mean(In_temporal(:,(24*i)-23:24*i),2);
end
DTIn_total = [DTIn_seasonal; DTIn_temporal];
for i = 1:TDays;
	DTIn_total(NIn_seasonal+NIn_temporal+1,i) = i;
end

for i = 1:TDays;
	for j = 1:(NIn_seasonal+NIn_temporal);
		minmaxVal(j,1) = min(DTIn_total(j,:));
		minmaxVal(j,2) = max(DTIn_total(j,:));
		temp(j,i) = (DTIn_total(j,i) - minmaxVal(j,1)) / (minmaxVal(j,2) -
		  minmaxVal(j,1));
	end
end
Fzero = find(temp == 0);
```

```
Szeros = size(Fzero,1);
for i = 1:Szeros;
	temp1 = Fzero(i);
	temp(temp1) = temp(temp1) + 0.0001;
end
DTIn_total_Nor = [temp(1:4,:); DTIn_total(5,:); temp(6:10,:);
DTIn_total(11,:)];

TI = DTIn_total_Nor(1:10,RInteger);

X = DTIn_total_Nor(1:10,:);
Y = DTIn_total_Nor(11,:);
X(:,Day) = [];
Y(:,Day) = [];
DSW = fitcknn(X', Y', 'NumNeighbors', NSD);
[DSWClass CN1 CN2] = predict(DSW, TI');

SD_dummy = find(CN1 ~= 0);
SD = Y(1,SD_dummy);
```

B-II. Baseline Energy Use Prediction

```
TrIn_total = zeros(NIn_seasonal+NIn_temporal,1);
for o = 1:NSD;
	temp = In_total(:,(SD(1,o)*24)-23:SD(1,o)*24);
	TrIn_total = [TrIn_total temp];
end
TrIn_total = TrIn_total(:,2:(24*NSD)+1);

temp5_size = [];
temp4_energy = [];
temp4_occ_dummy = [];
for i = 1:NSD;
	temp4_size = [];
	temp3_energy = [];
	temp3_occ_dummy = [];
	for j = 1:10;
		temp3_size = [];
		temp2_energy = [];
		temp2_occ_dummy = [];
		for k = 1:2;
			temp1_size = find(and(and(DB_energy(:,2) == j,
			  DB_energy(:,4) == SD(1,i)), DB_energy(:,5) == k));
			temp2_size = size(temp1_size,1);
			temp3_size = [temp3_size; temp2_size];
			temp1_energy = mean(DB_energy(temp1_size,6:29),1);
			temp2_energy = [temp2_energy; temp1_energy];
			temp1_occ = mean(DB_occ(temp1_size,6:29),1);
			temp2_occ_dummy = [temp2_occ_dummy; temp1_occ];
		end
		temp4_size = [temp4_size; temp3_size];
		temp3_energy = [temp3_energy; temp2_energy];
		temp3_occ_dummy = [temp3_occ_dummy; temp2_occ_dummy];
	end
	temp5_size = [temp5_size temp4_size];
	temp4_energy = [temp4_energy temp3_energy];
	temp4_occ_dummy = [temp4_occ_dummy temp3_occ_dummy];
end
```

```
TrOut_size = temp5_size;
TrOut_energy = temp4_energy;
TrOut_energy(isnan(TrOut_energy)) = 0;
TrOut_occ = temp4_occ_dummy;
TrOut_occ(isnan(TrOut_occ)) = 0;

temp4_size = [];
temp3_energy = [];
temp3_occ = [];

for i = 1:10;
	temp3_size = [];
	temp2_energy = [];
	temp2_occ = [];
	for j = 1:2;
		temp1_size = find(and(and(DB_energy(:,2) == i, DB_energy(:,4)
		  == Day), DB_energy(:,5) == j));
		temp2_size = size(temp1_size,1);
		temp3_size = [temp3_size; temp2_size];
		temp1_energy = mean(DB_energy(temp1_size, 6:29),1);
		temp2_energy = [temp2_energy; temp1_energy];
		temp1_occ = mean(DB_occ(temp1_size, 6:29),1);
		temp2_occ = [temp2_occ; temp1_occ];
	end
	temp4_size = [temp4_size; temp3_size];
	temp3_energy = [temp3_energy; temp2_energy];
	temp3_occ = [temp3_occ; temp2_occ];
end
AcOut_size = temp4_size;
AcOut_energy = temp3_energy;
AcOut_energy(isnan(AcOut_energy)) = 0;
AcOut_occ = temp3_occ;
AcOut_occ(isnan(AcOut_occ)) = 0;

for i = 1:20;
	tic;
	eval(['OANN_EUG' num2str(i) ' = feedforwardnet([10 10 10 10 10 10 10
	  10 10 10]);' ]);
```

```
    eval(['OANN_EUG' num2str(i) '.trainParam.epochs = 1000;']);
    eval(['OANN_EUG' num2str(i) '.trainParam.max_fail = 50;']);
    eval(['OANN_EUG' num2str(i) '.trainParam.min_grad = 1e-20;']);
    eval(['OANN_EUG' num2str(i) '.trainParam.showWindow = false;']);
    eval(['OANN_EUG' num2str(i) '.trainParam.showCommandLine =
      false;']);
    temp1 = find(TrOut_size(i,:) ~= 0);
    temp2 = size(temp1,2);
    if temp2 == NSD;
        TrIn = TrIn_total(5:10,:);
        TrOut = TrOut_occ(i,:);
    else
        temp4 = [];
        temp6 = [];
        for j = 1:temp2;
            temp3 = TrIn_total(5:10, (24*temp1(j))-23:24*temp1(j));
            temp4 = [temp4 temp3];
            temp5 = TrOut_occ(i, (24*temp1(j))-23:24*temp1(j));
            temp6 = [temp6 temp5];
        end
        TrIn = temp4;
        TrOut = temp6;
    end
    eval(['OANN_EUG' num2str(i) ' = train(OANN_EUG' num2str(i) ', TrIn,
      TrOut);']);
    TrTime(1,i) = toc;
end

TOut_Occ = [];
for i = 1:20;
    eval(['temp = OANN_EUG' num2str(i) '(TIn_temporal);']);
    TOut_Occ = [TOut_Occ; temp];
end
TOut_Occ = abs(TOut_Occ);

for i = 1:20;
    for j = 1:24;
        temp1_energy = 0;
```

```
            temp1_occ = 0;
            for k = 1:NSD;
                temp_energy = TrOut_energy(i,(24*(k-1))+j);
                temp_occ = TrOut_occ(i,(24*(k-1))+j);
                temp1_energy = temp1_energy + temp_energy;
                temp1_occ = temp1_occ + temp_occ;
            end
            temp2_energy(i,j) = temp1_energy;
            temp2_occ_dummy(i,j) = temp1_occ;
        end
end
temp6_energy = [];
temp6_occ = [];
for i = 1:20;
        temp3_energy = find(TrOut_size(i,:) ~= 0);
        temp4_energy = size(temp3_energy,2);
        RE_energy = temp2_energy(i,:)/temp4_energy;
        RE_occ = temp2_occ_dummy(i,:)/temp4_energy;
        temp6_energy = [temp6_energy; RE_energy];
        temp6_occ = [temp6_occ; RE_occ];
end
TrOut_energy_rep = temp6_energy;
TrOut_occ_rep = temp6_occ;

CCoef = zeros(30,2);
for q = 1:20;
        [R,P] = corrcoef(TrOut_energy_rep(q,:)',TrOut_occ_rep(q,:)');
        temp7 = R(2,1);
        temp8 = P(2,1);
        CCoef(q,1) = temp7;
        CCoef(q,2) = temp8;
end

for i = 1:20;
        tic;
        eval(['EANN_EUG' num2str(i) ' = feedforwardnet([10 10 10 10 10 10 10
          10 10, 10]);' ]);
        eval(['EANN_EUG' num2str(i) '.trainParam.epochs = 1000;']);
```

```
    eval(['EANN_EUG' num2str(i) '.trainParam.max_fail = 50;']);
    eval(['EANN_EUG' num2str(i) '.trainParam.min_grad = 1e-20;']);
    eval(['EANN_EUG' num2str(i) '.trainParam.showWindow = false;']);
    eval(['EANN_EUG' num2str(i) '.trainParam.showCommandLine =
false;']);
    temp1 = find(TrOut_size(i,:) ~= 0);
    temp2 = size(temp1,2);
    if temp2 == NSD;
        if and(CCoef(i,1) > 0.5, CCoef(i,2) < 0.05);
            TrIn = [TrIn_total(1:4,:); TrOut_occ(i,:)];
            TrOut = TrOut_energy(i,:);
        else
            TrIn = TrIn_total(1:4,:);
            TrOut = TrOut_energy(i,:);
        end
    else
        temp4 = [];
        temp6 = [];
        temp8 = [];
        for j = 1:temp2;
            temp3 = TrIn_total(1:4, (24*temp1(j))-23:24*temp1(j));
            temp4 = [temp4 temp3];
            temp5 = TrOut_energy(i, (24*temp1(j))-23:24*temp1(j));
            temp6 = [temp6 temp5];
            temp7 = TrOut_occ(i, (24*temp1(j))-23:24*temp1(j));
            temp8 = [temp8 temp7];
        end
        if and(CCoef(i,1) > 0.5, CCoef(i,2) < 0.05);
            TrIn = [temp4; temp8];
            TrOut = temp6;
        else
            TrIn = temp4;
            TrOut = temp6;
        end
    end
    eval(['EANN_EUG' num2str(i) ' = train(EANN_EUG' num2str(i) ', TrIn,
     TrOut);']);
    TrTime(2,i) = toc;
```

```
end

TOut_Energy = [];
for t = 1:20;
	if and(CCoef(t,1) > 0.5, CCoef(t,2) < 0.05);
		eval(['TIn = [TIn_seasonal; TOut_Occ(t,:)];']);
		eval(['temp = EANN_EUG' num2str(t) '(TIn);']);
	else
		eval(['TIn = TIn_seasonal;']);
		eval(['temp = EANN_EUG' num2str(t) '(TIn);']);
	end
	TOut_Energy = [TOut_Energy; temp];
end
TOut_Energy = abs(TOut_Energy);
```

B-III. Post-retrofit Energy Use Prediction

```
Period = 1;
Nhours = Period*24;
Nmins = Nhours*60;
T_outdoor = OutT_total(:,Day);
CS_period = CStype;
Lv_floor = LvF;
Lv_surface = LvS;
M_temp_floor = MTF;
for k = 1:Nmins;
    t_series(k,1) = k;
end

if CS_period == 1;
    for i = 1:20;
        temp = mean(TOut_Occ(i,:));
        for j = 1:24;
            temp1 = TOut_Occ(i,j);
            if temp1 >= temp;
                TOut_Occ_dummy(i,j) = 1;
            else
                TOut_Occ_dummy(i,j) = 0;
            end
        end
    end
else
    for i = 1:20;
        temp = mean(TOut_Occ(i,:));
        for j = 1:24;
            temp1 = TOut_Occ(i,j);
            temp2 = find(BeOcc == i);
            if size(temp2,1) == 0;
                if temp1 >= temp;
                    TOut_Occ_dummy(i,j) = 1;
                else
                    TOut_Occ_dummy(i,j) = 0;
                end
```

```
                else
                        TOut_Occ_dummy(i,j) = 1;
                end
        end
    end
end

for i = 1:20;
    temp = mean(TOut_Occ(i,:));
    for j = 1:24;
        temp1 = TOut_Occ(i,j);
        if temp1 >= temp;
            TOut_Occ_real(i,j) = 1;
        else
            TOut_Occ_real(i,j) = 0;
        end
    end
end

for i = 1:20;
    R_occ_dummy = TOut_Occ_dummy(i,:)';
    R_occ_real = TOut_Occ_real(i,:)';
    V_avail_dummy = Ven';
    temp4_occ_dummy = [];
    temp4_occ_real = [];
    temp4_ven = [];
    for j = 1:Nhours;
        temp2_occ_dummy = R_occ_dummy(j,1);
        temp3_occ_dummy = [];
        temp2_occ_real = R_occ_real(j,1);
        temp3_occ_real = [];
        temp2_ven = V_avail_dummy(j,1);
        temp3_ven = [];
        for j = 1:60;
            temp3_occ_dummy = [temp3_occ_dummy;
             temp2_occ_dummy];
            temp3_occ_real = [temp3_occ_real; temp2_occ_real];
            temp3_ven = [temp3_ven; temp2_ven];
```

```
            end
            temp4_occ_dummy = [temp4_occ_dummy; temp3_occ_dummy];
            temp4_occ_real = [temp4_occ_real; temp3_occ_real];
            temp4_ven = [temp4_ven; temp3_ven];
        end
        R_occupancy_dummy(:,i) = temp4_occ_dummy;
        R_occupancy_real(:,i) = temp4_occ_real;
        V_avail = temp4_ven;
end

RE_energy = [];
RE_indoor = [];
RE_floor = [];
RE_outdoor = [];
RE_PMV = [];
RE_occ = [];
RE_energy_h = [];
RE_occ_h = [];

for i = 1:20;
        temp1 = rem(i,3);
        if temp1 == 1;
            simOut =
sim('Model_single','SaveOutput','on','OutputSaveName','All_results');
        else
            if CS_period == 0;
                M_temp_floor = MTF - 5;
                simOut =
                  sim('Model_double','SaveOutput','on','OutputSaveName',
                  'All_results');
            else
                simOut =
                  sim('Model_double','SaveOutput','on','OutputSaveName',
                  'All_results');
            end
        end
        temp2 = simOut.get('All_results');
        temp2_PMV = temp2(:,5).*temp2(:,6);
```

```
    temp3_energy = temp2(2:1441,1);
    temp3_indoor = temp2(2:1441,2);
    temp3_floor = temp2(2:1441,3);
    temp3_outdoor = temp2(2:1441,4);
    temp3_PMV = temp2_PMV(2:1441,1);
    temp3_occ = temp2(2:1441,6);
    for j = 1:24;
        temp4_energy(1,j) = sum(temp3_energy((60*j)-59:60*j,1),1);
        temp4_occ(1,j) = mean(temp3_occ((60*j)-59:60*j,1),1);
    end
    RE_energy = [RE_energy temp3_energy];
    RE_indoor = [RE_indoor temp3_indoor];
    RE_floor = [RE_floor temp3_floor];
    RE_outdoor = [RE_outdoor temp3_outdoor];
    RE_PMV = [RE_PMV temp3_PMV];
    RE_occ = [RE_occ temp3_occ];
    RE_energy_h = [RE_energy_h; temp4_energy];
    RE_occ_h = [RE_occ_h; temp4_occ];
end
RE_energy_h = RE_energy_h/1000;
```

B-IV. Energy Saving Calculation

```
temp3_TOut = zeros(20,2);
temp3_RE = zeros(20,2);
for i = 1:20;
	for j = 1:24;
		temp1_TOut = TOut_Energy(i,j);
		temp1_RE = RE_energy_h(i,j);
		temp2_TOut = TOut_Occ_real(i,j);
		temp2_RE = RE_occ_h(i,j);
		if temp2_TOut > 0;
			temp3_TOut(i,1) = temp3_TOut(i,1) + temp1_TOut;
		else
			temp3_TOut(i,2) = temp3_TOut(i,2) + temp1_TOut;
		end
		if temp2_RE > 0;
			temp3_RE(i,1) = temp3_RE(i,1) + temp1_RE;
		else
			temp3_RE(i,2) = temp3_RE(i,2) + temp1_RE;
		end
	end
end

for i = 1:20;
	temp1_present = temp3_TOut(i,1) - temp3_RE(i,1);
	temp1_vacant = temp3_TOut(i,2) - temp3_RE(i,2);
	if temp1_present > 0;
		temp2_PreTotal(i,1) = temp1_present;
	else
		temp2_PreTotal(i,1) = 0;
	end
	if temp1_vacant > 0;
		temp2_PreTotal(i,2) = temp1_vacant;
	else
		temp2_PreTotal(i,2) = 0;
	end
end
```

```
Pre_energy = temp3_TOut;
Pre_potential = temp2_PreTotal;

temp1 = sum(TrOut_size,1);

temp4 = [];
for i = 1:20;
	temp2 = TrOut_size(i,:);
	temp3 = (temp2*100)./temp1;
	temp4 = [temp4; temp3];
end
temp5 = mean(temp4,2);
temp6 = temp5*temp1(1)/100 ;

temp2_Pre = [];
temp4_Pre = [];
for i = 1:20;
	temp1_Pre = Pre_potential(i,:)*temp6(i);
	temp3_Pre = Pre_energy(i,:)*temp6(i);
	temp2_Pre = [temp2_Pre; temp1_Pre];
	temp4_Pre = [temp4_Pre; temp3_Pre];
end
TPre_potential = sum(temp2_Pre, 1);
TPre_potential(3) = sum(TPre_potential(1:2));

TPre_energy = sum(temp4_Pre, 1);
TPre_energy(3) = sum(TPre_energy(1:2));

TPre_rate = TPre_potential(3)/TPre_energy(3)*100;

T_results = [TPre_potential TPre_energy TPre_rate];
```

國 文 抄 錄

建物 에너지 效率 向上을 위한 狀況별 制御 戰略

에너지 절약에 대한 관심이 증대됨에 따라, 건물 생애주기 동안 에너지 수요 관리를 위한 노력이 이루어 지고 있다. 설계단계에서는 건물 단열성능 향상 및 고효율 전기/기계설비 설치와 같은 기술적 방안을 활용하여 에너지 소비를 줄이고 있다. 또한, 건물 운영단계에서는 전기/기계설비의 효율적인 운영을 통해 지속적으로 에너지를 절약하고 있다. 이러한 에너지 절약 방안 중에, 최근 연구는 상대적으로 적은 투자비용으로 높은 에너지 절약효과를 거둘 수 있는 운영적 방안을 대상으로 진행되고 있다.

이처럼 건물 운영단계 수요 관리의 중요성이 높아져가고 있는 가운데, 상당수의 연구가 냉난방 설비(HVAC) 스케줄링을 통한 에너지 절약 효과를 분석하였다. 그러나 이러한 노력에도 불구하고 멀티 존 건물(multi-zone buildings)에서 냉난방 설비의 최적 제어 전략을 수립하는 과정에서 두 가지 문제점이 존재한다. 첫째, 건물 재실자의 열 쾌적을 만족시키지 못한다는 점이다. 비록 기존 연구에서 구역(zone) 단위로 냉난방 설비를 운영하는 제어방법을 제시하였지만, 하나의 구역이 서로 다른 패턴을 가진 여러 개의 실(room)로 구성될 경우에 재실자의 열 쾌적을 보장하기 어렵다.

또한, 이러한 한계점을 개선하기 위해 실 단위로 냉난방 설비를 운영한다면, 제어변수 설정에 많은 시간이 소요되는 한계점을 갖게 된다. 둘째, 냉난방 설비 스케줄링의 효과가 상황에 따라 어떻게 변화하는지 알 수 없다. 비록 몇몇 연구에서 환경 변화에 따른 냉난방 설비 스케줄링의 효과를 분석하였지만, 모든 구역이 동일한 에너지 소비패턴을 가진 것으로 가정하였다. 따라서 구역에 따라 다양한 에너지 소비패턴을 갖는 멀티 존 건물에서 최적 냉난방 설비 제어전략을 수립하기에는 한계가 있다.

이러한 문제점을 해결하기 위해, 본 연구에서는 멀티 존 건물에서 시간 및 날씨 변화에 따른 냉난방 설비 스케줄링의 효과를 분석한다. 이러한 목표를 달성하기 위해, 대한민국 서울에 위치한 대학 기숙사 건물을 대상으로 대표적인 에너지 사용자 그룹을 조사한다. 이후 해당 건물에서 냉난방 설비 스케줄링의 에너지 절약 효과를 계산하기 위해 다음의 두 가지 모델을 개발한다. 첫째, 에너지 사용자 그룹별 기준 에너지 소비량을 예측하는 데이터 마이닝 기반의 예측모델을 제안한다. 둘째, 냉난방 설비가 제어된 상황에서 소비되는 에너지를 예측하는 열역학적 모델을 구축한다. 다음으로, 개발된 모델들을 활용하여 다양한 시간 및 날씨 상황에서 에너지 성능 시뮬레이션을 수행함으로써, 냉난방 설비 스케줄링의 에너지 절감량을 비교분석한다.

에너지 성능 시뮬레이션의 결과는 다음과 같다. 첫째, 냉난방 설비 스케줄링 대안으로서 온도 제어 및 비재실 운영 차단 등을 적용함으로써, 사례 건물에서 상당한 에너지 절약을 거두었다.

이러한 결과를 통해, 기존 사례건물에서 냉난방 설비가 비효율적으로 운영되었다고 볼 수 있다. 둘째, 냉난방 설비 스케줄링에 의한 에너지 절약효과가 외부 기온과 강의학기에 따라 변화하였다. 이는 상황에 따라 최적 제어전략이 변화한다는 것을 의미한다. 하지만, 모든 사례에서 상황 변수와 최적 제어전략간의 일관된 경향성을 보이지 않았다.

본 연구는 멀티 존 건물에서 시간 및 날씨에 따른 냉난방 설비 스케줄링의 효과에 대한 이해를 높였다. 구체적으로 설명하면, 본 연구는 멀티 존 건물에서 에너지 사용자 그룹의 상황적 거동을 분석하였다는 점에서 그 의의가 있다. 또한, 에너지 사용자 그룹 특성이 건물 에너지 소비 예측 성능에 어떻게 영향을 미치는지 분석하였다. 마지막으로, 본 연구에서 개발된 에너지 소비 예측 모델은 시설 관리자가 재실자의 열 쾌적을 만족시키면서, 효율적으로 냉난방 설비를 운영할 수 있도록 지원한다.

주요어: 에너지 절약, 수요 관리, 멀티 존 건물, 제어 전략, 데이터 마이닝, 머신 런닝, 에너지 시뮬레이션
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