CALIBRATION OF BUILDING ENERGY SIMULATIONS WITH OCCUPANCY AND PLUG-LOAD SCHEDULES DERIVED FROM METERED BUILDING ELECTRICITY CONSUMPTION

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by
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ABSTRACT

High oil prices, diminishing natural resources, and global warming are causing developed countries to investigate ways to reduce their energy consumption. Commercial buildings account for nearly 18% of the national energy consumption of the United States, which produces approximately 12% of the annual global greenhouse gas emissions. Therefore, there is a pressing need to evaluate and understand the energy performances of commercial buildings during design and operation phases in an effort to increase their energy efficiency and conservation. However, some buildings fail to perform as their designers intended, in part because users do not or cannot properly operate the buildings or behave differently than designers expect. Therefore, a relationship between the occupancy patterns and building energy consumption is important. Prior studies have shown that occupant behavior, occupancy rate and occupancy presence/absence have a direct effect on building energy consumption. These studies revealed the importance of occupancy patterns not only for actual building energy consumption, but also for the accuracy of building energy simulations to predict the building energy consumption. However, it is hard to normalize the occupancy patterns to use as an input parameter for energy simulations.

The main objective of this dissertation research is to improve the accuracy of the building energy simulations by accounting for occupancy patterns from data available in actual buildings. This objective resulted in a methodology based on metered electric data to derive occupancy schedules for input into building energy simulations. The development of this methodology was divided into three steps. First, this study quantified the effect of occupancy rates on the electricity consumption in office and campus buildings. Second, this study developed and validated a methodology to derive occupancy schedules from sub-metered electricity consumption for input into energy simulations. Third, this study examined the energy simulation
accuracy with occupancy schedules derived from filtered hourly electricity consumption, when sub-metering is not available.

To develop and demonstrate the methodology, this study used three buildings in Pennsylvania, USA, including Building 101 at Navy Yard in Philadelphia, as well as Forest Resources and Borland Buildings at the Penn State campus in State College. For these buildings, the study analyzed the occupancy rates and electricity consumption data. The correlation coefficients between the total electricity consumption and number of occupants was significant for the three studied buildings ($R^2 \approx 40\%-70\%$). In the case study for Building 101, the plug-load consumption is more directly related to the occupancy rate ($R^2 \approx 70\%-80\%$) when compared to the relationship between the total electricity consumption and the occupancy rates ($R^2 \approx 40\%-60\%$). Nevertheless, typical buildings do not have detailed plug-load consumption data because of the costs associated with the instrumentation as well as the data collection and analysis. For buildings without sub-metering instrumentation, such as Forest Resources and Borland Buildings, this study found that the occupancy rates are significantly correlated to the fluctuations in the total energy consumption ($R^2 \approx 70\%$). Therefore, for the studied commercial buildings, the electricity consumption can be used to derive occupancy patterns for input into energy simulations.

This study proposed a methodology to derive the occupancy schedules from the hourly electricity consumption data for input into building energy simulations. Most importantly, with these occupancy schedules, building energy simulations were successfully calibrated because when the simulation results are compared to the actual energy consumption, they satisfied the stringent accuracy requirements by the ASHARE Guideline 14 (CVRMSE < 15\% for daily data).
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Chapter 1. Introduction

1.1 Background

High oil prices, diminishing natural resources, and global warming are causing developed countries to investigate ways to reduce their energy consumption. Commercial buildings account for nearly 18% of the national energy consumption of the United States, which produces approximately 12% of the annual global greenhouse gas emissions [38]. Therefore, there is a pressing need to evaluate and understand the energy performances of commercial buildings during the design and operation phases in an effort to increase their energy efficiency and conservation [2].

With increasing demand for more energy efficient buildings, the construction industry is faced with the challenge of ensuring that the energy performance predicted during the design stage is achieved once a building is in use [3]. There is extensive evidence to suggest that buildings usually do not perform as well as predicted [4-5]. Some buildings fail to perform as their designers intended, in part because users do not or cannot properly operate the buildings or some occupants behave differently than designers expected [6]. The differences between real and predicted energy use depends on the differences between the predicted and actual final realization of the construction, technical installations, and the real use of the built systems operated by occupants. Recently, it has been shown that occupant behavior plays a fundamental role in the amount of energy used in buildings [7]. Energy modeling software has been widely used by designers and engineers to simulate and predict buildings’ energy performances during design, and help them make better-informed decisions about the most appropriate systems for their buildings [8].

However, in reality, energy modeling tools oftentimes use simplistic and idealistic data inputs that are unrepresentative of actual building systems and occupancy. As a result, large discrepancies are being observed between predicted and actual energy performance, typically averaging around 30% and reaching as high as 100% in some cases [2, 3].
1.2 Problem Statement

Currently, wide varieties of building energy simulation programs are available (ESP-r, TRNSYS, DOE-2, BLAST, EnergyPlus, IDA ICE, Virtual Environment, etc.). Their complexity levels range from steady-state calculations to very sophisticated programs, including CFD simulation [34]. Assuming that the simulation is a theoretical representation of the status and operation of a building, it cannot perfectly replicate the real dynamics that govern energy use. For example, the actual climate can vary from the meteorological data available, and the systems may not work exactly as expected from the curves of the load operation, performance may also vary with the age of the plant, the actual number of hours worked, and scheduled maintenance activity. Above all, energy performance can be affected by the actual behavior of the building occupants.

Building simulation tools, on the other hand, are based on heat transfer and thermodynamic equations, and typically model occupancy behavior (operation of lights, blinds, and windows) basing on predefined fixed schedules or predefined rules (the window is always open if the indoor temperature exceeds a certain limit). These tools often reproduce building dynamics using numerical approximations of equations modeling only deterministic (fully predictable and repeatable) behaviors. In such a way, “occupant behavior simulation” could refer to a computer simulation generating “fixed occupant schedules,” representing the fictional behavior of a building occupant over the course of a single day [35]. The occupancy behavioral parameters are an effort to better understand the typical 30% to 100% discrepancies that are being observed between predicted and actual energy use in buildings [2].

1.3 Research Hypothesis

Prior studies have shown that occupancy behavior, occupancy rate and occupancy presence/absence have an effect on building energy consumption. The electricity consumption demonstrates a significant positive correlation (63-69%) with the occupancy rates in the different types of
buildings. Also, it is common knowledge that the presence and activity of building occupants have a significant impact on the required cooling load of buildings and the performance of simulation results demonstrate that building occupancy data play a critical role in building cooling load prediction and that their use significantly improves the predictive accuracy of cooling load models [Simon S.K. Kwok et al., 2011]. Building electricity consumption patterns can be used to derive occupancy schedules and improve the accuracy of energy simulation results.

Most of the previous studies were conducted with several case studies of specific buildings. These studies helped to understand the impact of occupants’ behaviors and the importance of occupancy parameters in energy simulations. However, it is hard to normalize the occupants’ effects for use as an input parameter for energy simulations. Also, most of the studies were not done with actual building data with measured occupancy. After reviewing these issues, the simplest acceptable methodology to derive the occupancy schedules will be a more practical use for projects with limited resources.

1.4 Research Objectives

The objective of this dissertation is to develop a methodology to derive an occupancy model for building energy simulation. The development of this method can be divided into three steps.

1. Quantify the effects of occupancy rates on the electricity consumption in office and campus buildings
2. Develop and validate a methodology to derive occupancy schedules from sub-metered electricity consumption for energy simulations
3. Examine the energy simulation accuracy with occupancy schedules derived from filtered hourly electricity consumption, when sub-metering is not available
Chapter 2. Literature Review

2.1 Building energy consumptions

In most countries the office sector is the largest user of floor space and energy in the commercial sector. It is a typology quite uniform across the building stock, both in envelope and building services, with three key energy end uses, HVAC, lighting, and equipment, together accounting for about 85% of the total [Table 2-1] [37].

Table 2-1. Building energy uses [16]

<table>
<thead>
<tr>
<th>Energy End Uses</th>
<th>USA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HVAC</td>
<td>49</td>
</tr>
<tr>
<td>Lighting</td>
<td>22</td>
</tr>
<tr>
<td>Equipment</td>
<td>13</td>
</tr>
<tr>
<td>DHW</td>
<td>4</td>
</tr>
<tr>
<td>Refrigeration</td>
<td>3</td>
</tr>
<tr>
<td>Others</td>
<td>11</td>
</tr>
</tbody>
</table>

Any device that plugs into wall outlets distributed throughout a building is a plug-load. These loads do not relate to general lighting, heating, ventilation and cooling or water heating. Plug-loads account for an average of 9% but as much as 28% of the electricity consumption in office buildings depending upon the nature of the building system. However, plug-load can also increase cooling loads, decrease heating needs, and affect the associated HVAC energy use.

There are many factors that affect energy consumption. Table 1-2 shows the main factors from eight types of buildings. An “o” indicates that a particular factor affects the corresponding building and an “x” means that it does not [19, 20]. The table illustrates that most buildings are affected by building size, building envelop (wall, roof, window), indoor temperature, and occupancy.
Table 2-2. Factors that affect energy consumption in different types of building

<table>
<thead>
<tr>
<th>Factors</th>
<th>Building Type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High-rise office buildings</td>
</tr>
<tr>
<td>Building area</td>
<td>o</td>
</tr>
<tr>
<td>Number of stories</td>
<td>o</td>
</tr>
<tr>
<td>Building orientation</td>
<td>o</td>
</tr>
<tr>
<td>Window-to wall ratio</td>
<td>o</td>
</tr>
<tr>
<td>Indoor temperature</td>
<td>o</td>
</tr>
<tr>
<td>Illumination (lighting)</td>
<td>o</td>
</tr>
<tr>
<td>Running time of electrical installation</td>
<td>o</td>
</tr>
<tr>
<td>Occupant density</td>
<td>o</td>
</tr>
<tr>
<td>Water consumption</td>
<td>o</td>
</tr>
<tr>
<td>Total number of factors</td>
<td>9</td>
</tr>
</tbody>
</table>

Most of the factors related to building energy consumption are examined through various methods including a statistical study (Artificial Neural Networks, Support Vector Machines, Regression analysis) or energy simulation (EnergyPlus, DOE-2, BLAST) [20]. Occupancy diversity factors have not been studied as extensively as the diversity factors for lighting and plug loads. This may be because of limitations in accessing existing occupancy datasets and challenges in interpreting the data. Due to the random nature of individuals’ behaviors and challenges in accessing accurate data, current studies include the creation of deterministic schedules where a standard workday profile is the same for the whole workweek and both weekend days have the same profile [10].
2.2 Occupants’ Effects on Building Energy Consumption

The influence of occupants on a building can be broken down into several means of interactions (as discussed by [21]), each of which can be represented by a stochastic model as shown in Figure 1-1 [22]. Being present within the building is clearly a necessary condition for being able to interact with it. Occupant presence is an input parameter in all models and the model for occupant presence will be central to the family of other stochastic models. As each human being emits heat and “pollutants” (such as water vapor, carbon dioxide, odors, etc.), it is presence that directly modifies the indoor environment in such areas as temperature changes, increases in CO₂ concentration, and so on. Occupants also interact with a building to enhance their personal comfort. For example they will heat, cool, or ventilate their environment to improve their thermal comfort and they will adjust lighting systems or blinds to optimize their visual comfort. Finally occupants’ interactions also relate to the tasks that they are required to perform. In an office building occupants may use various electrical equipment that contribute to internal heat gain and the consumption of electricity. A pattern of presence of occupants in a building is therefore of paramount importance in simulating their behavior within a building and their effects on the buildings’ demands for resources such as energy (in the form of heating, cooling, and electricity).
Some of the researchers studied building energy consumption during different time periods and found that 19-28% of the building energy (electricity and HVAC) was used during the unoccupied time period of the weekends. Also, from 26% to 65% of building energy was used during non-working hours including nights and weekends. As shown in Figure 1-2, six studies show that 15-40% of energy can be saved with an installation of intelligent occupancy sensors. Studies 1, 5, and 6 focused on office buildings and studies 2, 3, and 4 focused on campus buildings.
Table 2-3. Building energy use over the week [17] (* includes nights and weekends)

<table>
<thead>
<tr>
<th>Author</th>
<th>% of energy use during weekend</th>
<th>% of energy use during non-working hours*</th>
</tr>
</thead>
<tbody>
<tr>
<td>O.T. Masoso et al.</td>
<td>19-28%</td>
<td>49-65%</td>
</tr>
<tr>
<td>B. VonNeida et al.</td>
<td>14-24%</td>
<td>26-44%</td>
</tr>
<tr>
<td>Y. Agarwal et al.</td>
<td>28%</td>
<td>60%</td>
</tr>
<tr>
<td>C. Martani et al.</td>
<td>26%</td>
<td>64%</td>
</tr>
</tbody>
</table>

Figure 2-2. % of energy saving potential with intelligent occupancy sensors

2.3 Occupants’ Behavior and Energy Consumption

Occupant behavior may affect indoor climate and can cause large variations in energy consumption. It may also work the other way around, that the indoor climate may affect occupant behavior, which could lead to a change in energy consumption. Moreover, occupants interact with a building to enhance their personal comfort and needs. For example, they may adjust the lighting systems or blinds to optimize their visual comfort and reset the air-conditioning systems to improve their thermal comfort. These interactions will in turn affect the building’s HVAC system and the related energy
consumption. If a change occurs and produces discomfort, people will act to restore their comfort [28]. Several studies have investigated occupants’ behavior patterns and building energy consumption [26, 27]. There were many different aspects of occupant behavior, such as opening windows and adjusting the heating or cooling. Sonderegger [33] measured gas consumption used for heating in 205 townhouses located in the same group of houses as the study done by Seligman et al.[31] and Socolow [32]. He found the highest consumption to be more than three times as high as the lowest consumption and 54% of the variance in gas consumption was explained by the design features of the houses, such as number of rooms, area of windows etc., which left 46% of the variance unexplained by the design features. The Figure 2-3 shows a 5-80% change in energy consumption due to occupants’ behavior. Thermal energy consumption changed from 5% to 18%, electricity consumption changed from 10% to 38%, lighting consumption changed from 65% to 80% and total energy consumption changed from 22% to 70%. Several different behaviors were considered in each study. Studies 1, 4, and 5 measured electric equipment use behavior. Studies 2, 3, and 6 counted window opening behavior. Studies 7 and 8 counted control of the light switch.

<table>
<thead>
<tr>
<th>No</th>
<th>Behavior</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Electric equipment</td>
<td>E. Azar et al.</td>
</tr>
<tr>
<td>2</td>
<td>Window openings</td>
<td>H.B. Rijal et al.</td>
</tr>
<tr>
<td>3</td>
<td>Blind/Window opening</td>
<td>G.R. Newsham</td>
</tr>
<tr>
<td>4</td>
<td>Electric equipment</td>
<td>C.M. Clevenger</td>
</tr>
<tr>
<td>5</td>
<td>Electric equipment</td>
<td>A. C. Menezes</td>
</tr>
<tr>
<td>6</td>
<td>Blind/Window opening</td>
<td>P. Hoes</td>
</tr>
<tr>
<td>7</td>
<td>Blind/Lighting switch</td>
<td>E. Azar et al.</td>
</tr>
<tr>
<td>8</td>
<td>Cooling/Heating set point/ Lighting switch</td>
<td>T. Hong et al.</td>
</tr>
</tbody>
</table>

Figure 2-3. Change in energy consumption by occupants’ behavior

Several studies on occupancy and building energy consumption explain that depending on the occupants’ type and building usage style, the correlation between occupancy and energy consumption is
different. Much of the literature focuses on electricity consumption, with more recent studies assessing the levels of use in relation to human occupancy. Claudio Martani et al. (2012) investigated the influence of occupant numbers on energy consumption in a real building situation. The study assumes Wifi usage as a representative value for the occupancy number. In the results from the study, occupancy accounted for 63% and 69% of the variation in electricity consumption for campus buildings [1]. Ardeshir Mahdavi et al. (2011) statistically analyzed the rule of the quantitative influence of the occupancy ratio on lighting consumption in office buildings. The correlation changes were from 70% to 90% [39]. The lighting energy consumption demonstrates a significant positive correlation with the occupancy rates in the different types of buildings.

The mere presence of people within a thermal zone will emit metabolic heat causing a rise in temperature, the magnitude of which and the split between radiant, convective and latent will depend upon the environmental conditions [29]. They are not directly related to thermal energy consumption. Different types of buildings show similar results. Campus buildings have a weak correlation with occupancy and HVAC system energy use [1]. Hotels have a better correlation with steam consumption for heating in the winter [24].

<table>
<thead>
<tr>
<th></th>
<th>Campus Buildings</th>
<th>Office Buildings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>Electricity</td>
<td>Heating</td>
</tr>
<tr>
<td></td>
<td>63-69%</td>
<td>Weak</td>
</tr>
</tbody>
</table>

However, there were several studies with thermal mass dynamic models including occupancy information. For the cooling load prediction, when the model includes the occupancy schedule and occupied area information, Figure 2-4 shows that the accuracy of the model prediction is improved [27, 30]. In Figure 2-4 (a), simulation 1, only six external weather parameters were adopted in the input layer.
and the total cooling load was the only output parameter. In simulation 2, the effect of the building occupancy rate and occupied area information on the accuracy of the model predictions was analyzed. This result shows that by the inclusion of internal factors, occupied area and occupancy rate (with CO$_2$ concentration), the accuracy of the model prediction is improved.

![Variables](image)

**Variables**

- *External Weather Condition*
- *Occupied Area Information (Occupancy Space Power Demand)*
- *CO$_2$ concentration (Occupancy Rate)*

Figure 2-4. The accuracy of the cooling load prediction increased with occupancy information

(a) simulation 1, (b) simulation 2

By far, the most complex processes taking place within buildings are those that result from occupancy behavior - we are intrinsically unpredictable animals. Moreover, these interactions have important implications for a building’s energy balance, affecting both the indoor microclimate and the demands for applied energy. People enter a building, leave it and move within it in stochastic ways - albeit informed by common practice for arrival, departure and key breaks. The presence of people within a thermal zone leads directly to the emission of metabolic heat gains, the magnitude and split between radiant, convective and latent depending upon the environmental conditions, their activity and their clothing level. Clearly, human interactions which influence the energy balance also depend on presence. Examples include interactions with:

(i) window and door openings: influencing air flow,
(ii) shading device/blinds: influencing radiation transmission and glass surface temperature,

(iii) lighting controls: influencing electricity consumption and casual heat gains,

(iv) electrical appliances: influencing electricity consumption and casual heat gains,

(v) heating, ventilating and cooling system controls: influencing thermal and electrical energy consumption and associated heat injection/rejection.

Waste is also produced, from which energy may be derived, and water is consumed.

Due to current studies about building energy and occupancy, occupancy behavior and number of occupants are important in predicting the energy consumption in buildings. However, the prediction of occupancy behavior is not easy to clearly define. Currently, the most common way of considering occupant presence within simulation tools is by using so called “diversity profiles” [23]. The diversity factors are different depending on the building type and energy end-use type.

**Occupancy and building energy simulation tools:** Currently, a wide variety of simulation programs are available (ESP-r, TRNSYS, DOE-2, BLAST, EnergyPlus, IDA ICE, Virtual Environment, etc.). Their complexity levels range from steady-state calculations to very sophisticated programs, including CFD simulation [34]. Assuming that the simulation is a theoretical representation of the status and operation of a building, it cannot perfectly replicate the real dynamics that govern energy use. For example, the actual climate can vary from the meteorological data available, and the systems may not work exactly as expected from the curves of the load operation, performance may also vary with the age of the plant, the actual number of hours worked, and scheduled maintenance activity. Above all, energy performance can be affected by the actual behavior of the building occupants.

Building simulation tools, on the other hand, are based on heat transfer and thermodynamic equations, and typically model occupancy behavior (operation of lights, blinds, and windows) based on predefined fixed schedules or predefined rules (the window is always open if the indoor temperature exceeds a certain limit). These tools often reproduce building dynamics using numerical approximations
of equations modeling only deterministic (fully predictable and repeatable) behaviors. In such a way, “occupant behavior simulation” could refer to a computer simulation generating “fixed occupant schedules,” representing the fictional behavior of a building occupant over the course of a single day [35]. The occupancy behavioral parameters are an effort to better understand the typical 30% to 100% discrepancies that are being observed between predicted and actual energy use in buildings [2].

Table 2-5 shows the occupancy related parameters in the building energy simulation tools. The energy simulation tools have a plug-load parameter, a thermal sensible parameter, an indoor air quality related parameter, and a temperature set related parameter. Information from an ASHRAE standard 55 was used as a temperature set point in the building [32].

Table 2-5. Occupancy related parameters in the building energy simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power/plume</td>
<td>Heat gain from a work station, computer terminal, plus any task of lighting</td>
<td>watt/person</td>
</tr>
<tr>
<td>Activity level</td>
<td>Depending on the activity level</td>
<td>Related to thermal comfort</td>
</tr>
<tr>
<td>Occupied set point</td>
<td>ASHRAE55</td>
<td>Heating set point 22.2 °C, (72F)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cooling set point 23.9 °C, (75F)</td>
</tr>
<tr>
<td>Unoccupied set point</td>
<td>ASHRAE55</td>
<td>Heating set point 16.7 °C, (62F)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cooling set point 29.4 °C, (85F)</td>
</tr>
<tr>
<td>Outdoor air flow</td>
<td>Outdoor air per person</td>
<td>0.00944 (m³/s)/person = 20cfm/person</td>
</tr>
<tr>
<td></td>
<td>( \frac{O A_{people}}{O c c_{zone}}(O A Flow per person) )</td>
<td></td>
</tr>
<tr>
<td>CO₂ generation</td>
<td>CO₂ generation rate</td>
<td>0.0084 cfm/met/person</td>
</tr>
<tr>
<td>Heat gain</td>
<td>Convective heat transfer, latent sensible energy</td>
<td></td>
</tr>
</tbody>
</table>

\*\(O A\) = outdoor air volume flow rate based on occupancy, \([m/\text{s}]\), \(O c c_{zone}\) = number of occupants in zone, \([\text{people}]\)
The presence of people and these interactions are handled in entirely deterministic ways (if at all) in current simulation programs; typically based on some predefined schedule. People are assumed to arrive and leave according to some perfect and repeated schedule. If ventilation openings are controlled, this is likely to be based on either a time schedule, with no environmental stimulus, or due to an environmental stimulus, but this will be repeated. Shading devices, if controlled (they are normally not), react in a perfect and repeated way according to some physical stimulus such as transmitted solar radiation. Lighting control is similar, but based on some illuminance threshold [which itself may be derived from a daylight factor, or based on links with detailed and computationally expensive lighting simulation software]. Electrical appliances are normally operated according to some repeated time schedule, often coinciding with occupant presence, and at some average intensity (e.g. based on average power demand). However, in reality, these assumes are frequently overridden and, where the control exists, set points may vary both spatially and with time. It is not easy to predict building energy consumption accurately with typical schedules in reality.

**Occupants’ effect in EnergyPlus:** The occupant statement is used to model the occupant’s effect on the space conditions. The following definition addresses the basic affects as well as providing information that can be used to report the thermal comfort of a group of occupants. The Fanger, Pierce Two-Node, and Kansas State University Two-Node thermal comfort models are available in EnergyPlus. A user may select any of these models for each people statement by simply adding the appropriate choice. Thermal comfort calculations will only be made for people statements that include specific requests for these thermal comfort models. The object also requires input of carbon dioxide generation rate based on people activity level for zone carbon dioxide simulations.

Number of people calculation has three different choices in the simulation:

- People: with this choice, the method used will be a straight insertion of the number of occupants.
- People/Area: with this choice, the method used will be a factor per floor area of the zone.
• Area/Person: with his choice, the method used will be a factor of floor area per person.

The object models equipment in the zone which consumes electricity, such as computers, televisions, and cooking equipment, also known as “plug-loads.” All of the energy consumed by equipment becomes a heat gain in the zone or is lost (exhausted) as specified below.

The field for electric equipment is a key/choice field that tells which of the next three fields are filled and is descriptive of the method for calculating the nominal electric equipment level in the Zone. The key/choices are:

• Equipment Level: with this choice, the method used will be a straight insertion of the electric equipment level (watts) for the zone.
• Watts/Area: with this choice, the method used will be a factor per floor area of the zone.
• Watts/Person: with this choice, the method used will be a factor of equipment level (watts) per person. This factor (watts/person) is used, along with the number of occupants (people) to determine the maximum equipment level as described in the design level field. The choice from the method field should be “Watts/Person”.

The recommended load factors for various types of offices can be converted to watts/person. Table 2-6 shows the recommended equipment power load factor.
Table 2-6. Recommended Load Factors for Various Types of Offices [43]

<table>
<thead>
<tr>
<th>Load Density of Office</th>
<th>Load Factor (W/ft$^2$)</th>
<th>Description of Equipment Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Light</td>
<td>0.5</td>
<td>(6) Computers, (6) Monitors, (1) Laser Printer, (2) Fax Machine</td>
</tr>
<tr>
<td>Medium</td>
<td>1.00</td>
<td>(8) Computers, (8) Monitors, (1) Laser Printer, (1) Fax Machine</td>
</tr>
<tr>
<td>Medium/Heavy</td>
<td>1.5</td>
<td>(10) Computers, (10) Monitors, (1) Laser Printer, (1) Fax Machine</td>
</tr>
<tr>
<td>Heavy</td>
<td>2.0</td>
<td>(12) Computers, (12) Monitors, (1) Laser Printer, (1) Fax Machine</td>
</tr>
</tbody>
</table>

Based on the W/ft$^2$ load factor, direct conversions to Watts per Person are shown in Table 2-7. Load factor is calculated based on values provided in Table 2-6 and is based on 40,000 ft$^2$ with 302 persons.

Table 2-7. Plug Load Factor Benchmark Based on W/Person

<table>
<thead>
<tr>
<th></th>
<th>Average Watts/Person (W)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poor</td>
</tr>
<tr>
<td>Occupied Demand</td>
<td>100+</td>
</tr>
<tr>
<td>Unoccupied Demand</td>
<td>90+</td>
</tr>
<tr>
<td>Combined Demand</td>
<td>190+</td>
</tr>
</tbody>
</table>
From previous studies, occupancy information for building energy simulation should define more practically and accurately. It is learned that building electricity consumption can be used as occupancy information for building energy simulation. However, total electricity consumption does not exactly follow the number of occupancy compared to plug-load consumption. Building energy disaggregation was suggested to find the plug-load consumption with limited metered data from the building.

2.4 Building Energy Disaggregation

Disaggregation allows us to take a whole building (aggregate) energy signal, and separate it into specific data (i.e. plug or end use data) [35, 36]. There is a simplified energy performance assessment method for existing buildings, which is based on energy bill disaggregation and energy performance analysis. This method requires very limited building energy data and can effectively assess the energy performance at building and system levels, and disaggregate the whole-building consumption into consumptions of three groups of end-uses. This method is based on two basic energy balance principles, i.e., the electricity consumption balances at building level and the cooling energy balances between the demand side and supply side of HVAC systems [40]. The deviations between the calculated and measured values are 10-20% depending on the buildings.

Figure 2-5. Data flow and the schematic of the proposed method [40]
2.5 Summary

This section summarizes the knowledge gap relevant to the presented topic based on the literature review presented in this chapter and addresses solutions proposed in this dissertation study.

The list of knowledge gap and suggested solutions are:

1. Number of occupants is important information to estimate accurate building energy consumption. The limitations to collect the actual occupancy data from the building level and even if it is possible to collect accurate total number of occupants, it needs to modify for accurate building energy simulations:

   From reviewed literatures, hourly electricity consumption can be used as occupancy information for building energy simulations. This dissertation study suggests deriving occupancy schedules with hourly building electricity consumption. This is practical methodology with limited building energy information to improve the simulation accuracy. Derived occupancy rates are used to building energy simulations to improve the accuracy.

2. Occupants are important in building energy simulations, occupancy behavior and number of occupants are important parameters predicting the energy consumption in the buildings. However, the prediction of occupancy behavior is not clearly defined for building energy simulations:

   Occupants behavior is different depending on the area and occupants. This dissertation study suggests to find the kW/person to normalized the occupants effect on the building. The kW/person is different depending on the building area information and it counts the occupants behavior by simple way to normalize for the whole building level.
3. Detailed building energy consumption information is tremendously important for accurate building energy simulation results. However, sub-metering system for whole building needs a lot of efforts and money.

This dissertation study suggests the filtering methodology when the sub-metering system is not available. Total electricity consumption can be filtered-adjusted to derive the occupancy schedule. This methodology can help to save the money and efforts.
Chapter 3. Research Methodology

Figure 3-1. Research framework to define adjusted occupancy model for building energy simulation

3.1 Data Collection Procedure

This study analyzes building occupancy rates and electricity consumption in four commercial buildings. The analysis used data from an office building in Philadelphia, PA, and three campus buildings in University Park, PA.

Figure 3-2. Building 101 in Philadelphia, PA
Figure 3-2 shows the office building in Philadelphia, PA. The total area of Building101 is 66,088 square feet, and is composed of three stories and one ground floor. The building has 40% open offices, 60% common areas, and includes conference rooms.

Three campus buildings were used from Pennsylvania State University: the Borland Building, the Forest Resources Building, and the Carnegie Building. The total area of the Borland Building is 74,700 square feet and it has three stories, (including a ground floor). The building includes 17.3% classrooms, 31.5% common areas, 41.5% offices, and 9.6% laboratories. The 96,490 square foot Forest Resources Building contains 26% research laboratories, 10% classrooms, 10% specialized teaching laboratories, 19% offices, and 35% common areas. The buildings are certified as sustainable architecture by LEED (Leadership in Energy and Environmental Design). The Forest Resources Building has Penn State’s first green roof, which advances the University’s sustainability initiatives by reducing storm water run-off, lowering the costs to heat and cool the building, and extending the life of the roof. The atrium and other interior spaces in the Forest Resources Building feature local hardwoods. The total area of the Carnegie Building is 35,950 square feet and it has three stories, (including a ground floor). The building includes 59% offices, 9% classrooms, 24% laboratories and 8% common areas. This building includes a theater, counted as a common area.
Figure 3-3. Borland Building at the Pennsylvania State University, University Park, PA

Figure 3-4. Forest Resources building at the Pennsylvania State University, University Park, PA
The occupancy rates are measured by the people counters (Sensource), and energy consumption data comes from building metering and sub-metering systems. As a result of data availability, this pilot study utilized aggregated data on energy consumption at the building level.

**Occupancy sensors installation:** For the Penn State campus buildings and Building 101, occupancy sensors were installed in front of each entrance. Depending on the building features, it was difficult to install the people counters in some of the places. One main entrance at the Borland Building has a lamp, which can create a hidden area within the detecting area of the sensor. So a sensor was installed at the edge of the lamp. Also, there were two big entrances to the Forest Resources Building, and they have very high ceilings which cannot be reached to install the people counters. To alleviate this problem, a steel support was installed on which to attach the people counters.
3.2 Data Analysis Procedure

The number of occupants was collected by using people counters. For the Penn State campus buildings, IR thermal sensors (PC-THI60-N, Sensource) were used and for Building 101, video based detecting sensors (PC-VID2-N, Sensource) were used. People counters were installed at every entrance to each of the three buildings. The accuracy of the sensors is within a 5% error rate. However, there are ways to miss people. For example, a group of people passing a particular point might not be accurately counted and pre-processed optical motion detectors for monitoring a specific area may not detect a motion. Figure 3-7 shows the results of the occupancy of the buildings over a day. Figure 3-7 (a) was derived using data from people counters that reported aggregate counts every 15 minutes from seven doors at the Forest Resources Building, Figure 3-7 (b) from the four doors at the Borland Building, and Figure 3-7(c) from four doors at Building 101. The Figure shows that the occupancy trend has a negative number at certain points and a positive number at the end of the day, even if there are no people in the building. This is impossible and needs to be corrected.
Sensors that record count data often contain strong patterns reflecting the underlying rhythms of human activity. This periodic, predictable activity is referred to as “usual activity.” What makes these measurement streams complex, however, are random bursts of unusual or “event” activity, appearing as unusually high measurements, or unusually low measurements. The noise problem arises because the sensors are imperfect, with noise corresponding to both under- and over-counting. The sensors used in this study are pairs of optical sensors that register a count when an optical beam is interrupted. More commonly, people entering in groups at the same time can cause under-counting such as is captured in the right panel.

One approach to resolve this noise is to simply enforce two constraints on the raw data: (1) that occupancy can never be negative, and (2) that early every morning and at the end of the day, the building population should be zero [9]. To avoid having a negative number for the trend and having an unreasonable number at the end of the day, six steps were used for this study [Figure 3-8]. First, by comparing the two data sets (occupants In and occupants Out), a decision was made about which data has more noise and should be fixed. Second, the highest value of the selected data set should be picked. Third, each data item will be divided by the highest value of the data set. Fourth, the sum of all divided numbers will be calculated. This number is called A. Fifth, number A will be divided by the number difference between In and Out. This number is identified as B. Sixth, all the data will be multiplied by number B.
Figure 3-8. The method for the occupancy data fixing

Figure 3-9. shows the adjusted occupancy data after the data fixing. After processing the data to reduce the errors, the adjusted occupancy trend exactly follows the raw data and has a reasonable number at the end of the day.

Figure 3-9. Fixed occupancy data (a) Forest resources building (b) Borland building (c) Building 101

3.2.1 Correlation between Occupancy Rates and Energy Consumption

With the overall target of using the buildings as a test bed to examine the energy efficiency of the built environment, this study presents an initial study of the energy usage patterns of three campus buildings and one office building. These buildings were chosen from the Penn State Campus buildings which can provide aggregated data on energy consumption. In order to compare this against energy consumption, data was collected on electricity supply, the heating system, and the cooling system. Prior
to analysis data on energy consumption was converted into a standardized unit, kilowatt (kW), in order to draw comparisons between the datasets.

In order to determine if human occupancy could be used as an indicator of energy consumption, measured occupancy rates were compared to building energy consumption. To find the correlation between occupancy rates and building energy consumption, a linear regression analysis was used. Linear regression consists of finding the best-fitting straight line through the points on the x-y graph. In a simple linear regression, we predict scores on one variable from the scores on a second variable. The variable we are predicting is called the criterion variable and is referred to as Y. The variable we are basing our predictions on is called the predictor variable and is referred to as X. For this study, the number of occupants is X and the building energy consumption is Y.

R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination. The definition of R-squared is fairly straightforward; it is the percentage of the response variable variation that is explained by a linear model. R-squared is always between 0 and 100%. 0% indicates that the model explains none of the variability of the response data around its mean. 100% indicates that the model explains all the variability of the response data around its mean. The higher the R-squared, the better the model fits the data.

Regression methods perform a statistical test to compute a probability, called a p-value, for the coefficients associated with each independent variable. The null hypothesis for this statistical test states that a coefficient is not significantly different from zero (in other words, for all intents and purposes, the coefficient is zero and the associated explanatory variable is not helping your model). Small p-values reflect small probabilities, and suggest that the coefficient is, indeed, important to your model with a value that is significantly different from zero (the coefficient is not zero). You would say that a coefficient with a p-value of .01, for example, is statistically significant at the 99% confidence level and the associated variable is an effective predictor.
3.2.2 Building Energy Disaggregation

Figure presents the schematic of the proposed method for energy performance assessment of existing buildings. It consists of three function modules, i.e., input module, calculation module, and output module. In the input module, the required data mainly include total electricity consumption in the building, general building design data, weather conditions, and operation data of the HVAC system. For most existing buildings, these input data can be obtained from already available resources or by simple audit.

All parameters can be fitted into the calculation model for energy performance analysis and total energy disaggregation. By using the proposed method, an existing building is viewed as a whole where the energy conversion flows from various electricity consumers into the cooling load of the HVAC systems are essential to distinguish the characteristics of different energy users and to analyze their energy performances. All end-users are classified into three categories. The distribution of total energy consumption between consumers obeys the constraints set by two energy balances. The first energy balance concerns building level electricity consumption which indicates that the sum of the consumptions of all consumers must be equal to the total consumption given by the total energy consumption. The second energy balance concerns the building level cooling energy, which represents the fact the cooling energy supplied by the HVAC system should equal the sum of the cooling load at the demand side and cooling energy loss in the delivering process. An optimization algorithm is developed to minimize the
residual of the second balance and to solve other equations in the calculation module.

Figure 3-10. Energy performance analysis and bill disaggregation [40]

The outputs include the disaggregated energy consumptions and the energy performance indicators of the HVAC systems, e.g., the building cooling load for the demand side performance assessment and the system efficiencies for the supply side performance assessment.

Breaking down the aggregated total electricity consumption from energy data into individual end-users is the first step in distinguishing the energy use characteristics and to assess the energy performance of different end-users. Using this method, all building end-users are classified into three categories, i.e. HVAC-consumers, internal consumers (consisting of electric lightings, office equipment and appliances) and other-consumers (e.g., lift, mechanical ventilation fans, water heaters, etc.). There are two reasons to support such a classification. The first reason is that the energy use characteristics of each type of consumer are different. HVAC-consumers take charge of indoor thermal comfort. Internal-consumers work mainly to provide office services while other-consumers provide basic living services (e.g., lift, hot water, etc). It may provide a more fair assessment when both the energy consumption and the associated services are considered. Another reason is that the conversion traces from the electricity consumption to the building cooling load of each group of end-users are very distinctive. Concerning a particular month, the electricity energy consumption balance at building level is established as:

\[ E_{Building} = E_{HVAC} + E_{Internal} + E_{Others} \]
Where $E_{Building}$ is the total energy consumption of the entire building. $E_{HVAC}$, $E_{Internal}$ and $E_{Others}$ are the energy consumptions of HVAC-consumers, internal-consumers and other-consumers respectively.

Cooling energy consumption (i.e., cooling load) at the building level is an overall indicator to assess the demand side performance. The building cooling load is generally formed from external and internal loads (heat gains). The external loads mainly include the heat gain through building envelopes and the heat sources inside the air-conditioned space. These internal sources mainly include occupants, lighting, office equipment, and other plugged-in appliances. It is well known that the instantaneous building cooling load is not equal to the instantaneous building heat gain due to the thermal storage effect of the building mass. However, the cumulated cooling load over a long period of time (e.g., a month) equals the cumulated heat gains from all heat sources. That has been implied in many recognized cooling load calculation methods [Al-Rabghi, ASHARE Fundamentals Handbook 2001, 41, 42]. Therefore, the cooling load on the demand side can be estimated by summing all those individual heat gains as:

$$CL_{Demand} = (Q_{Envelope} + Q_{Air})_{External} + (Q_{Occupant} + Q_{Lighting} + Q_{Equipment} + Q_{Plugged})_{Internal}$$

where $CL_{Demand}$ is the total building cooling load on the demand side.

$Q_{Envelope}$ is the heat gain contributed by building envelopes. $Q_{Air}$ is the heat gain associated with outdoor fresh air. $Q_{Occupant}$ is the heat gain (both sensible and latent) released by occupants. $Q_{Lighting}$, $Q_{Equipment}$, $Q_{Plugged}$ are the heat gains converted from the electricity consumptions of lighting, office equipment and other plugged-in appliances (i.e., internal-consumers) in air-conditioned space, respectively.

$CL_{Supply} = HVAC$ energy use
Building Energy Filtering

For campus buildings, weekend data has some trends without occupancy. During weekends, the buildings were assumed to be in an unoccupied condition. However, these buildings have a peak early in the morning and this peak appears at the same time and same way in the weekday trend. These peaks were caused from the building operating schedule. Also, it was affected by weather conditions. This is the reason that the peaks of the energy trends don’t follow the occupancy trends in the building. To avoid the noise from the building energy trends, an averaged weekend energy consumption trend was used. The averaged weekend energy consumption trend was subtracted from the weekday total energy consumption. Filtered energy consumption data was used to derive that occupancy schedule for the building energy simulation.

3.3 Energy Modeling

The Designbuilder program was used to build the building model. The Energyplus program was used to modify and simulate the building model.

3.3.1 Derived Occupancy Rates through Measured Building Energy

According to the results from the case study at Building 101, the occupancy rate is directly related to plug-load consumption ($R^2 = 87\%$). The plug-load consumption can be used to derive occupancy schedules to improve the accuracy of energy simulation results. Figure 3-10 presents the schematic of the method for occupancy schedules and plug-load equations of the case study. It consists of two different data sets for deriving the equation and validating the equation. First, two weeks of data is used to derive the occupancy schedules equation with plug-load consumption. Also, the plug-load consumption equation is derived by calculated occupancy rates. The calculated occupancy schedule and plug-load consumption equation will be used in energy simulations to verify the accuracy of the energy simulation results.
Figure 3-11. Schematic of the method for occupancy schedules and plug-load equation
Chapter 4. Occupancy Rates and Building Energy Consumption

Electricity consumption in domestic buildings is determined by two main factors: the type and number of electrical equipment in the property and the use of this equipment by the occupants of the building. In order to determine if human occupancy could be used as an indicator of energy consumption, the occupancy rate was compared to electricity consumption. Occupancy rate is directly related to plug load density and lighting energy consumption in the building. [1]

The heating ventilation and air-conditioning system is the one of the main factors that plays a vital part in the energy consumption of a building [11]. Software tool designers have made great process in the simulation of this factor and high quality measures of climate data is available at a reasonably fine temporal resolution. However, current practices in modeling the presence and actions odd of people in buildings do not display the necessary level of sophistication to reflect the complexity of people’s passive and active impact on building performance. Human interactions have important implications for a building’s energy balance, affecting both the indoor microclimate and the demands for applied energy.

4.1 Number of Occupants in Commercial Buildings

One office building and two university buildings include classrooms, offices, commons, laboratories, and service areas, but the diversity factor per space type was not calculated. Instead the complete building information was shown with the fraction of the areas. In each building, the occupancy profiles were shown differently depending on whether it was a weekday or weekend. For the sample data, the hottest two weeks in August, 2013 were selected. The first week was before classes started at Pennsylvania State University (PSU) and the second week was the first week of the fall semester. Figure 4-1 shows that the occupancy schedules for the Forest Resources Building and the Borland Building changed considerably after classes started. The highest number of occupants was more than twice as high as the first week. However, the number of occupants in the Building 101 did not change much, except
when there was a special event in the building. The occupancy schedules are comparable depending on the building use type. As can be seen in Figure 5-1, the profiles for the Forest Resources Building and the Borland Building show similar characteristics and occupancy begins to increase and decline at the same time. Also on weekends, compared to weekdays, the occupancy rate is very small. For PSU buildings, the increase in the occupancy gradient is steep compared to the decrease gradient. However, for the office building, the increase in the occupancy gradient is similar to the decrease gradient.

![Figure 4-1. Occupancy Schedule in Campus Building (a) Borland Building (b) Forest Resources Building (c) Office Building (Building 101)](image_url)

The numbers of occupants in different buildings were collected in different seasons. The mean number of occupants in Building 101 was 33 with a standard deviation of 39. The mean number of occupants in the Borland Building was 52 with a standard deviation of 78. For the Forest Resources Building, the mean of occupants was 61 with standard deviation 92. For the Carnegie Building, the mean of occupants was 13 with a standard deviation 23. The results showed that Building 101, an office type building did not have a big variation in the number of occupants. It only changed when there was a big
meeting in the building. However, campus buildings varied a lot depending on the season and semester. When classes start the transactions of the occupants increased incredibly compared to the vacation season.

4.2 Energy Consumption in Commercial Buildings

The electricity consumption in different buildings was collected in different seasons. Figure 4.2 shows the energy consumption in three case studies during the hottest two weeks in the summer of 2013. The electricity consumption in the Building 101 varies from 40 kW to 250 kW. The mean number was 97.8 kW with a 57.61 kW standard deviation. The Borland Building mean was 48 kW with a standard deviation of 17 kW. For the Forest Resources Building, the mean of electricity consumption was 159 kW with a standard deviation of 18 kW. For the Carnegie Building, the mean of electricity consumption was 40 kW with a standard deviation of 16.8 kW. As the results show, Building 101, an office type of building did not have a big variation on the electricity consumption. However, campus buildings varied a lot when the semester started.

Figure 4-2. Electricity Consumption in Campus Building (a) Borland Building (b) Forest Resources Building (c) Office Building (Building 101)

4.3 Correlation between Occupancy Rates and Energy Consumption
4.3.1 Electricity consumption

Linear regression analysis was used to find the correlation between occupancy and electricity consumption. Occupancy and electricity consumption data were divided by area. As explained in the previous section, occupancy rates during the weekends are small compared to weekdays. The only data used for this analysis was that of the weekdays. The results demonstrate that the occupancy rates have a significant correlation with the overall amount of electricity used ($R^2 = 44\%$ to $80\%$, $p<0.001$). The coefficient of determination varies with the building type (from $0.1652$ to $1.3228$). Linear regression analysis was used to find the equation (1) of the straight line:

$$y = \beta_0 + \beta_1 x,$$

where $y$ is the predicted electricity consumption, $x$ represents the occupancy number, $\beta_0$ is the baseline electricity consumption, and $\beta_1$ is the corresponding regression coefficient.

In Figure 4-3, when the occupancy number changes, total electricity consumption changes with a corresponding coefficient. When the plug-load consumption and total electricity consumption trend compared with the number of occupants, the plug-load consumption directly changed when the number of occupant changes.

Total building electricity consumption includes different kinds of electricity consumption such as equipment, heating, cooling, ventilation, lighting, and water heating. Some of the parameters are related to occupancy but some of them are related to the building operating systems. Occupants have an effect on the plug load and lighting schedule by using computers and other electric equipment in the building. To verify the assumption, Building 101 was used to breakdown the end electricity energy use. Building plug-load data was collected and analyzed with the occupancy rate. Figure 5-4 shows that the plug-load consumption trend follows the occupancy schedule. When the building occupancy rate increases in the morning, the plug-load consumption increases and when people leave the building at lunch time, the plug-
load decreases. After office hours, the occupancy rate decreases to zero and the plug-load consumption returns to the baseline.

![Figure 4-3. Total electricity consumption, plug load consumption, occupancy number in Building 101](image)

According to the results, plug-load consumption was significantly correlated to the occupancy rates in the building. Occupancy rates were able to account for 70% to 79% of the variation shown in the plug-load levels in Building 101. Compared with the correlation between total electricity consumption and the occupancy schedule ($R^2 = 44\%$ to 62\%), plug-load usage has a higher correlation [Table 4-1]. Figure 4-4 shows the difference between total electricity consumption and the plug-load’s baseline and gradient in different seasons. Total electricity use has a higher baseline energy consumption and a higher value for the gradient. The plug-load consumption is a higher correlation compared to the total electricity consumption in that it counts the computers, printers, and other office equipment which were connected to the wall power outlets. In an office building, when people come into the building, they consume electricity by using their own workstations. However, total electricity counts not only plug-load but also
lighting, cooling, heating, and fan energy consumption, which are not directly related to occupants. These parameters are more related to the schedule of the building operation and the outdoor weather conditions.

Table 4-1. Comparison of the correlation between total electricity consumption and plug-load use with occupancy number in the building 101

<table>
<thead>
<tr>
<th></th>
<th>Total Electricity Consumption</th>
<th>Plug-load Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² (%)</td>
<td>56</td>
<td>87</td>
</tr>
<tr>
<td>Coefficient</td>
<td>1.323</td>
<td>0.1643</td>
</tr>
</tbody>
</table>

Figure 4-4. Comparison graph (total electricity consumption versus occupancy number and plug load consumption versus occupancy number)

From Figure 4-4, the correlation between occupants and plug-load consumption and the correlation between occupants and total electricity consumption are different depending on the seasons. The correlation in summer had the lowest number. In summer, the cooling system consumes electricity by
using pumps and fans. These systems were not operating directly related to occupants; the system was operated with set points, outdoor weather conditions, and operating schedules. However, in other seasons, the heating system does not use electricity to increase the temperature in the building. This is the reason that during the summer the correlation between electricity and number of occupants has the lowest number.
Figure 4-5 shows the correlation between occupants and total electricity consumption in campus buildings. The Borland Building had from 72% to 81% correlation and the Forest Resources Building had from 58% to 72%. Depending on the season changes, these two buildings had similar results to Building 101. During the summer, total electricity consumption had a low correlation to occupants. These two buildings do not have a sub-metering system, so it is not easy to directly compare the effects of occupants on plug-load consumption.

In another approach to find an occupancy effect on the building, we looked at the electricity consumption differences between weekdays and weekends, compared in Figure 4-6. Compared to the weekday occupancy schedule, the weekend schedule is low enough to assume an unoccupied condition. When the buildings are unoccupied, the trend in electricity consumption on the weekends could be considered the baseline (unoccupied condition) for electricity consumption for the whole building. Also,
on weekends, both buildings have some trends with peaks. These peaks appeared on the electricity consumption for the weekdays and they did not follow the occupancy trend in the buildings.

![Figure 4-6. Electricity consumption and occupancy schedule at the Forest Resources building and Borland building](image)

To erase the values that do not follow the occupancy trends and unexpected error points, an averaged weekend schedule was used as baseline energy consumption for the building. The baseline energy consumption was subtracted from the total electricity consumption. Figure 4-7 shows the comparison between total electricity consumption and cleaned electricity schedule (total electricity consumption – weekend schedule) in the buildings. After subtracting the weekend electricity schedule from the total weekday electricity consumption, unexpected wired peaks were erased.
To verify this approach, a regression analysis was used with the filtered electricity data and the number of occupants. As seen in Figure 4-8, the correlation between electricity and occupancy increased after erasing the fluctuations and unoccupied energy use schedule in the building. For the Forest Resources Building, the correlation increased from 57% to 66% and for the Borland Building, the correlation increased from 70% to 72%. Compared to the Borland Building, the Forest Resources Building uses more area for laboratories (Forest Resources Building: 36%, Borland Building: 9.7%). Usually, the energy consumption for laboratories is not directly related to occupancy and is not easy to predict. This is the reason why the results for the Forest Resources Building improved more than the Borland Building results.
Figure 4-8. Correlations between the number of occupants with total electricity consumption and the filtered electricity consumption
Table 4-2. Summary of building area usage and occupancy number

<table>
<thead>
<tr>
<th></th>
<th>Forest Resources Building</th>
<th>Borland Building</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Electricity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumption</td>
<td></td>
<td></td>
</tr>
<tr>
<td>After filtered</td>
<td></td>
<td></td>
</tr>
<tr>
<td>the fluctuation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R² (%)</td>
<td>57</td>
<td>66</td>
</tr>
</tbody>
</table>

The correlation between total electricity consumption and the occupancy number varies in the three buildings (56% to 70%). Table 5-4 shows the different ratios of the use areas in each building. Compared to the Borland Building, the Forest Resources Building and Building 101 include more laboratory and common areas: the Borland Building 40%, the Forest Resources Building 72%, Building 101 60%. Laboratories and common areas are more unpredictable in energy use depending on the area type and schedule, compared to classrooms and office areas.

In the case study from Building 101, the plug-load consumption is directly related to the occupancy rate (87%) compared to total electricity consumption in the building. Most of the plug-load consumption data comes from the first floor and second floor office areas. However, total electricity consumption includes interior lighting, exterior lighting, and the HVAC system. Some parts of the electric consumption such as exterior lighting and the HVAC system are not affected by the presence and behavior of occupants. This is the reason that total electricity consumption has a weaker correlation with occupancy rate compared to plug-load consumption.
Table 4-3. Summary of correlation between electricity consumption and the number of occupants

<table>
<thead>
<tr>
<th></th>
<th>Building 101</th>
<th>Borland Building</th>
<th>Forest Resources Building</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>R² (%)</strong></td>
<td>Total Electricity</td>
<td>Plug-load</td>
<td>Total Electricity</td>
</tr>
<tr>
<td><strong>Spring</strong></td>
<td>52</td>
<td>78</td>
<td>80</td>
</tr>
<tr>
<td><strong>Summer</strong></td>
<td>49</td>
<td>70</td>
<td>74</td>
</tr>
<tr>
<td><strong>Fall</strong></td>
<td>61</td>
<td>71</td>
<td>73</td>
</tr>
<tr>
<td><strong>Winter</strong></td>
<td>62</td>
<td>77</td>
<td>75</td>
</tr>
</tbody>
</table>

From the correlation studies on case studies, it is possible to expect to find that the occupants have an effect on the building energy consumption. This study tried to find the “kW/person” from each building. The coefficient of kW/person can be used with the base-line energy consumption to estimate the building electricity consumption. Table 4-2 shows the building area information with kW/person. The coefficient of kW/person was found from the regression analysis between the number of occupants and electricity consumption. When the building has more office area, the building has a higher kW/person; Building 101 has a higher number compared to campus buildings.

With the building area information and kW/person, the equation for estimating the kW/person is derived. The assumptions to derive the equation were:

a. occupants’ behaviors are different depending on the purpose of the area

b. building areas were separated according to purpose (ex. office, classroom, laboratory, common area)

c. people in the common area do not consume the electricity by themselves

The following equation was found:
By using equation (1), the kW/person in the Carnegie Building was calculated with the building area information. The result from the calculation was 0.56 kW/person. To verify the accuracy of the equation, the number of occupants and the electricity consumption in the Carnegie Building were used. The actual coefficient of kW/person in the Carnegie Building was 0.53, the results are not very different from the calculation.

Table 4-4. Summary of kW/person and building area ratio

<table>
<thead>
<tr>
<th>Building</th>
<th>kW/person</th>
<th>Office (%)</th>
<th>Classroom (%)</th>
<th>Laboratory (%)</th>
<th>Common Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>101</td>
<td>1.0</td>
<td>40</td>
<td>0</td>
<td>0</td>
<td>60</td>
</tr>
<tr>
<td>Borland</td>
<td>0.3</td>
<td>42</td>
<td>16</td>
<td>10</td>
<td>32</td>
</tr>
<tr>
<td>Forest Resources</td>
<td>0.2</td>
<td>19</td>
<td>10</td>
<td>36</td>
<td>35</td>
</tr>
<tr>
<td>Carnegie</td>
<td>0.53</td>
<td>59</td>
<td>9</td>
<td>24</td>
<td>8</td>
</tr>
</tbody>
</table>

With the Carnegie Building area information and kW/person, the equation was derived again to verify the assumptions in the previous equation. The new equation was:

\[0.36 (\text{office area}) - 0.7 (\text{classroom}) + 0.05 (\text{laboratory}) = \left(\frac{\text{kW}}{\text{person}}\right) \times (10^4)\] (2)

Equation 2 has similar coefficients for each term. Also, the number for the common area is small enough to ignore. The coefficient number in each term does not mean the power consumption for each occupant. These numbers are more related to the characteristics of the area. For example, if the building has a lot of office area, most of the occupants are working in the office area and they increased the kW/person in the building. However, if the building has more classroom areas, the kW/person in that building is not large. In the classroom, most of the occupants are sitting and following the lecture. They do not do any activity to consume energy.
The electricity consumption per occupant can be used to derive the occupants schedule with the total electricity consumption in the building level. Also, this information can be useful to estimate the occupancy schedule without actual data for the occupants.

4.3.2 Cooling energy consumption

There are two main factors affecting building cooling load demands. External load factors refer to external climate conditions and internal load factors address such things as building usage characteristics and occupants’ behaviors. As seen in Figure 4-9, cooling energy consumption (chilled water consumption and condensing unit energy consumption) follow the occupancy rate hourly trend. Figure 4-9 (a) shows that the chilled water consumption trend does not have any correlation with the occupancy rate. Figures 4-9 (b) and 4-9 (c) show that Borland Building chilled water consumption and the condensing unit energy consumption in Building 101, increase at the time the occupancy rate increases and decreases at night.

A linear regression analysis was used to find the correlation between occupancy and cooling energy consumption. Only the data for weekdays was used for this analysis. The results demonstrate that the occupancy rates do not have a significant correlation with the overall amount of cooling energy used ($R^2 = 14\%$ to $40\%$). The coefficient of determination varies with the building type [Table 4-3].
Table 4-5. Correlation between total cooling energy consumption and occupancy number

<table>
<thead>
<tr>
<th>Building</th>
<th>Forest Resources Building</th>
<th>Borland building</th>
<th>Building 101</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>14%</td>
<td>40%</td>
<td>35%</td>
</tr>
<tr>
<td>Baseline/ft$^2$</td>
<td>0.0003</td>
<td>0.0006</td>
<td>0.0005</td>
</tr>
<tr>
<td>coefficient</td>
<td>0.0521</td>
<td>0.037</td>
<td>0.571</td>
</tr>
</tbody>
</table>

Figure 4-10. Cooling energy consumption versus occupancy number

The results from the simple linear regression analysis show that occupancy rate affects the cooling energy use (chilled water consumption and condensing unit energy use), but it is not directly significantly related to the cooling energy use. To identify the driving variables for cooling energy use (chilled water consumption and condensing unit energy use) in the buildings, a stepwise regression analysis was used. The goal of the stepwise analysis was to choose a small subset from the large set so that the resulting regression model is simple, yet has a good predictive ability. Stepwise regression analysis enters and removes predictors, in a stepwise manner, until there is no justifiable reason to enter or remove more. For predictor variables, this study used the occupancy schedule, indoor temperature,
outdoor temperature, relative humidity (RH), lighting, solar radiation, and plug-load consumption. The dry-bulb temperature affects the thermal response of a building and heat gain/loss infiltration through the building envelope. Energy is required to maintain the designed indoor environment. The RH represents the amount of humidification or de-humidification required. Solar radiation is crucial to the building cooling load in connection with the design and operation of the cooling system, usage characteristics and occupants’ behaviors. Occupancy activities have significant impacts on building cooling load demand [13-15]. It is well known that the operation of office equipment and lighting affects heat gain in a building [12].
Table 4-6. Summary of variables which related to cooling energy consumption

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Stddev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupancy</td>
<td>-</td>
<td>0</td>
<td>137</td>
<td>24.88</td>
<td>32.08</td>
</tr>
<tr>
<td>Total electricity</td>
<td>KW</td>
<td>35.53</td>
<td>258.73</td>
<td>121.39</td>
<td>57.37</td>
</tr>
<tr>
<td>Cooling</td>
<td>KW</td>
<td>0.629</td>
<td>126.47</td>
<td>44.37</td>
<td>31.66</td>
</tr>
<tr>
<td>Lighting</td>
<td>KW</td>
<td>9.89</td>
<td>58.28</td>
<td>32.62</td>
<td>16.79</td>
</tr>
<tr>
<td>Outdoor Temperature</td>
<td>F</td>
<td>64.54</td>
<td>90.43</td>
<td>75.94</td>
<td>5.52</td>
</tr>
<tr>
<td>RH</td>
<td>%</td>
<td>37.65</td>
<td>92.36</td>
<td>70.13</td>
<td>0.63</td>
</tr>
<tr>
<td>Indoor Temperature</td>
<td>F</td>
<td>68.71</td>
<td>82.91</td>
<td>77.21</td>
<td>2.49</td>
</tr>
<tr>
<td>Solar radiation</td>
<td>W/m²</td>
<td>0</td>
<td>894.9</td>
<td>169.9</td>
<td>243.1</td>
</tr>
</tbody>
</table>

Eight variables were considered as parameters related to building thermal energy. Each parameter’s minimum, maximum, mean, and standard deviation values were defined [Table 4-4]. A multivariate regression analysis, the relationship among predictors was done. The current study shows that the occupancy number and plug-load consumption are highly correlated (87%) with each other. Also, total building electricity consumption includes the plug-load consumption and it is correlated with the occupancy rate in the building. To avoid the conflict of correlation between predictors, total electricity consumption was selected as a representative variable for occupancy rate and plug-load consumption. For the analysis, total electricity consumption, lighting power consumption, indoor air temperature, outdoor air temperature, and solar radiation intensity were used as predictors.

Table 4-7. Result from the stepwise regression analysis for cooling energy consumption

<table>
<thead>
<tr>
<th>Step</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-20.06</td>
<td>-18.67</td>
<td>-48.50</td>
<td>-52.84</td>
<td>-78.65</td>
</tr>
<tr>
<td>Total Electricity (KW)</td>
<td>0.5308</td>
<td>0.7623</td>
<td>0.7679</td>
<td>0.7750</td>
<td>0.7785</td>
</tr>
<tr>
<td>T-Value</td>
<td>76.83</td>
<td>100.15</td>
<td>99.98</td>
<td>98.07</td>
<td>100.19</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Lighting Power Sum</td>
<td>-0.904</td>
<td>-0.889</td>
<td>-0.872</td>
<td>-0.884</td>
<td></td>
</tr>
<tr>
<td>T-Value</td>
<td>-34.75</td>
<td>-34.18</td>
<td>-33.13</td>
<td>-34.16</td>
<td></td>
</tr>
<tr>
<td>P-Value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Indoor temperature</td>
<td>0.37</td>
<td>0.42</td>
<td>0.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Value</td>
<td>3.57</td>
<td>4.02</td>
<td>5.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>P-Value</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>solar radiation</td>
<td>-0.0038</td>
<td>-0.0069</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T-Value</td>
<td>-3.29</td>
<td>-5.28</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P-Value</td>
<td>0.001</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The regression equation is:

\[
\text{cooling} = -73.2 + 0.779 \text{ Total Electricity (KW)} - 0.886 \text{ LP1 Instantaneous Power Sum} + 0.202 \text{ out temperature} - 0.0209 \text{ RH} - 0.00718 \text{ solar radiation} + 0.509 \text{ in door T}
\]

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coef</th>
<th>SE Coef</th>
<th>T</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-73.21</td>
<td>11.67</td>
<td>-6.27</td>
<td>0.000</td>
</tr>
<tr>
<td>Total Electricity (KW)</td>
<td>0.778813</td>
<td>0.007779</td>
<td>100.12</td>
<td>0.000</td>
</tr>
<tr>
<td>LP1 Instantaneous Power Sum</td>
<td>-0.88622</td>
<td>0.02602</td>
<td>-34.07</td>
<td>0.000</td>
</tr>
<tr>
<td>out temperature</td>
<td>0.20233</td>
<td>0.06279</td>
<td>3.22</td>
<td>0.001</td>
</tr>
<tr>
<td>RH</td>
<td>-0.02094</td>
<td>0.02384</td>
<td>-0.88</td>
<td>0.380</td>
</tr>
<tr>
<td>solar radiation</td>
<td>-0.007176</td>
<td>0.001342</td>
<td>-5.35</td>
<td>0.000</td>
</tr>
<tr>
<td>in door T</td>
<td>0.5088</td>
<td>0.1063</td>
<td>4.78</td>
<td>0.000</td>
</tr>
</tbody>
</table>

\[ S = 4.42306 \quad R^2 = 98.1\% \quad R^2(\text{adj}) = 98.0\% \]

Table 4-8. Summary of result from multivariate regression analysis with equation

In the results from the regression analysis, each variable had a different covariance. Depending on the value of the covariance, the total electricity consumption has a large enough number to say it is correlated with cooling energy consumption (chilled water consumption and condensing unit energy use).

Only one building was used for occupancy and heating energy correlation analysis. Figure 4-11 shows the steam energy consumption and occupancy schedule for the Forest Resources Building. As the graphs depict, steam energy consumption does not follow the occupancy schedule. To verify the correlation between occupancy and steam energy consumption, a linear regression analysis was used. The results show that only 15% of the data can explain the occupancy schedule. Also, from results shown on the table, the coefficient number (0.00296) is small compared to the building baseline energy consumption (2.14). Heating energy consumption did not have a significant correlation with occupancy,
but was more related to weather conditions. The figure shows that on 2/23 and 2/24, a weekend, the occupancy schedule is small but the steam consumption has the same shape. The figure also shows that steam consumption does not increase depending on the occupancy number.

Table 4-9. Correlation between total heating energy consumption and occupancy number

<table>
<thead>
<tr>
<th>Building</th>
<th>Forest Resources Building</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>15%</td>
</tr>
<tr>
<td>Baseline</td>
<td>2.14</td>
</tr>
<tr>
<td>coefficient</td>
<td>0.00296</td>
</tr>
</tbody>
</table>

Figure 4-11. Heating energy consumption and occupancy schedule at the Forest resources building
53

Figure 4-12. Heating energy consumption versus occupancy number

This study analyzed the cooling and heating energy consumption with occupancy rates. The Forest Resources Building has a similar correlation of the $R^2$ value for cooling and heating as the occupancy rate. Cooling energy consumption from the Borland Building and Building 101 have a 40% and 35% correlation with the occupancy rate [Table 4-8].

Table 4-10. Summary of the correlation between thermal energy consumption and number of occupants

<table>
<thead>
<tr>
<th>Building</th>
<th>Forest Resources Building</th>
<th>Borland building</th>
<th>Building 101</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>cooling</td>
<td>heating</td>
<td>cooling</td>
</tr>
<tr>
<td>$R^2$</td>
<td>14%</td>
<td>15%</td>
<td>40%</td>
</tr>
<tr>
<td>Baseline/ft$^2$</td>
<td>0.0003</td>
<td>2.14</td>
<td>0.00006</td>
</tr>
<tr>
<td>coefficient</td>
<td>0.0521</td>
<td>0.00296</td>
<td>0.037</td>
</tr>
</tbody>
</table>
4.4 Summary

This chapter shows occupants’ effect on the building energy consumption with three different case studies. Number of occupants was measured with occupancy sensors which installed in front of each doors in buildings.

Occupancy rates were able to account for 70% to 79% of the variation shown in the plug-load levels in Building 101. Compared with the correlation between total electricity consumption and the occupancy schedule ($R^2 = 44\%$ to $62\%$), plug-load usage has a higher correlation. When sub metering system is not available, filtered electricity consumption was used to compare with occupancy in campus buildings. For the Forest Resources Building, the correlation increased from 57\% to 66\% and for the Borland Building, the correlation increased from 70\% to 72\%.

When occupancy rates were compared to cooling energy consumption, the correlation varies 14\% to 40\% depending on the buildings. Cooling energy consumption does not have high correlation with the occupancy rate. Chilled water consumption and cooling load demands are more correlated to the outdoor weather conditions. When multivariate regression analysis was used to find the parameter which related to cooling energy consumption, there were different sources which generate the heat in the building effect on the cooling energy consumption.

The steam consumption can be used as a heating source for the building. When occupancy rates were compared to heating energy consumption, the correlation was 15\% on Forest Resources building. As steam consumption trend shown in figure 4-11. The steam consumption does not follow the occupancy rates. It has high peak on early in the morning and it is more related to the set-point and building operating schedules.
Chapter 5. Building Energy Simulation with Different Occupancy Rates

5.1 Derived Occupancy Rates

According to the results from the case study at Building 101, the occupancy rate is directly related to plug-load consumption ($R^2 = 87\%$). The plug-load consumption can be used to drive occupancy schedules to improve the accuracy of energy simulation results. Figure 5-1 presents the schematic of the method for occupancy schedules and plug-load equation of the case study. It consists of two different data sets for deriving the equation and validating the equation. First, two weeks of data is used to derive the occupancy schedules equation with plug-load consumption. Also, the plug-load consumption equation is derived by calculated occupancy rates. The calculated occupancy schedule and plug-load consumption equation will be used in energy simulations to verify the accuracy of the energy simulation results.

![Figure 5-1. Schematic of the method for occupancy schedules and plug-load equation](image-url)
5.1.1 Derived Occupancy Rates with Measured Building Energy

Figure 5-2 presents the correlation between the number of occupants and plug-load consumption. The calculated occupancy schedules will be used in EnergyPlus to simulate the workday. On the day which has the highest peak for actual occupancy, the building had a big meeting so there were lots of visitors who did not contribute to the plug-load in the building. In this case, the calculated occupancy schedule would not have a better correlation with plug-load consumption.

Table 5-1 presents four cases derived from combinations of the two different input parameters. To validate a derived occupancy schedule and plug-load consumption equation, the required input parameters are as below. The default schedule and plug-load consumption schedule in the energy simulation were used in Case 1. In Case 2, an averaged actual occupancy schedule and averaged plug-load consumption schedule were used. In Case 3, an actual occupancy schedule and the plug-load consumption equation are used. Case 4, calculated occupancy schedule and plug-load consumption equation were used.
Figure 5-3 and Table 5-2 present four case studies. For Case 1, two default schedules were used and 48% of the coefficient of variation of the root means squared error (CVRMSE). As long as actual schedules, the plug-load equation, and calculated occupancy schedules were added, the results improved from 34% to 5%. From ASHRAE guideline 14-2002, For a satisfactory calibrated model, CV(RMSE) for a day-level comparison (i.e., comparison between simulation model predicted and measured data on a daily basis) should meet the following criterion, CV (RMSE) <15% - 30%. For a hourly-level comparison should meet the 30%. From case 4, the result shows 5% for the daily and it meets the criteria.

Table 5-2. CV (RMSE) results for four cases with plug-load consumption

<table>
<thead>
<tr>
<th>Building 101</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupancy Schedule</td>
<td>Default</td>
<td>Averaged Occupancy Schedule</td>
<td>Actaul Occupancy Schedule</td>
<td>Calculated Occupancy Schedule</td>
</tr>
<tr>
<td>Electricity Consumption</td>
<td>Default</td>
<td>Averaged Schedule</td>
<td>Plug-load Consumption Equation</td>
<td>Plug-load Consumption Equation</td>
</tr>
<tr>
<td>CV(RMSE)* Plug-load Hourly</td>
<td>34</td>
<td>22</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>CV (RMSE)* Plug-load Daily</td>
<td>23</td>
<td>23</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>
Table 5-3 shows the result with the total electricity consumption in Building 101. The table has 4 cases and the estimated total electricity consumption was compared with building metering data. As plug-load consumption was successfully calibrated with actual calculated schedule with plug-load consumption equation, total electricity consumption was also successfully calibrated. The accuracy of the energy simulation results improved from 67% to 21% in hourly basis and 27% to 21% in daily basis.
Table 5-3. CV (RMSE) results for four cases total electricity consumption in Building 101

<table>
<thead>
<tr>
<th>Building 101</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupancy Schedule</td>
<td>Default</td>
<td>Averaged Occupancy Schedule</td>
<td>Actual Occupancy Schedule</td>
<td>Calculated Occupancy Schedule</td>
</tr>
<tr>
<td>Electricity Consumption</td>
<td>Default</td>
<td>Averaged Schedule</td>
<td>Plug-load Consumption Equation</td>
<td>Plug-load Consumption Equation</td>
</tr>
<tr>
<td>CV(RMSE)* Total Electricity Hourly</td>
<td>67</td>
<td>30</td>
<td>38</td>
<td>21</td>
</tr>
<tr>
<td>CV (RMSE)* Total Electricity Daily</td>
<td>27</td>
<td>16</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>

5.1.2 Derive Occupancy Rates with Filtered Building Energy

According to previous section, filtered building energy consumption has higher correlation to the number of occupants. These correlations were comparable to plug-load consumption and it can be used to derive the occupancy rates for the building energy simulation. For the campus buildings, which does not have sub-metering system to collect the plug-load consumption, filtered building energy consumption method can be used as plug-load consumption.
Table 5.4. Four cases for Borland building energy simulation

<table>
<thead>
<tr>
<th>Input Parameters</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupancy Schedule</td>
<td>Default</td>
<td>Averaged</td>
<td>Actual</td>
<td>Calculated</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Occupancy Schedule</td>
<td>Occupancy</td>
<td>Occupancy</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Schedule</td>
<td>Schedule</td>
</tr>
<tr>
<td>Electricity Consumption</td>
<td>Default</td>
<td>Averaged</td>
<td>Filtered</td>
<td>Filtered</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Schedule</td>
<td>Electricity</td>
<td>Electricity</td>
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<td></td>
<td></td>
<td></td>
<td>Consumption</td>
<td>Consumption</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Equation</td>
<td>Equation</td>
</tr>
</tbody>
</table>

Table 5.3 shows four case studies with filtered electricity consumption equation and a calculated occupancy schedule in Borland. For case 1, the building energy simulation used the default value of the occupancy schedule and electricity consumption. For Case 2, the building energy simulation used the averaged occupancy schedule in the building with the averaged plug-load electricity consumption. In case 3, the building energy simulation used the actual occupancy schedule with filtered electricity consumption equation for weekdays. Case 4, the building energy simulation used the calculated occupancy, which was derived from the filtered electricity consumption and filtered electricity consumption equation.

When the electricity consumption is filtered by the weekend-averaged data, the baseline of the building energy decreased from 46 kW to 10 kW. This filtered number can provide the negative when the building is in an un-occupied condition or building energy consumption is smaller than the averaged-weekend data. In this case, the filtered data cannot be directly used in the building energy simulation. For the adjustment of the filtered electricity consumption, the building system needs to be studied to justify the amounts of energy use in other parts: the HVAC system, lighting, etc. When these building system energy usages are justified, other amounts of energy can be used as a baseline plug-load consumption with the filtered electricity consumption.

For the Borland Building, the baseline of the filtered data decreases from 46 kW to 10 kW. After being justified, the baseline is increased to 15kW. An increased baseline with a coefficient of 0.3
kW/person can be used as a plug-load consumption in the Borland Building for building an energy simulation.

For the Forest Resources Building, the baseline of the filtered data decreases from 160 kW to 10 kW. After being justified, the baseline is increased to 50kW. An increased baseline with a coefficient of 0.22 kW/person can be used as a plug-load consumption in the Forest Resources Building for building an energy simulation.

5.2 Building Energy Performance Simulation

5.2.1 Building Energy Simulation with Default Occupancy Rates

To find the difference between the energy simulation results from default schedules and real-building energy consumption results, DesignBuilder was used for an energy simulation. Figure 5-4 shows the default schedule for office equipment and the office occupancy schedule. The default occupancy rates and schedule were different depending on the building type. Figure 5-4a shows the office type and Figure 5-4b shows the campus building type.

![Figure 5-4](image)

Figure 5-4. (a) Occupancy schedule in office type of building (b) in university building

The CV(RMSE) of total electricity consumption in Building 101 with default schedules is 67% and plug-load consumption is 34%. Office type sample values can have similar trends in occupancy
however it needs to be adjusted depending on the building. Not all of the offices have the same number of occupants/ area and the same periods.
Figure 5-5. Estimated electricity consumption with default schedules in campus buildings

Figure 5-5 shows the results from the Borland Building and the Forest Resources Building. For these buildings, a default campus occupancy schedule and equipment schedule were used. The hourly CV(RMSE) of the Borland Building is 128% and the Forest Resources Building is 156%. The results are compared with daily basis energy consumption, they have 85% of CVRMSE for the Borland Building and the 61% of CVRMSE for Forest Resources Building. Compared to hourly energy consumption it is small. This is the reason that the error of each hour can be cancelled out with positive and negative differences.

5.2.2 Building Energy Simulation with Averaged Occupancy Rates

Figure 5-6 shows the averaged schedule for office equipment and an office occupancy schedule. Figure 5-7a shows the Borland Building’s averaged occupancy schedule and electricity consumption and
Figure 5-7b shows the Forest Resources Building’s averaged occupancy schedule and electricity consumption. The default occupancy rates and schedule are different depending on the building type.

Figure 5-6. Estimated total electricity consumption with averaged schedules and real data in the building.
Figure 5-7 shows the results of the sample period with averaged schedules. The hourly basis CV(RMSE) of total electricity consumption in Borland building is 46% and Forest Resources building is 48%. The daily basis CV (RMSE) are 35% and 25% for Borland building and Forest Resources building. With an averaged occupancy schedule and an averaged total electricity consumption, the CV(RMSE) is decreased, compared to the results with the default schedules.
5.2.3 Building Energy Simulation with Actual Occupancy Rates and Plug-load Consumption Equation (Measured Building Energy Consumption)

Figure 5-8 shows the results of Building 101 with an actual occupancy schedule, plug-load consumption, total electricity consumption, estimated plug-load consumption, and estimated total electricity consumption for the energy simulation. For these pictures, actual occupancy schedule was used with the plug-load consumption equation. The estimated plug-load consumption and actual plug-load consumption have very similar trends. However, the estimated plug-load consumption has a peak on one day because it is directly related to the number of occupants. When the building has big meetings, the number of occupants can increase a lot without an increase in the plug-load consumption because most visitors do not use workstations to consume electricity. To reduce the possibility of error, the number of occupants will be derived from the plug-load consumption and it will be used for the building energy simulation.
The hourly basis CV(RMSE) of total electricity consumption in Building 101 is 38% and the plug-load consumption is 10%. The daily basis CV(RMSE) of total electricity consumption and plug-load consumption are 12% and 5%.

5.2.4 Building an Energy Simulation with Actual Occupancy Rates (Filtered Building Energy Consumption)

Figure 5-9 shows the actual occupancy schedule for the Borland Building and Forest Resources Building. The filtered electricity consumption equation with adjusted baseline is:
Figure 5-9. Estimated total electricity consumption with actual occupancy schedule with filtered electricity consumption equation

Figure 5-9 shows the results from the Borland Building and Forest Resources Building. For these buildings, a default actual occupancy schedule and filtered-adjusted electricity equation was used. The
hourly basis CV(RMSE) of the Borland Building is 40% and the Forest Resources Building is 32%. The daily basis CV(RMSE) of Borland Building is 20% and the Forest Resources Building is 25%. When the results are compared with the simulation results with default schedules, they have improvements for the Borland Building and the Forest Resources Building.

5.2.5 Building Energy Simulation with Derived Occupancy Rates (Filtered Building Energy Consumption)

Figure 5-10 explains how to use the derived occupancy schedule to apply the energy simulations. For Building 101, the occupancy schedule was derived with plug-load consumption. The derived occupancy schedule was used with the plug-load consumption equation. For the Borland Building and Forest Resources Building, the occupancy schedules were derived with filtered-adjusted electricity consumption. The derived occupancy schedules were used with the electricity consumption equation.

![Figure 5-10. Derived occupancy schedules with hourly electricity consumption](image-url)
The hourly basis CV(RMSE) of total electricity consumption in Building 101 is 21% and the plug-load consumption is 5%. The daily basis CV(RMSE) of total electricity consumption is 12% and the plug-load consumption is 5%. Figure 5-11 shows that the derived occupancy with the plug-load consumption equation does not have the peak anymore and it exactly follows the plug-load consumption trend. This methodology is reasonable to use.
Figure 5-11. Estimated total electricity consumption and plug-load consumption with derived occupancy schedule and plug-load consumption equation

Figure 5-12 shows the results of the sample period, the hourly basis CV(RMSE) of total electricity consumption in the Borland Building and the Forest Resources Building were 31% and 16%. The daily basis CV(RMSE) of total electricity consumption in the Borland Building and the Forest Resources Building were 12% and 13%.
Figure 5-12. Estimated total electricity consumption with derived occupancy rates and filtered electricity consumption equation
Table 5-4 shows the overall simulation accuracy improvements with four cases in three building studies. Hourly comparison between simulated results and building energy results, For Building 101, the CV(RMSE) decreased from 67% to 21% and for daily basis it decreased from 27% to 12%. Table 5-5 and 5-6 show the hourly basis CV(RMSE) of the Borland Building and Forest Resources Building also decreased from 128% to 31%, and 156% to 16%. The daily basis CV(RMSE) of the Borland Building and Forest Resources Building decreased from 85% to 12% and 61% to 13%. In different types of buildings, by using the same methodology, the accuracy of the simulation is increased.

Table 5-5. Four cases of CV(RMSE) in Building 101

<table>
<thead>
<tr>
<th>Building 101</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupancy Schedule</td>
<td>Default</td>
<td>Averaged Occupancy Schedule</td>
<td>Actual Occupancy Schedule</td>
<td>Calculated Occupancy Schedule</td>
</tr>
<tr>
<td>Electricity Consumption</td>
<td>Default</td>
<td>Averaged Schedule</td>
<td>Plug-load Consumption Equation</td>
<td>Plug-load Consumption Equation</td>
</tr>
<tr>
<td>CV(RMSE)* Total Electricity Hourly</td>
<td>67</td>
<td>30</td>
<td>38</td>
<td>21</td>
</tr>
<tr>
<td>CV (RMSE)* Total Electricity Daily</td>
<td>27</td>
<td>16</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>
Table 5-6. Four cases of CV(RMSE) in Borland Building

<table>
<thead>
<tr>
<th>Borland Building</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Occupancy</td>
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<td></td>
<td>Schedule</td>
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<td></td>
<td>Default</td>
<td>Averaged</td>
<td>Actual</td>
<td>Calculated</td>
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<tr>
<td></td>
<td></td>
<td>Occupancy</td>
<td>Occupancy</td>
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<td>Schedule</td>
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<td>Electricity</td>
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<td>Consumption</td>
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<td>Filtered</td>
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<td>Consumption</td>
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<td>Equation</td>
<td>Equation</td>
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<td></td>
<td>CV(RMSE)*</td>
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<tr>
<td></td>
<td>Total Electricity</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Hourly</td>
<td>128</td>
<td>48</td>
<td>40</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>31</td>
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<tr>
<td></td>
<td>CV (RMSE)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Electricity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Daily</td>
<td>85</td>
<td>35</td>
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<td>12</td>
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</tbody>
</table>

Table 5-7. Four cases of CV(RMSE) in Forest Resources Building

<table>
<thead>
<tr>
<th>Forest Resources</th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
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<tbody>
<tr>
<td></td>
<td>Occupancy</td>
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<td>Schedule</td>
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<tr>
<td></td>
<td>Default</td>
<td>Averaged</td>
<td>Actual</td>
<td>Calculated</td>
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<tr>
<td></td>
<td></td>
<td>Occupancy</td>
<td>Occupancy</td>
<td>Occupancy</td>
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<td></td>
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<td>Schedule</td>
<td>Schedule</td>
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<td></td>
<td>Electricity</td>
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<td></td>
<td>Consumption</td>
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<td>CV(RMSE)*</td>
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<tr>
<td></td>
<td>Total Electricity</td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>Hourly</td>
<td>156</td>
<td>46</td>
<td>32</td>
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<td></td>
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<td>CV (RMSE)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Electricity</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Daily</td>
<td>61</td>
<td>25</td>
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<td>13</td>
</tr>
</tbody>
</table>
5.3 Summary

In this chapter, suggested methodology was verified with 4 different case studies. The accuracy of the building energy simulation increased with the occupancy schedule and electricity consumption equations. Compared to the default schedules of the building energy simulation, detailed input information provided a decrease of the CV(RMSE). The hourly basis CV(RMSE) of Building 101
decreased from 67% to 21%, the Borland Building and Forest Resources Building also decreased from 128% to 31%, and 156% to 16%. The daily basis CV(RMSE) of Building 101 decreased from 27% to 12%, the Borland Building and Forest Resources Building decreased from 85% to 12% and 61% to 13%.
Chapter 6. Discussion of Building Energy Disaggregation Approach

The main objective of this dissertation research project was to improve the accuracy of building energy simulations with occupancy schedules obtained from electricity consumption data. This study selected three different buildings in Pennsylvania, USA, including one office building and two campus buildings. The office building had a sub-metering system to explore the details of the building energy consumption. Two campus buildings format the Pennsylvania State University did not have sub-metering systems, which is typical due to the costs associated with a sub-metering system. These two buildings were carefully selected with different purposes of the areas used. Because the campus buildings do not have a sub-metering system, this study had access only to the aggregated building-level energy consumption data.

Figure 6-1. Schematic of building energy disaggregation procedure
When the sub-metering system is unavailable, the building energy can be disaggregated with a building energy disaggregation methodology, which uses three energy balance equations to find the plug-load consumption. A disaggregation with weather conditions, building operating system schedules, and other internal heat gain parameters was attempted in this study. However, the delay of the heat transfer from the building to the indoors and other inaccurate energy consumption parameters caused an error for the hourly results. For the hourly energy disaggregation, the results were of low quality with tremendous effort required to produce them. To obtain this conclusion, it took more than four months to analyze all of the collected data. As an example, Figure 6-2 shows calculated cooling load demand and cooling load supply. Based on the assumption of perfect response by the cooling system, these two results need to be the same, but they are not.

![Figure 6-2. Calculated cooling load demand and cooling load supply](image)

The cooling load demand and cooling load supply are calculated using the following equations:

1. \( Q_{\text{envelope}} + Q_{\text{occupancy}} + Q_{\text{internal}} = E_{\text{AHU}} + E_{\text{CU}} \)
2. \( \text{Total } E = E_{\text{HVAC}} + E_{\text{Internal}} + E_{\text{Other}} \)
3. \( CL_{\text{Demand}} = (Q_{\text{envelope}} + Q_{\text{Air}})_{\text{External}} + (Q_{\text{Occupant}} + Q_{\text{Lighting}} + Q_{\text{Equipment}} + Q_{\text{Plugged}})_{\text{Internal}} \)
4. \( CL_{\text{Supply}} = HVAC \text{ energy use} \)
where $Q_{envelope}$ was calculated with outdoor weather conditions, number of occupants was used for $Q_{occupancy}$, and internal electricity consumption was used as $Q_{internal}$. After calculated cooling load demand, $E_{\text{internal}}$ was calculated with following equation:

$$E_{\text{Internal}} = \text{Total E} - E_{\text{AVC}}(= CL_{\text{demand}}) + E_{\text{Other}} = E_{\text{AVC}} - Q_{\text{Envelope}} - Q_{\text{Occupant}}$$

Figure 6-3. Calculated plug-load consumption compared with actual energy consumption

Figure 6-2 shows similar trend between cooling load demand and cooling load supply part. With these cooling load supply part, $E_{\text{internal}}$ was calculated. When this result is compared with actual plug-load consumption, the results has a lot of fluctuations with big difference from plug-load consumption. The condensing unit not only consider about the out door weather condition it also operated with building system setting. Also, the delay of the heat transfer from the building to the indoors and other inaccurate energy consumption parameters caused an error on the hourly results.

However, the filtered-adjusted electricity consumption data has a good correlation to occupants. This methodology is reasonable to use instead of building energy disaggregation. An averaged weekend energy consumption trend can represent the baseline building energy consumption. This methodology erased the peak of un-occupied building condition. Filtered- adjusted electricity consumption and occupancy data can improve the accuracy of the building energy simulation results. Different buildings
have different kinds of operating systems and different types of metering systems. So it is not realistic to say that there is one simple method or equation to improve the simulation results.

All buildings are different, so this study suggests installing occupancy sensors to find the effects of the number of occupants on a building. If it is impossible, determine the kW/person with the area information of the building. This coefficient can be used with the filtered-adjusted baseline electricity consumption to derive the occupancy schedule and to make an equation to simulate. Derived occupancy schedule includes the different effect of occupancy behavior depending on the area usage and this is more practical to use instead of actual occupancy schedule.
Chapter 7. Conclusions and Recommendations for Future Work

Prior studies have shown that occupant behavior, occupancy rates, and occupancy presence/absence have a significant effect on building energy consumption. The electricity consumption demonstrates a significant positive correlation ($R^2 \approx 60\%-70\%$) with the occupancy rates in different types of buildings. Therefore, building electricity consumption patterns can be used to derive occupancy schedules and improve the accuracy of energy simulation results.

According to the results, the plug-load consumption was significantly correlated to the occupancy rates in the studied buildings. For example, occupancy rates accounted for 70 to 79% of the variation shown in the plug-load levels in Building 101. Compared with correlations between the total electricity consumption and the occupancy schedule ($R^2 \approx 40\%-60\%$), plug-load usage has a higher correlation coefficient. Furthermore, Borland Building has $R^2 \approx 70\%-80\%$ and Forest Resources Building has $R^2 \approx 60\%-70\%$. The correlation coefficients between the electricity consumption and occupancy rates increased after filtering the fluctuations and unoccupied energy use schedule in the building. For Forest Resources Building, the correlation increased from 57% to 66% and for the Borland Building, the correlation increased from 70% to 72%.

For a building with a large area occupied by office space, the electricity consumption expressed as kW/person is relatively high. For example, Building 101 has a higher kW/person electricity consumption (1.0 kW/person) compared to the consumption of campus buildings (Borland Building: 0.3 kW/person, the Forest Resources Building: 0.2 kW/person, the Carnegie Building: 0.53 kW/person). The electricity consumption per occupant can be used to derive the occupancy schedule from the total electricity consumption in a building.

The accuracy of the building energy simulations increased with the occupancy schedule and electricity consumption equations. Compared to the default schedules in the building energy simulations, detailed occupancy schedule inputs provided a decrease of the CV(RMSE). The hourly basis CV(RMSE)
for Building 101 decreased from 67% to 21%. For Borland Building and Forest Resources Building, CV(RMSE) also decreased from 128% to 31%, and 156% to 16%, respectively. The daily basis CV(RMSE) for Building 101 decreased from 27% to 12%, and CV(RMSE) for Borland Building and Forest Resources Building decreased from 85% to 12% and 61% to 13%, respectively. Overall, the reduced CV(RMSE) values satisfy ASHRAE Guideline 14 requirements for calibrated energy simulation models capable of producing reliable building energy consumption data.

This study found an effective methodology to calibrate the building energy simulations. The method required the hourly total electricity consumption and occupancy schedules from the building. The occupancy schedules were derived from the building electricity consumption. Other studies also showed that the actual occupancy schedules can improve the accuracy of the building energy simulations. However, as shown in the present study, not all of occupants in the building consume the electricity at the same pattern, and this diverse energy consumption pattern depends on the building area type. In buildings with the large area occupied by office space, most of occupants consume the electricity by using their own work stations and they increase the electricity consumption in the building. However, in common areas and classrooms, not all of occupants consume the electricity. Most of these occupants are attending the classes or other events without consuming the electricity. Therefore, the number of occupants derived from the hourly building electricity consumption is a reasonable proxy for occupancy schedules. Overall, this study found that accurate building energy consumption simulations require the occupancy rates directly associated with the use of electricity.

7.2 Development of kW/person Database

This study found that the electric energy use per occupant depends on the building area use type. This study derived an equation to calculate the electric energy consumption in kW/person by using building area usage information. The information of building size and area usage were combined to derive
the kW/person equation. This study used four different buildings including office type and campus buildings. With three different buildings, the equation for kW/person was derived and verified with 4th building. However, this methodology and derived equation are limited by the small number of buildings included in the development and deployment of this equation.

Future studies can establish a database of key inputs for kW/person equation. The suggestion is to collect additional data from different types of buildings, which include different area usage. Adding more buildings would improve the fidelity and accuracy of the equation for kW/person. Finally, this equation could help to derive the occupancy rates from hourly building energy consumption and improve the accuracy of the building energy simulations with limited actual building data.
References


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APPENDIX

Weather data

Two types of weather data was used for this study. For building 101 simulation, Philadelphia, PA AMY (Actual Meteorological Year) data was used. For Pennsylvania State Campus buildings, University Park, PA, AMY data was used. Typically, TMY3 (Typocal Meteorological Year) and AMY data area recommended in the building industry. TMY3 weather data is a source for the HVAC engineers to design HVAC systems based on hourly weather data for a typical year in a specific location. However, when a specific period of time is interested, TMY3 weather data does not provide sufficient weather information for the specific time. Therefore, actual weather data was suggested for specific building energy simulations. This study collects and cleans 15 minute and hourly weather data for University Park and Philadelphia. Table A-1 summaries the sources for the weather data used in this study.

<table>
<thead>
<tr>
<th>Location</th>
<th>Weather Station 1</th>
<th>Weather Station 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>University Park, PA</td>
<td>University Park Airport Weather Station</td>
<td>NOAA* Weather Station</td>
</tr>
<tr>
<td>Philadelphia, PA</td>
<td>Philadelphia Airport Weather Station</td>
<td></td>
</tr>
</tbody>
</table>

- NOAA stands for National Oceanic and Atmospheric Administration
Building Energy Model Calibration Guideline

ASHRAE 14-2002 Measurement of Energy and Demand Savings

This guideline uses the following three indices to represent how well a mathematical model describes the variability in measured data. These indices shall be computed for the single mathematical model used to describe the baseline data from all operating conditions (i.e., both summer and winter shall be consolidated in one model for evaluating these indices).

1. **Coefficient of variation of the standard deviation (CVSTD)**

   \[ CVSTD = 100 \times \left[ \Sigma (y_i - \bar{y})^2 / (n - 1) \right]^{1/2} \bar{y} \]

2. **Coefficient of variation of the root mean square error (CVRMSE)**

   \[ CVRMSE = 100 \times \left[ \Sigma (y_i - \bar{y})^2 / (n - p) \right]^{1/2} \bar{y} \]

3. **Normalized mean bias error (NMBE)**

   \[ NMBE = \frac{\bar{y}_i - \bar{y}}{(n-p) \times \bar{y}} \times 100 \]

   For calibrated simulations, the CVRMSE and NMBE of modeled energy use shall be determined by comparing simulation-predicted data \( \bar{y} \) to the utility data used for calibration \( y_i \), with \( p=1 \).

Whole building calibrated simulation performance path. Compliance with this path requires the following:

a. The simulation tool used to develop models for buildings shall be a computer-based program for the analysis of energy use in buildings. It shall be commercially available or in the public domain. The tool shall be able to adequately model the facility and ECM(s), performing calculations for each hour of the time period in question, e.g., for a one-year period the model shall perform 8,760 hourly calculations. In addition, it shall be able to explicitly model at least the following:
- 8,760 hours per year,
- Thermal mass effects,
- Occupancy and operating schedules that can be separately defined for each day of the week and holidays,
- Individual setpoints for thermal zones or HVAC components,
- Actual weather data
- User-defined part-load performance curves for mechanical equipment and
- User-defined capacity and efficiency correction curves for mechanical equipment operating at non-rated conditions.

b. Provide a complete copy of the input data, indicating which data are known and which are assumed. Report the source of all data described as “known,” and assess its level of uncertainty.

c. Report the name and version of simulation software used

d. Report the source and accuracy of the calibration data.

e. Calibration data shall contain at a minimum all measured monthly utility data from 12 bills spanning at least one year.

f. The computer model shall have an NMBE of 5% and a CV(RMSE) of 15% relative to monthly calibration data. If hourly calibration data are used, these requirements shall be 10% and 30%, respectively.

g. With each savings report, show at least the level of uncertainty and confidence interval for the annual savings determined during the post-retrofit period

h. The level of uncertainty must be less than 50% of the annual reported savings, at a confidence level of 68%
**Occupancy Rates**

For building energy simulation, three case studies used three different occupancy rates from measured occupancy schedule.

a. Averaged occupancy rates from actual number of occupants

b. Actual occupancy rates from measured data

c. Derived occupancy rates from hourly electricity consumption

Averaged occupancy rates were averaged actual occupancy rates. It is averaged from actual occupancy so it has similar trend but different level. Derived occupancy rates from hourly electricity consumption has very similar trend with actual occupancy rates but it has some differences. The differences are come from occupants’ behavior. Not all of occupants in the building act to consume the building energy. Derived occupancy only counts the occupants who affect to the building energy consumption. This derived occupancy schedule can help to improve the accuracy of building energy simulation.

![Three occupancy schedules for the Building 101 energy simulation](image)

Figure A-1. Three occupancy schedules for the Building 101 energy simulation
Figure A-2. Three occupancy schedules for the Borland Building energy simulation

Figure A-3. Three occupancy schedules for the Forest Resources Building energy simulation
Geometry for Building Energy Simulations

Figure A-4. The geometry of building 101

Figure A-5. The geometry of Borland Building
Figure A-6. The geometry of Forest Resources Building

Figure A-4 to A-6 show the shapes that geometry for case studies in this dissertation study. The building geometry was build up with Designbuilder program.
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• “Improvement of Building Energy Simulation Accuracy with Occupancy Schedules derived from Hourly Building Electricity Consumption,” Kim, Y.S., Srebric, J., accepted, ASHRAE transactions