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Actual Building Energy Use Patterns and Their Implications for Predictive Modeling

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Abstract

The main goal of this study is to understand the patterns in which commercial buildings consume energy, rather than evaluating building energy use based on aggregate utility bills typically linked to building principal tenant activity or occupancy type. The energy consumption patterns define buildings as externally-load, internally-load, or mixed-load dominated buildings. Penn State and Harvard campuses serve as case studies for this particular research project. The buildings in these two campuses use steam, chilled water, and electricity as energy commodities and maintain databases of different resolutions to include minute, hourly, daily, and monthly data instances depending on the commodity and available data acquisition system. The results of this study show monthly steam consumption directly correlates to outdoor environmental conditions for 88% of the studied buildings, while chilled water consumption has negligible correlation to the outdoor environmental conditions. Thus, in terms of monthly chilled water consumption, 86% of buildings are internally-load and mixed-load dominated, respectively. Chilled water consumption is better suited for the daily analyses compared to the monthly and hourly analyses. While the influence of building operation schedules affects the analyses at the hourly level, the monthly chilled water consumptions are not good indicators of the building energy consumption patterns. Electricity consumption at the monthly (or seasonal) level can support the building energy simulation tools for the building energy retrofits. A granular electricity data, e.g. interval hourly or 15-minute, could reveal building operation schedules. Overall, the steam consumption for these campus buildings located in the Northeastern United States indicated a stronger correlation to the outdoor conditions than the operation schedules. The energy consumption patterns for the reviewed campus buildings suggest opportunities for the campuses to benefit from a better: (i) interactions of the steam generation/distribution systems with the building heating demand, (ii) chilled water data collection systems to optimize the cooling demand and operation schedule of the buildings, and (iii) electricity consumption with relying on daylighting and variable operation schedules during summer and winter seasons.

Key Words

Campus Buildings, Building classification, Internally-load dominated, Building Energy Use Patterns, Urban Environments

1. Introduction

Analyzing energy consumption for a large number of buildings, such as university campus buildings located in an urban neighborhood, could offer insights to building energy consumption patterns and potentially provide opportunities to reduce energy consumption of buildings at large scales. Current building benchmarking practices or Commercial Building Energy Consumption Survey (CBECS) do not provide detailed information about campus buildings. Here, this study offers a classification of building energy consumption patterns at higher granularity to assess energy efficiency of buildings and improve the accuracy of campus building energy models.

Common methods for the building energy modeling are: (1) Degree day calculations, (2) Estimated savings based on the utility bills (disaggregation), (3) Temperature bin spreadsheet calculations, (4) 8760-hour spreadsheet calculations, (5) Energy Utilization Index (EUI), and (6) Whole building energy simulations. The researchers successfully used the degree day method to evaluate the building's energy and components performance [1-3]. The reviewed methods vary in terms of their time/effort and accuracy/quality of results. Energy managers usually use methods (1) to (5) to evaluate the energy consumption of buildings due to their simplicity, but the tradeoff is the accuracy and applicability of the analyses. The whole building energy simulation method is rarely used due to its complexity, but if properly calibrated, it can predict energy consumption of the buildings accurately [4-6]. For most practical applications, methods (1) to (5) include weather and building-related variables that are adequate [7-9]. Although the degree day method is simple and reliable in most cases, its disadvantage is the assumption that buildings consume energy uniformly during a day. For buildings with intermittent energy consumption during a day, this method is less appropriate. Nevertheless, for buildings that operate 24/7, such as typical university campus buildings, this assumption is appropriate. This paper modifies the original idea of the degree day method to consider the sol-air temperature alongside the outdoor dry bulb and dew point temperature for cooling analysis.

Inexpensive sub-metering of buildings now provide 15-minute or hourly utility data known as "interval data" to replace the commonly used monthly utility bills. A more detailed sub-metering approach collects energy consumptions for all of building end-uses, including plug loads, interior lighting and ventilation end-uses to assess efficacy of the existing inverse energy models [10, 11]. Although this kind of sub-metering for all of the end-uses could provide detailed information about the building energy consumption patterns, it is more expensive. A limited number of case studies of install smart sub-meters have been done but data is typically not publically available [12]. It is useful, therefore, to assess tradeoffs in granularity of energy consumption data accuracy (usefulness) for energy models. This study assesses the implication of the building energy consumption data granularities, including hourly, daily, and monthly, on the building energy analyses.

The granularity of energy data will influences the accuracy of simulation models, and hence, is important to assessing benefits of retrofits. Utility data is used retrospectively to assess energy efficiency measures (EEMs) [13]. In cases where there is missing data for one of the energy commodities, such as steam or chilled water (CHW) consumptions, monthly electricity consumption is used as a proxy to calibrate the building energy models [14]. Availability of the energy data is an important factor in the energy analyses. With the existence of detailed sub-metered data for all of the energy end-uses, the EEMs can be assessed with the detailed sub-metered data [13]. At present, monthly utility data is commonly available [15]. Given that our campus buildings have fine resolution of energy consumption, we characterized energy utilization for different building topologies based on simulations (and actual data) using various time averaged energy data. This approach allows quantifying the influence of energy consumption data granularity on the accuracy of calibrated energy simulation models.

This study is part of a long-term collaborative effort to create a building energy database for the building stock located in different climate zones with various occupancy types, areas, ages as well as fuel types for multiple years to reclassify buildings based upon their energy use patterns [16, 17]. University campuses offer a portfolio of different building topologies along with detailed energy metering [17]. Many university, the reviewed universities among them, are aggressively pursuing energy reduction to meet greenhouse gas reduction targets [18]. The current study provides a methodology to normalize energy consumption of campus buildings and classify them in the Northeastern United States climate zones as a starting point in generating a comprehensive database for the U.S. This study selects 78 buildings with documented energy usage from the 300 buildings at Penn State's University Park campus and 600 buildings at Harvard's Cambridge campus.

2. A framework to benchmark campus building energy consumption

Table 1 outlines four steps to benchmark campus building energy consumption and provide inputs for the building energy simulations. In the first step, weather data is characterized based on the outdoor conditions defined by cooling degree days (CDDs), heating degree days (HDDs), and outdoor air temperatures. Then, hourly HDDs and CDDs are converted to average daily and monthly HDDs and CDDs. Additionally, this study suggests using sol-air based CDD, and dew point temperature for the weather analyses. Sol-air temperature is a fictitious temperature that considers the effects of radiative exchanges and provides the same heat transfer rate. Next, buildings are categorized based on their occupancy type and sub-space energy consumption to develop a building selection methodology. In the third step, three building energy commodities, including chilled water, electricity, and steam consumption are collected. In the fourth step, the collected weather and energy data are analyzed to classify the buildings and provide inputs for the building energy simulations.

Table 1. A four step methodology to benchmark campus buildings and provide inputs for the building energy analyses

Step 1	Weather data characterization	• Collect hourly weather data variables: 1. Outdoor air temperatures 2. Dew point temperatures 3. Solar radiations 4. Wind speeds • Average daily weather data to monthly data • Derive monthly HDDs, CDDs as well as sol-air based and dew point temperature based CDDs
Step 2	Building selection	• Select five primary building categories: 1. Classrooms/Offices 2. Office areas 3. Research laboratories 4. Laboratory mixes 5. Residential facilities • Select eight secondary building categories: 6. Student activity centers 7. Health facilities 8. Sports/gym facilities 9. Auditoriums/theaters 10. Residential facility mixes 11. Hospitality services 12. Libraries 13. Museums
Step 3	Energy consumption database	• Collect three main energy consumption commodities: 1. CHW (Chilled Water) 2. Electricity 3. Steam • Consider two different methods for the analyses: ▪ Method 1: Heating season (January – May and September – December) and Cooling season (June – August) ▪ Method 2: Entire year
Step 4	Normalized energy consumption	• Normalize energy consumption with weather data • Interpret the normalized energy consumption results with response to environmental conditions • Derive different classes of buildings based upon their energy consumption • Derive the detailed information for the calibrated energy models from the utility data

To minimize influence of anomalous data monthly energy commodities, including steam, chilled water, and electricity consumption for five consecutive years, 2008-2012 was used. In a subsequent section, this study summarized how discontinuous energy and weather data where handled. For the Penn State campus, interval energy data, including chilled water, steam, and electricity consumptions for two years, 2012 and 2013, are selected to assess the granularity of the energy consumptions.

2.1 Step 1: Weather data characterization

The study used weather data from the closest weather stations with standardized reporting and instrument maintenance protocols from national and local weather stations [19-22]. Penn State and Harvard campuses are located in a "cool-humid" climate zone region with fairly similar daily distributions of outdoor air temperatures [17, 23]. A sensitivity analysis of the cooling energy consumption examined dry bulb temperatures, dew point temperatures, and sol-air temperatures derived from the nearest weather station. Depending on the reference outside air temperature T_o [°C], the sensitivity analysis uses: (1) dry bulb temperature for CDD10 and CDD18.3, (2) dew-point temperature for dew point based CDD10, and (3) sol-air temperature for sol-air based CDD10. In the definition of CDD, numbers 10 and 18.3 refer to the base point temperature in Centigrade for the calculation of CDD. For example, the number 10 in CDD10 means the CDD is the difference between the outdoor air temperature and 10°C. For each day in a year, HDD and CDD are defined as:

$$HDD_i = \frac{1}{n}\int (T_{BP} - T_o)dt \text{ for } T_{BP} > T_o \qquad (1)$$

$$CDD_i = \frac{1}{n}\int (T_o - T_{BP})dt \text{ for } T_{BP} < T_o \tag{2}$$

where HDD_i is heating degree days for one day [°C] ([°F]), CDD_i is cooling degree days for one day [°C], T_{BP} is the balance point temperature, which is 10 °C and 18.3 °C in this study for $CDD10$ and CDD18.3 respectively, T_o is the daily average temperature [°C] calculated from the hourly weather data.

This study uses Eq. (3) to derive sol-air temperatures [24].

$$T_{sol\text{-}air} = T_o + 1/h_o(\alpha I_o - \varepsilon \Delta R) \tag{3}$$

where h_o [m^2/W] is the external surface heat transfer coefficient, α [-] is the surface solar absorptance, I_o [W/m^2] is the total solar radiation incident on the surface, ε [-] is the surface emittance, and ΔR [m^2/W] is the net radiation exchange. For the external surface heat transfer coefficient, this study uses Eq. (4). Where D, E, and F are material roughness coefficients derived from experiments with different building enclosure materials available in the literature, and V_z is the local wind speed available from the local weather station [25].

$$h_o = D + EV_z + FV_z^2 \tag{4}$$

Use of different CDDs and temperatures enable this study to consider the influence of different outdoor conditions on energy consumption of the buildings. While dew point temperature and dew point based CDDs are measures to account for the moisture removal from the air [17], the sol-air temperature and sol-air based CDDs inherently account for the combined wind speed and solar radiation. Building designers usually use dew point temperature to design heating, ventilation and air-conditioning (HVAC) systems, while building energy analysts utilize the sol-air temperature in the energy modeling and simulation tools. Fig. 1 provides a summary and comparison between different CDD and HDD options for both Penn State and Harvard campuses. The results of CDDs and HDD indicate that both campuses experience similar outdoor conditions. Except CDDs based on dew point and sol-air, Harvard campus has a higher CDDs and HDD compared to the Penn State campus. The higher HDD suggests that buildings located at Harvard campus may consume higher steam consumption than the buildings located at the Penn State campus. In addition, a higher CDD based on the sol-air for the Penn State campus suggest that the contribution of infiltration and solar shading are more significant for the Penn State buildings than the Harvard buildings. Overall, in addition to the outdoor air condition, variables such as building type, construction, urban neighborhood, and building operation, among the other influential variables determine the building energy consumption patterns. Figure A1 in the Supplementary Materials provide additional comparisons between the outdoor air temperatures for different years.

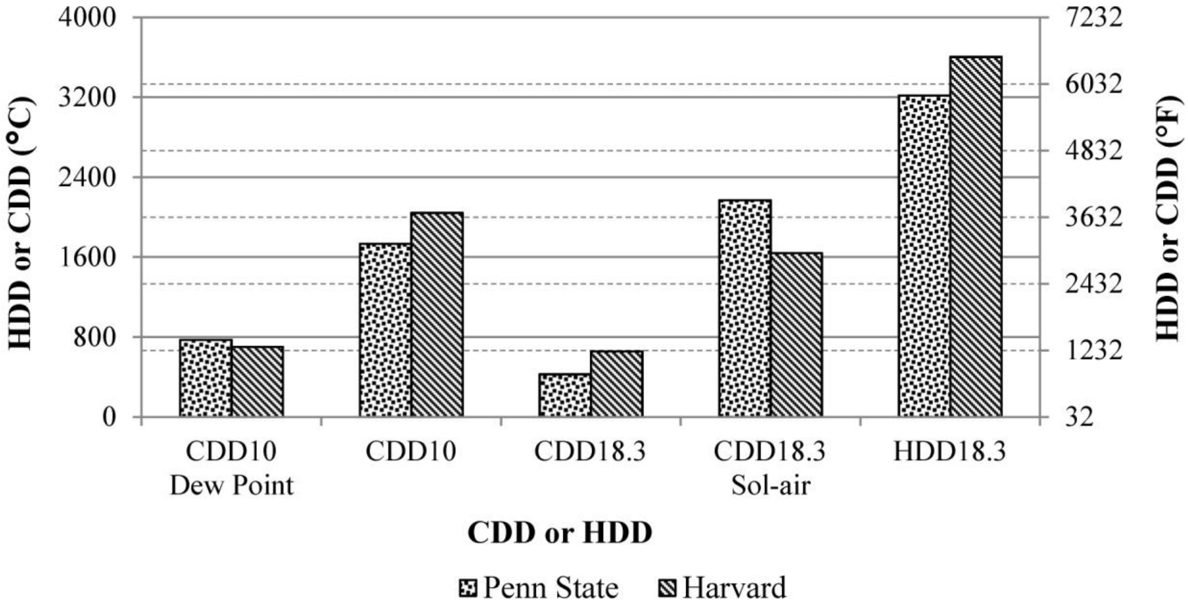


Figure 1. Annual HDD and CDD comparison between Penn State and Harvard campuses for 2010

2.2 Step 2: Building selection

Current building energy consumption benchmarking techniques usually categorize buildings based on the building's principal activity. One of the primary resources to classify university buildings is the postsecondary education facilities inventory and classification manual (FICM) [26]. Campuses do not always follow the FICM classification. For example, common building space types for Penn State campus are Office (Administrative, Multipurpose, and Faculty), Research (Engineering and Multipurpose), Multipurpose, Athletic, Residence (Men's/Women's/Coed), Classroom, Utility & Service, Cafeteria, Auditorium and Theaters, and Student Health Center [27]. A proposed new categorization is to utilize a combination of FICM and existing categories of the campus buildings [28, 29] to derive new categories relevant to energy consumption patterns. The existing categories do not inherently account for the intrinsic and extrinsic differences in the energy consumption patterns, occupant rate/behavior, and building operations. Therefore, the present study proposes a building categorization into thirteen categories based on the building's principal activity, energy use patterns, and occupant rate/behavior detailed in Table 2 and Table 3. Overall, existence of these definitions for the space types allows a fair comparison between buildings located at different campuses regardless of the institutional definition for the space types.

Table 2. Definitions of primary building categories based on the building's principal activity

1. **Classrooms / Offices**	This category is a combination of classroom and office areas where none of the classroom or office areas occupies more than 60% of the total building area. This type of the building represents a building that comprises both Full Time Employee (FTE) and visor/transient occupants. While the visitor/transient occupants influence the energy consumption pattern and operation schedule of the classroom space type, FTEs in the office space type affect the building's energy consumption patterns.
2. **Office Areas**	It is a category where more than 80% of the building area is used for academic and administrative office areas. This type of building represents buildings in which occupancy presence and behavior have more influence on the building energy use pattern [30]. In addition, it is expected that the operational schedule for this type of space be shorter compared to the Classrooms/Offices space types.
3**. Research Laboratories**	This category contains buildings that exhibit high-intensity in terms of energy consumption and more than 40% of the building area is occupied by research laboratories. This space type could include fume hoods, clean rooms, biosafety labs, ultralow freezers, and servers [31]. The occupancy pattern does not directly influence the building energy use pattern, and the intensity of the energy use of the facilities is the primary driver of the building energy consumptions [32]. Recent studies show that the behavior of the research facilities is directly correlated with the research facility energy consumption [32], suggesting that the operational schedule of the instruments in the laboratory buildings could significantly reduce the building's energy consumption.
4. **Laboratory Mixes**	Laboratory Mixes category includes a combination of Classrooms/Offices, Offices, and Research Laboratory areas. In this category, more than 20% of the building area is used for research laboratories, and each of the categories occupies at least 15% of the building area. Overall, this space type is one of the most common building among buildings in the campuses.
5**. Residential Facilities**	This category includes students, staff, and faculty housing buildings. The energy use pattern of this space type is highly correlated with the academic schedule, including low occupancy during the breaks. For example, during spring, summer, fall, and winter student breaks, the energy use pattern of these buildings is reduced dramatically.

Table 3. Definitions of secondary building categories based on the building's principal activity

6. Student Activity Centers	This category contains buildings where student activities account for 40% of the building area. Typically, each campus has a building with this purpose. The purpose of this space type is to consider spaces with different energy use patterns such as cooking kitchens or common areas with variations of visitors/transient occupants.
7. Health Facilities	Health facilities are buildings that provide patient care within university campuses. The energy use pattern in this space type is more dominated by the high intensity of internal loads.
8. Sports / Gym Facilities	It is a category dedicated to indoor student recreational activities and fitness centers. A unique feature of this space type is accessibility to the occupancy pattern of the building since gym facilities usually require using swipe cards.
9. Auditoriums / Theaters	This category is used for exhibition and performance buildings within university campuses. For this space type, it is difficult to understand the energy use pattern since the building is used intermittently.
10. Residential Facility Mixes	This category is a combination of residential facilities and areas allocated for food and cooking purposes. Compared to the residential facilities, the cooking facilities require additional energy consumption.
11. Hospitality Services	Hospitality services category contains temporary accommodation facilities, such as university hotels.
12. Libraries	This category defines university libraries. There are different kinds of libraries at the university campuses. Main library buildings are usually 7/24. Other libraries may have extended operation hours.
13. Museums	This category includes museum buildings within university campuses. The energy use patterns of these buildings are intermittent and there are no predictable energy use patterns.

This study selects six buildings for each of the five primary categories in both campuses, totaling in sixty campus buildings for both campuses. The secondary categories include eighteen buildings only from Penn State campus. Detailed information about the selection criteria for buildings, their gross floor area (GFA) and age can be found in the literature [17]. It is important to notice that even for these well-maintained and monitored systems, this study observes that irregularities in the data collection process occurred. Therefore, availability and quality of energy consumption data dictate the number of studied buildings.

2.3 Step 3: Energy consumption database

Steam, chilled water, and electricity consumption data was obtained from a data management client system for both campuses. The two campuses have central cooling and heating plants as sources of steam and chilled water similar to most university campuses in the U.S. In the first step, this study considers well-documented and reliable monthly utility data for both campuses to provide a framework when only the monthly utility data exist. To illustrate the benefits of relying on more granular energy utility data than the monthly data, this study examines 10 representative buildings at the Penn State campus with 15-minute utility data. For Penn State campus, two options for collection of the energy commodity consumption include: (1) metering and (2) bill tracking. The metering option captures the actual hourly energy commodity consumptions. The bill tracking is an option that records monthly commodity consumptions. To assure data quality, this study conducts the following database cleaning assumptions:

(1) When the steam or chilled water meters have reached their upper or lower bounds of meter accuracy, the readings are not accurate; consequently, the cleaning process ensures to remove these out-of-range readings.
(2) A comparison between the monthly data from the metering option and the bill tracking values shows differences. When these differences are more than a 15%, the bill tracking readings are used.
(3) Most of the residential facilities do not have chilled water. This study relies on steam and electricity consumptions for these buildings.

Fig. 2 shows energy consumption breakdowns of the primary space types for both campuses. The research laboratory space type consumes a significantly large amount of energy compared to the other space types. Total energy consumption and the standard deviation of total energy consumption for the research laboratory space type are very similar for both campuses, although the steam, chilled water, and electricity energy consumption patterns are different. The standard deviation for the total energy consumption of the research laboratory space type for Penn State with 470.5 kWh/m^2 and Harvard campuses with 490.9 kWh/m^2 confirm similarities between the total energy consumption in these two campuses. These patterns suggest that for energy intensive space buildings, such as research laboratories and lab mix space types, the total energy consumption is very similar, and the type of research laboratories determine the distribution of steam, chilled water, and electricity consumptions.

After the research labs, lab mix buildings are more energy intense compared to other space types. This is one of the common space types at the university campuses since the campus buildings are usually mixed-used buildings. Classroom/Office, office areas, and residential facilities have slightly different energy consumption patterns for both campuses. For example, while the standard deviation for the classroom/office space type for Penn State is 127.9 kWh/m^2 for the Harvard campus, the standard deviation is 68.9 kWh/m^2. In addition, for the office areas space type, the standard deviation of total energy consumptions is 93.8 kWh/m^2 and 79.2 kWh/m^2 for the Penn State and Harvard campuses, respectively. Fig. 2 illustrates that the total energy consumptions for office areas have no significant variations. Although the patterns are very similar for both office areas, the drivers for the internal loads are different. While FTE for the office areas are usually the main driver for increase in internal loads for this space type. In addition to the FTE, the transient occupants of the classroom/office buildings affect the energy consumption patterns for the classroom/office building types. The residential facilities at both campuses do not use chilled water for the cooling. Additional details of the energy use pattern statistical analyses for both campuses are available in the Supplementary materials, including Table A1, Table A2, and Figure A2 as well as in the literature [17].

As Fig. 2 indicates the energy consumption for both campuses have similarities and differences. The error bars in this figure specify the standard deviation for all the energy commodities. In terms of the median for the total energy consumption of the buildings, the research laboratories space type has similar total energy consumption patterns.

The median total energy consumption for Penn State campus is 848.0 kWh/m^2 and for the Harvard campus is 748.8 kWh/m^2. After the residential facilities, the lab mixes space type buildings with 509.1 kWh/m^2 and 470.6 kWh/m^2 for Penn State and Harvard campuses are the most similar building types in terms of total energy consumption. However, the buildings in the classroom/office and office areas have different total energy consumption patterns. The median energy consumption patterns for the classroom/office space type are 350.2 kWh/$m^2$and 191.3 kWh/m^2, respectively.

A comparison between the illustrated energy consumption data in Fig. 2, CBECS, and Residential Energy Consumption Survey (RECS) supports the necessity to consider campus buildings as a stand-alone portfolio of buildings. Specifically, the survey conducted on the U.S. building energy consumption patterns in 2012 (CBECS 2012) data do not include detailed information for the campus buildings. The closest category of buildings in the CBECS database to the campus buildings is the education category. While the EUI for New England, Middle Atlantic, and East North Central are 220.0, 276.8, and 229.4 kWh/m^2, respectively, except for the category of office/classroom buildings at Harvard campus, all the campus building categories for both Penn State and Harvard campuses have EUIs higher than the corresponding values in the CBECS database. In addition, office buildings in the CBECS database for New England, Middle Atlantic, and East North Central have EUIs of 259.1, 328.5, and 267.6 kWh/m^2, respectively, while the median EUI of office buildings for both campuses vary between 397.0 to 580.7 kWh/m^2. These differences between the campus building study and the current available building information confirms the need to study energy consumption patterns in campus buildings.

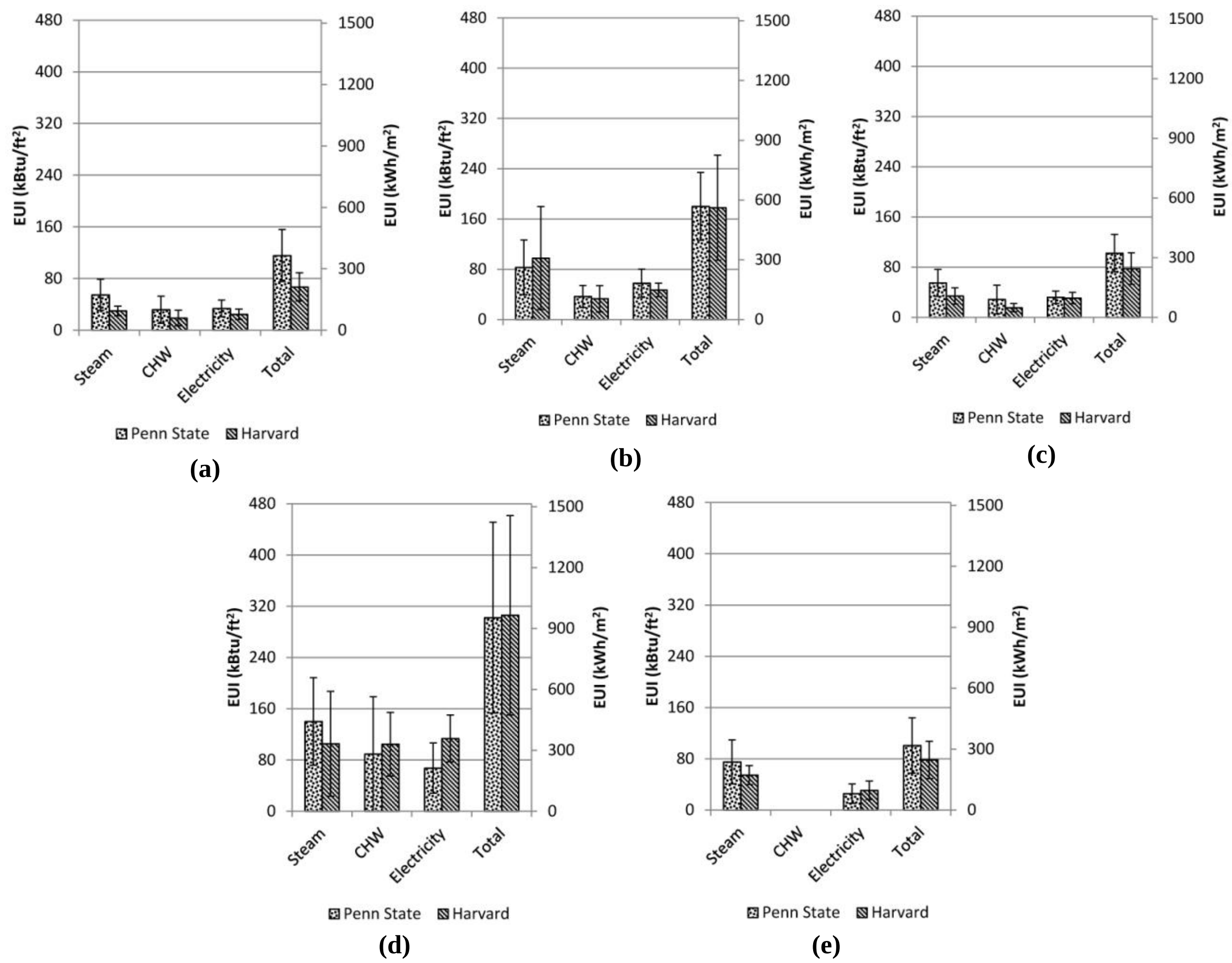


Figure 2. Energy commodity consumptions of five primary space types for two studied campuses: (a) Classroom/Office, (b) Lab mixes, (c) Office areas, (d) Research laboratories, and (e) Residential facilities

2.4 Step 4: Normalize energy consumption data

Normalization of energy consumption data allows comparisons of buildings with each other. One approach is to normalize the energy consumption with the area of the building. At the annual or monthly level, the commonly used variable is the building EUI. Building-weighted average or building-area-weighted average EUIs are two representative examples of using EUIs for the building energy data portfolios [16]. Another approach to benefit from the energy per area normalization is to identify the internal loads using the electricity consumption patterns, e.g. heat map graphs. Although EUI provides insights in the energy use consumption of the building, it does not account for the influence of the outdoor condition on the building energy consumption patterns. Therefore, a better approach accounts for the influence of the outdoor condition. This study selects two options for considering the energy consumption patterns of buildings throughout a year. Option one considers a three-month-long cooling season (June to August), during which there is a need to cool indoor spaces of buildings, and a nine-month-long heating season (January to May and September to December), during which there is a need to heat the indoor spaces of buildings. Option 2 considers the energy use pattern throughout the entire year, meaning the buildings require cooling and heating in all seasons. This option may lead to simultaneous heating and cooling of the building, which it is not an energy efficient approach. An example of using heating during the entire year is to benefit from steam during winter for space heating and steam/hot water during summer for the zone reheat of the cooling systems.

This study normalizes the monthly data for both campuses with weather data. Outdoor air temperature and HDDs are two variables to normalize steam consumptions. Similarly, for the cooling seasons, the chilled water consumption per building volume is used for the energy normalization with the outdoor air, sol-air, and dew point CDDs. As expected, the electricity consumptions for these types of buildings do not correlate to the outdoor weather conditions, so this study normalizes electricity consumptions with the building area. Existing studies have extensively used weather normalization of building energy consumptions to assess a regression model fit for different energy consumption and potential retrofit opportunities [4, 7], and inverse building energy modeling approaches [33, 34]. These inverse modeling approaches are usually associated with the “change point” models. The selection for the goodness of the regression usually depends on the purpose of the study. The results of the current study show that two-parameter, three-parameter normalization change point models for steam and chilled water can determine the significance of regression coefficients, baselines, and peak energy consumption of the buildings.

Results of the two-parameter and three-parameter models provide required inputs for building classification based on energy consumption. Order of magnitude for the regression analysis determines three types of buildings in terms of the energy consumption in response to the outdoor weather conditions. These types are: (1) externally-load dominated buildings, (2) internally-load dominated buildings, and (3) mixed-load dominated buildings. It is useful to determine whether internal, external or mixed-loads dominate building energy use patterns in order to inform design, retrofit and energy simulation efforts. Specifically, this energy use pattern classification determines focus areas for the calibration of energy simulation models. This study provides detailed descriptions of externally-load, internally-load, and mixed-load dominated buildings:

Externally-load dominated buildings have their energy consumption controlled by the outdoor weather conditions, ventilation systems, and heat loss/gain through the building envelope. In the literature, externally-load dominated buildings are sometimes called envelope-dominated or skin-load dominated [35] buildings for which the envelope-dominated word does not indicate the effects of the ventilation systems. Externally-load dominated buildings require additional focuses on the building envelop and ventilation systems. Space types such as single-family and warehouse buildings tend to be externally-load dominated [35, 36]. For the majority of the reviewed campus buildings located in the Northeastern of the U.S., the steam consumption do follow the outdoor condition, suggesting opportunities to benefit from a better space heating management strategies.

Outdoor conditions do not have significant influence on the energy consumption of the internally-load dominated buildings. Internal loads such as receptacle, occupancy, lighting loads and their schedules are the main drivers to control the energy consumption of these buildings. Space types such as offices, hospitals, and research laboratories tend to be more internally-load dominated [37]. The results of this study indicate that the research laboratories and laboratory mixes tend to be internally-load dominated.

In mixed-load dominated buildings, external and internal thermal loads have the same order of magnitude. Energy use patterns for these types of buildings are a combination of external and internal loads. The complex interaction of the heat transfer processes render mixed-load dominated buildings difficult to model. Modeling these buildings requires consideration of combined methodologies for externally-load and internally-load dominated building. Campus buildings with good management strategies usually are mixed-load dominated since the energy consumption during the peak time follows the outdoor condition while during off peak, e.g., nighttime, the building cooling does not follow the outdoor condition.

3. Energy analyses results

This investigation deployed the classification methodology based on the normalized energy consumption of forty eight buildings at the Penn State campus and thirty one buildings at the Harvard campus. The classification methodology evaluates each buildings energy needs separately for the steam, chilled water, and electricity commodities.

3.1 Steam consumption

The steam consumption for the reviewed case studies represent the space heating since the chilled water and electricity consumptions account for the space cooling and daily electric use of the building, respectively. Normalization of the steam consumption with respect to the outdoor condition provides the building response to the outdoor condition. Fig. 3 shows a comparison between two representative buildings located at Penn State and Harvard campuses for years of 2009 and 2010. The represented buildings are 1P (a classroom/office building) for Penn State and 7H (a lab-mixes building) for Harvard campus. In these particular buildings, the steam consumptions are correlated with the outdoor air temperature. It is worth to note that although the Harvard building is classified as a laboratory mix building, the results are similar to building 1P at Penn State campus. This steam consumption patterns suggest the operation schedules and internal loads have a lower influence level on the steam use patterns of these two representative buildings compared to the outdoor conditions.

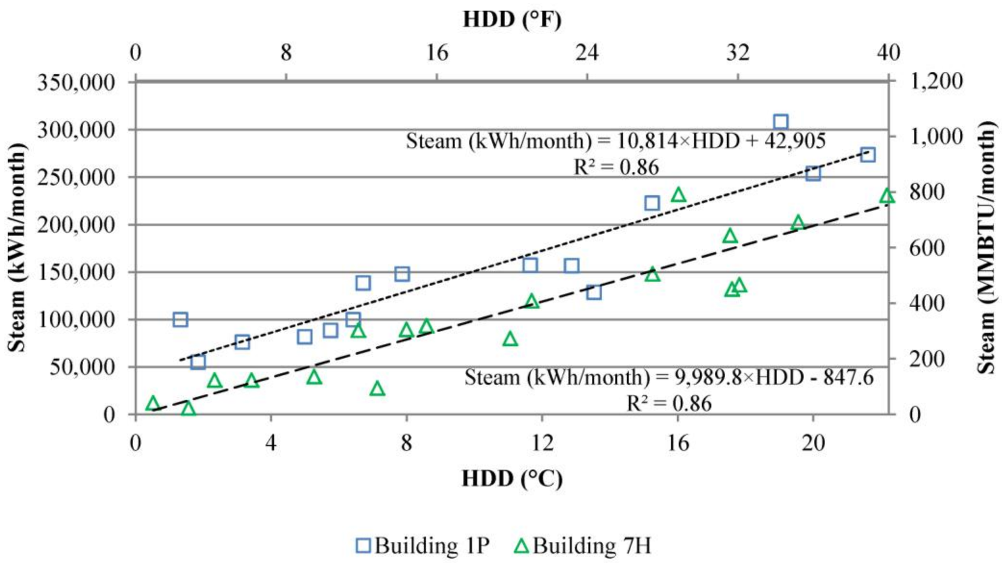


Figure 3. Normalized monthly steam consumption for building 7H at Harvard Campus and building 1P at Penn State Campus for years of 2009 and 2010

These results of normalizing the steam consumptions with the outdoor condition confirm possibility of using linear regression to normalize the steam consumption of buildings with outdoor air temperature or HDD for most of the studied buildings during a heating season. Based on the developed linear regression model, with most of the buildings at Penn State and Harvard campuses, there is a positive correlation between steam consumption and HDD. The results confirm that the building energy requirements during the heating season are strongly related to outdoor weather conditions, while other factors have a minimal effect.

Existing research studies show that outliers can greatly reduce the linear regression fit for the linear regression modeling of building energy consumption [38]. Therefore, two coefficients, including coefficient of determination (R^2) and Coefficient of Variation (CV), need to be used to predict whether a building is externally-load, mixed-load or internally-load dominated. Specifically, R^2 greater than 0.65 with CV less than 7% shows that a building is externally-load dominated for the normalized commodity. Furthermore, a building with R^2 greater than 0.4 and smaller than 0.65 with CV lower than 15% is a mixed-load dominated building. Finally, those buildings that cannot be modeled with the linear regression are internally-load dominated buildings. To illustrate this classification, Fig. 4

shows the CV with the R^2 for Penn State and Harvard buildings. Specifically, Fig. 4 shows results for the proposed classification system, based on the normalized steam per volume, applied to different campus buildings. As expected, the buildings can be categorized into externally-load dominated, mixed-load, and internally-load dominated:

(1) Buildings with $R^2 > 0.65$ are externally-load dominated (46% of buildings). Most of the buildings during heating seasons are externally-load dominated.

(2) 42% of buildings within the Penn State campus during the heating season are classified as mixed-load building. In these buildings, both external and internal loads have the same order of magnitude.

(3) 12% of the buildings are internally-load dominated during the heating seasons.

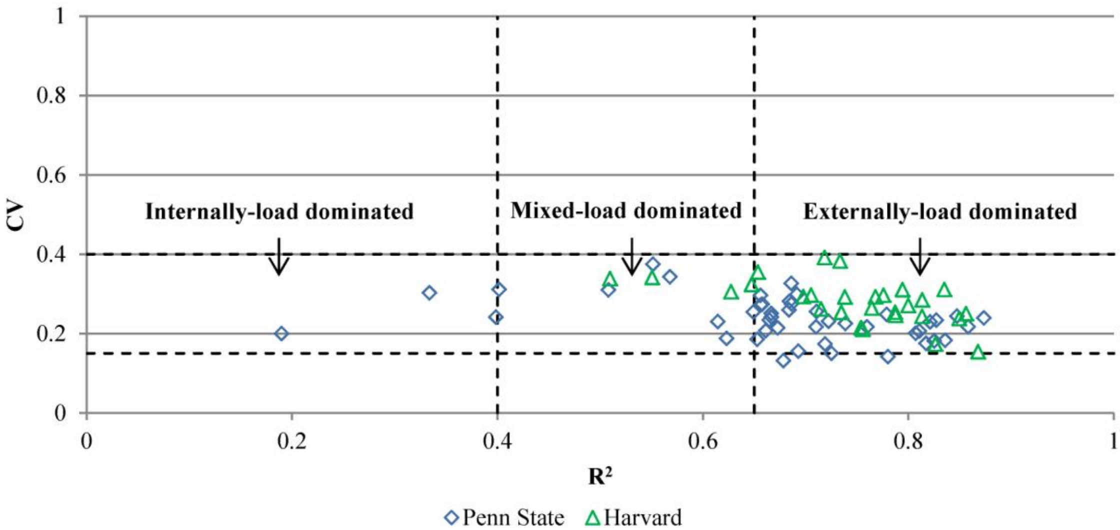


Figure 4. CV and R^2 for the Penn State and Harvard buildings based on the combined heating and cooling season method

Another approach benefits from the consideration of daily consumption to reduce the noise associated with the 15-minute (or hourly) interval data. As an example, Fig. 5 shows the normalized daily and hourly steam consumption for a classroom/office building. While Fig. 5(a) and (c) depict the averaged normalized daily steam consumption with averaged daily outdoor air temperature, Fig. 5(b) and (d) illustrate the averaged normalized hourly steam consumption with averaged hourly air temperature. The steam consumption normalized with outdoor air temperature shows more clear trend with the daily data than the hourly data. Fig. 5(c) shows that there are a few daily anomalous results for which the steam consumption is close to zero during warm days in the heating season or readings out of the meter accuracy. For this specific condition, the linear regression study did not consider the zero values. Only in these special few cases, the steam consumption is not correlated to the outdoor air temperature, but the rest of the data exhibits a strong correlation. Overall, the results show that the daily consumptions have a higher correlation to the outdoor condition than the hourly consumptions.

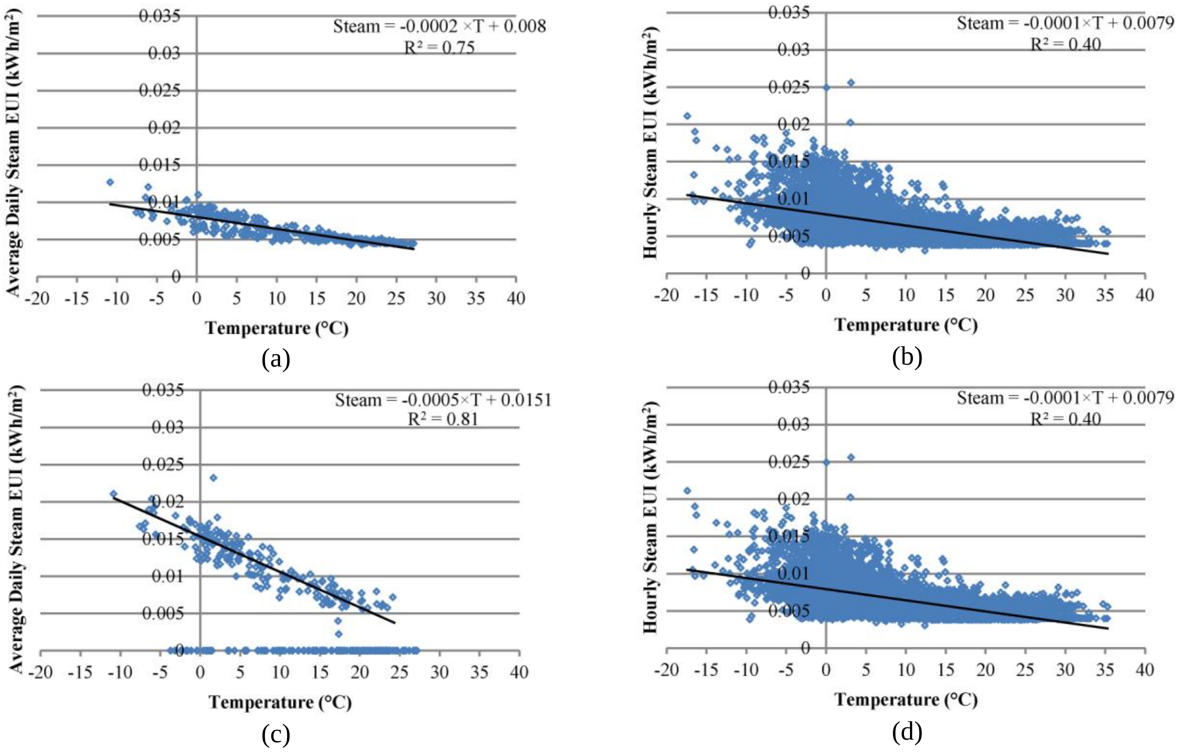
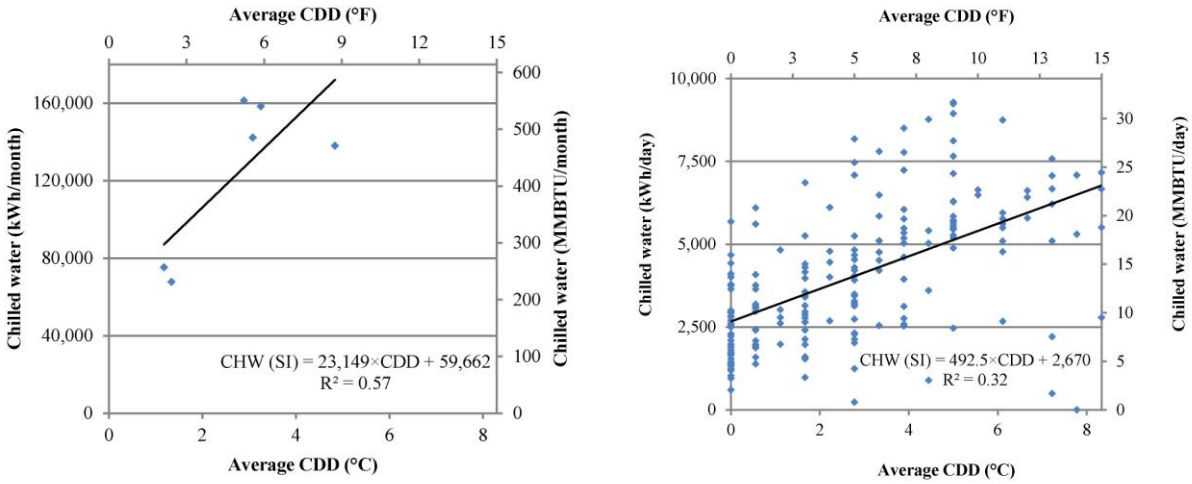


Figure 5. Normalized steam consumption for building 1P at Penn State Campus for 2009 and 2010: (a) daily 2009, (b) hourly 2009, (c) daily 2010, and (d) hourly 2010 normalized steam consumption

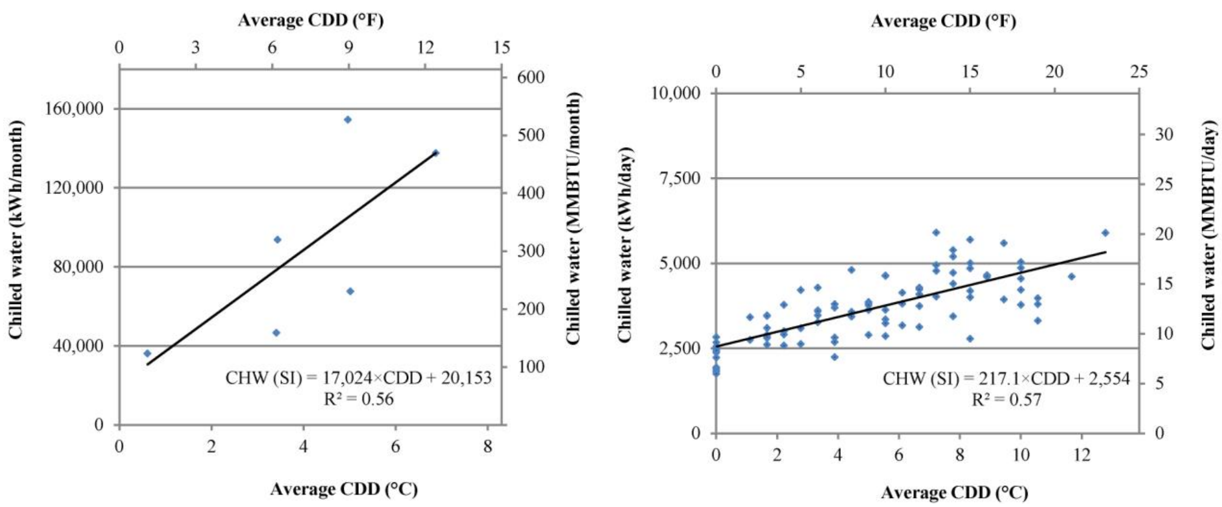
3.2 Chilled water consumption

Chilled water consumption for the selected campus buildings serve as the cooling end-use of the building. It is expected to observe that chilled water only being used in the cooling seasons, meaning only three months during summer. In contrast to the monthly steam consumption of the reviewed buildings, the monthly consumption is a function of both outdoor conditions and the operation schedules. The monthly chilled consumption during the cooling season is not as strongly correlated to the outdoor weather. Fig. 6 shows chilled water consumption at Penn State campus for monthly and daily chilled water consumption and associated CDD. For this particular building, 1P, functionally categorized as a classroom/office, the chilled water consumption and CDD are poorly correlated for 2009. The daily chilled water consumption and outdoor air temperatures have a better correlation in 2010. Fig. 7(a) and (b) confirm this pattern at Harvard campus. Overall, most of the buildings at both campuses have a similar relationship with CDDs.



(a) (b)

Figure 6. Normalized daily and total monthly chilled water for building 1P at Penn State campus during 2009 and 2010: (a) monthly, and (b) daily averaged data



(a) (b)

Figure 7. Normalized daily and total monthly chilled water for building 7H at Harvard campus during for 2009 and 2010: (a) 2009 and 2010 monthly, (b) 2010 daily averaged data

Fig. 8 summarizes results of the CHW data normalization with different CDDs. Fig. 8(a) illustrates the correlations between chilled water consumption and CDD10 based on the dew point. Among the figures, the CDD10 based on the dew point show the least correlation. Fig. 8(b) shows the chilled water consumption correlation with CDD10, and it provides a higher correlation compared to CDD10 based on the dew point temperature. Fig. 8(c) and Fig. 8(d) suggest the CDD18.3 and CDD18.3 based on the sol-air temperature have better correlation to the chilled water consumption compared to the other CDD methods. Among the CDDs, sol-air based CDDs provide a slightly better prediction than other CCDs. However, in general, monthly CHW consumptions are not strongly correlated with the CDDs. Therefore, roughly 50% of the buildings at Penn State campus are internally-load dominated during the cooling season based on the monthly energy and weather data. Furthermore, results for Harvard campus buildings confirm that the internal loads are dominant in defining the cooling energy requirements. Specifically, 36% and 14% of the studied Penn State and Harvard buildings are mixed-load and externally-load dominated based on the monthly CHW consumptions, respectively.

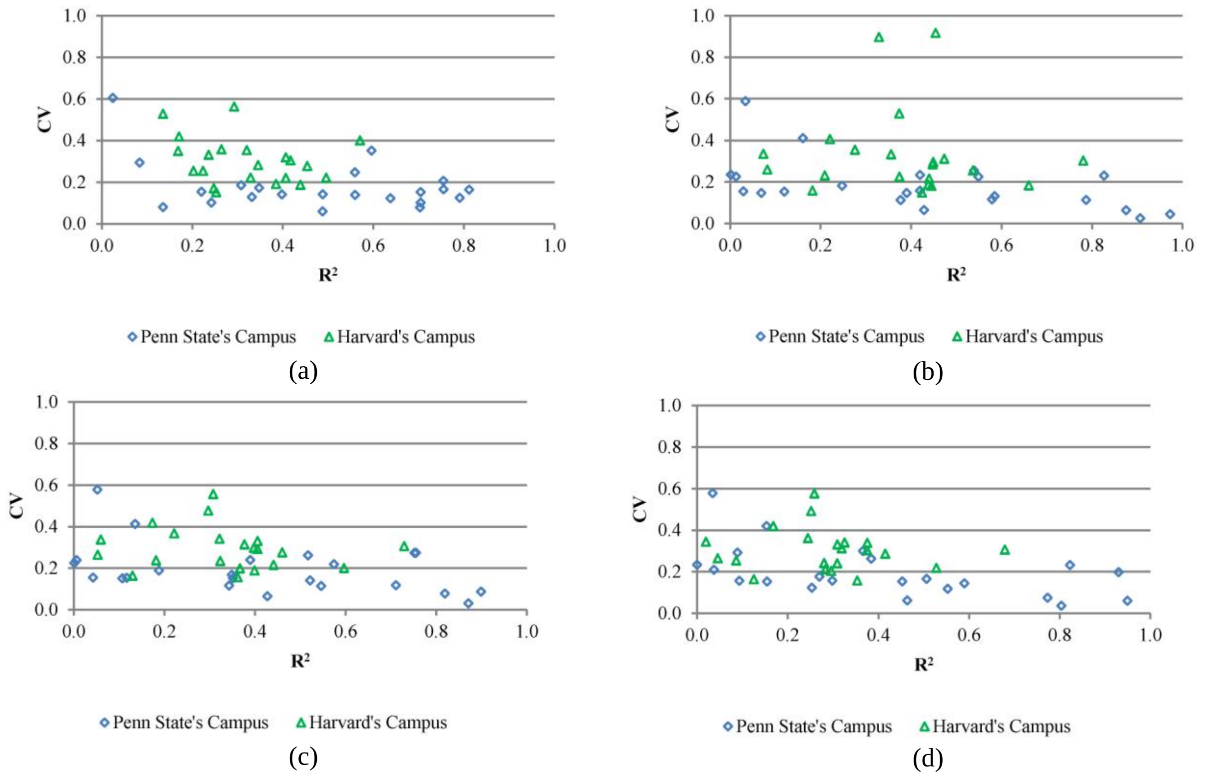
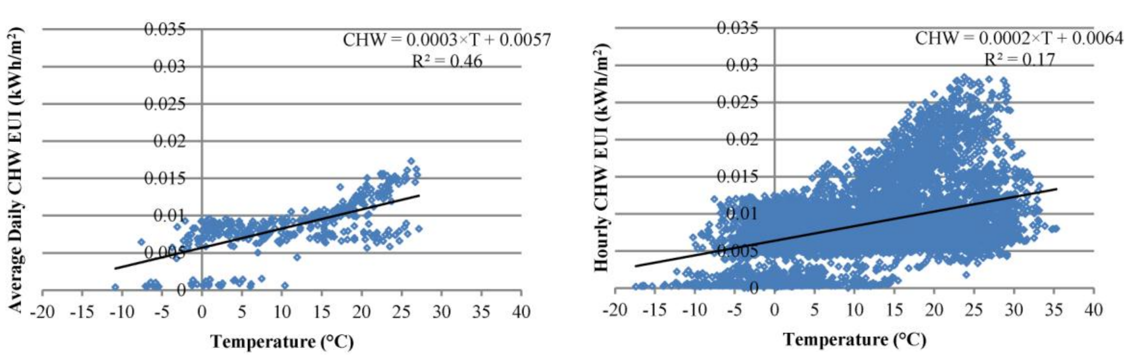


Figure 8. CV and R^2 for the Penn State and Harvard buildings: (a) CDD10 based on dew point based, (b) CDD10, (c) CDD18.3, and (d) CDD18.3 based on sol-air temperature

To summarize the chilled water consumption patterns, it is important to notice that there are factors that affect the energy use patterns of campus buildings during the cooling seasons. Specifically, a comparison of 15-minute and daily chilled water consumption indicate that the daily consumptions could provide a better measure for the inverse building energy modeling. Among the 78 buildings, 10 buildings have 15-minute chilled water consumption. The averaged 15-minute data are considered in the span of daily and monthly consumption levels to assess the impact of data granularity on the correlations. Fig. 9 illustrates distribution of 15-minute (or hourly), and daily normalized chilled water consumptions with averaged outdoor air temperatures. Fig. 9(a) and Fig. 9(b) depict daily and 15-minute chilled water consumption versus outdoor air temperature. The linear regression for the daily consumption provides a better correlation than the 15-minute chilled water consumption. Fig. 9(c) and Fig. 9(d) provide daily and 15-minute chilled water consumption for a building that has a baseline chilled water consumption. The chilled water consumption baseline is due to the laboratory need in the building. For this case, a fixed baseline with the linear regression show a strong correlation between the chilled water consumption and outdoor air temperature.



(a) (b)

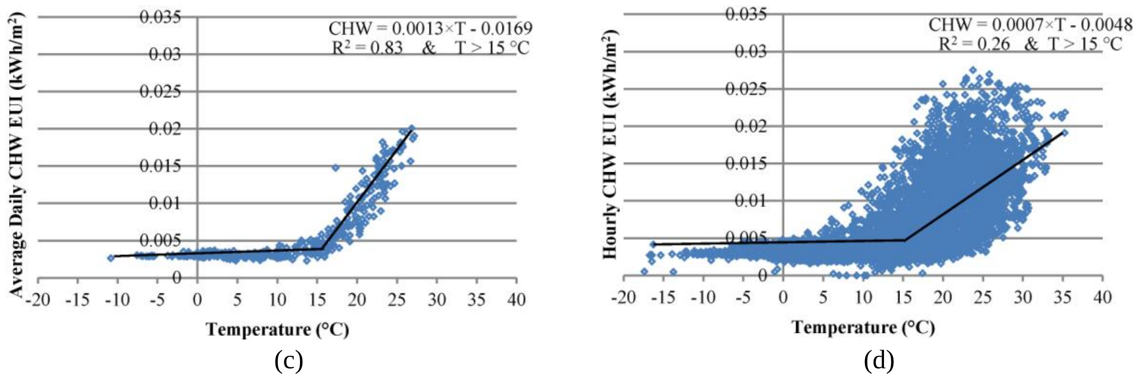


Figure 9. Influence of the normalized CHW consumption with different level of granularity during 2009 and 2010: (a) daily 2009, (b) 15-minute 2009, (c) daily 2010, and (d) 15-minute 2010 data

Although 15-minute (or hourly) and daily data have a stronger correlations with the outdoor air temperatures, the access to 15-minute (or hourly) as well as daily utility data is limited for a majority of existing buildings. Utility bills usually provide monthly consumptions, and existing benchmarking tools, such as Portfolio Manager, require submitting monthly energy consumptions [39]. Until availability of utility data with finer granularity for the majority of existing buildings improves, it is reasonable to develop analysis methodologies based on monthly energy consumptions.

This study also observes that for the chilled water consumption during summer, there is different schedule for weekdays and weekends. Fig. 10 illustrates a comparison between weekdays and weekends for a Lab Mix building. Therefore, using average monthly chilled water consumption in the analysis leads to poor correlation of the average chilled water consumption with the monthly CDDs. Therefore, a separation of weekdays and weekends correlations could improve the correlation. Furthermore, recently constructed campus buildings, specifically office areas, usually benefits from free cooling using economizers to save energy when outdoor conditions allow the use of this energy saving strategy. However, the research laboratories and lab buildings often contain servers and specific laboratory equipment that need to be continually ventilated and/or cooled. Therefore, for some buildings or building zones, HVAC systems use return air instead of outdoor fresh air. Overall, in these two university campuses due to cold winter and humid summer conditions, the fraction of return air to supply air, is relatively high in majority of the buildings to save energy.

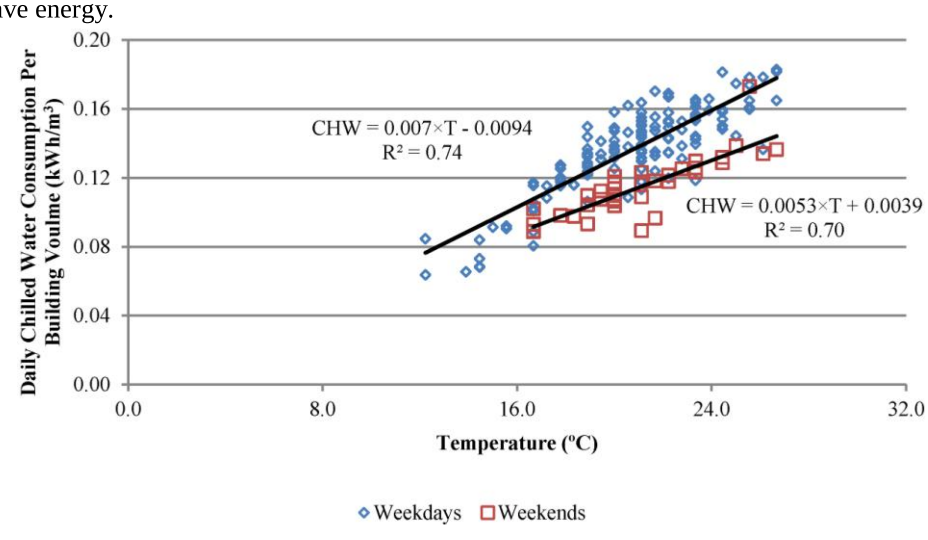


Figure 10. Daily chilled water per building volume for a Lab Mix building for weekdays and weekends

Another important factor for CHW consumption is the operation schedule changes. The HVAC systems utilize sensors and associated controller to automatically HVAC systems. However, in many buildings, the occupants or building managers changed the HVAC system setpoints. Occupants or building managers usually fine tune the HVAC temperature setpoints based on the occupants' feedback to provide a thermally satisfactory indoor environment. Recent studies show that human behavior is an important factor for the energy consumption of buildings [40]. For some buildings, occupant presence is obviously detectable, suggesting that some of the campus buildings benefited from the demand control strategies. For instance, after August 11 in 2010, there is a significant increase in chilled water consumption even though there is no detectable weather change (Fig. 11). In this case, it is worth noting that, for some universities, mid-August is the orientation period in which the university formally opens its doors to new and returning students.

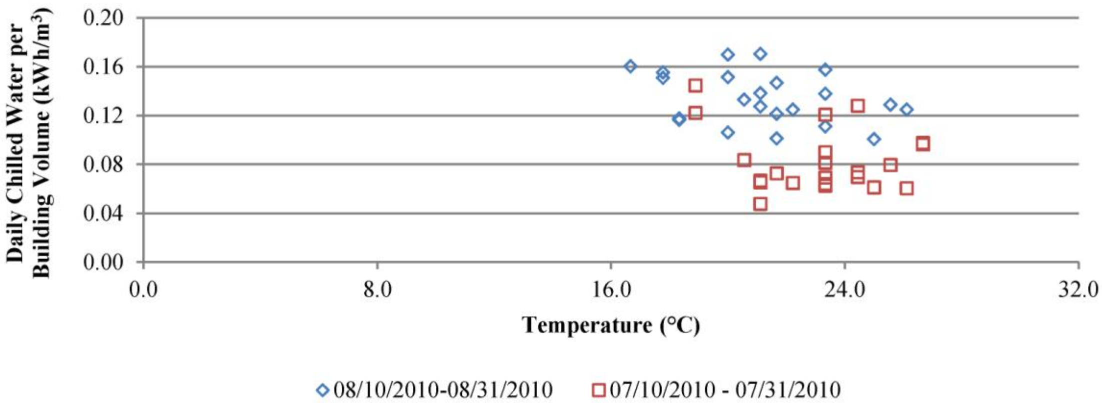


Figure 11. Daily chilled water per building volume for an Office/Classroom building for two different time periods

3.3 Electricity consumption

For campus buildings with available chilled water and steam consumption data, electricity consumption can identify the internal load density and schedules. As an example, the normalized electricity consumption per building area could represent a metrics to classify building internal loads [40, 41]. Many university campuses in the U.S. have publically accessible databases to provide the electricity consumption in different campus buildings. These databases can serve as a starting point to estimate the internal loads. Furthermore, current building compliance codes, e.g. ASHRAE Standard 90.1, or recommendations for the building energy modeling, e.g. DOE Reference Buildings, provide inputs for the estimations of the building internal loads, including lighting and plug loads [3, 42, 43]. A weighted average of the expected lighting and plug load densities with the space distribution from the campus building electricity consumption could identify whether the current assumptions for the building space type distribution is valid or not. Eq. (5) illustrates a weighted average lighting power density (LPD) for the campus buildings. Similarly, it is possible for the plug-loads, to derive a similar correlations [40].

$$LPD = \frac{\sum_{i=1}^{n} LPD_i \times W_{area,i}}{\sum_{i=1}^{n} W_{area,i}} \tag{5}$$

In Equation (3), LPD_i is the lighting power densities for the space "i", $W_{area,i}$ is the percentage of the area, and LPD is the overall lighting power density of the building.

The electricity consumption for campus buildings usually follows the building occupancy rates, suggesting that there are different occupancy periods for the buildings. Campuses usually have different occupancy rates during fall semester, spring semester, spring break, winter break, and any specific holidays. If the building total energy consumption is correlated with occupancy rates, it suggests that the building is internally-load dominated or “scheduled-dominated”. Therefore, as a starting point, one approach is to interpret the electricity consumption of the university buildings is to determine the variation of electricity consumption during summer and winter seasons. Eq. (6) provides this correlation.

$$ElecRatio_{\frac{Sum}{Win}} = \frac{Elec_{sum,3months}}{Elec_{win,9months}} \tag{6}$$

In Eq. (6), $Elec_{sum,3months}$ is the averaged summer electricity consumption, and $Elec_{win,9months}$ is the averaged winter electricity consumption.

Table 4 summarizes the result of statistical analyses for the ratio of electricity consumption per month during summer time to winter time. The results in Table 4 illustrate that there is little variation between summer and winter electricity consumption per month. A 95% confidence interval for Penn State and Harvard campus buildings shows that for the majority of buildings in both campuses the operation schedule of equipment and lighting do not change significantly over summer and winter seasons. This stable electricity consumption per month during heating and cooling seasons indicates that there are opportunities to retrofit existing buildings by deploying energy saving measures, such as relying more on daylight during the summer season to save electricity consumption.

Table 4. Statistical analyses for the ratio of summer to winter per month electricity consumptions

Campus	Min	Mean	Median	Standard Deviation	Max	95% Confidence Interval
Penn State	0.80	0.99	0.99	0.11	1.34	(0.95 , 1.03)
Harvard	0.62	0.94	0.95	0.17	1.42	(0.89 , 1.02)

Considering buildings with highly granular electricity data, e.g. interval 15-minute or hourly, could provide additional insights about the operation schedules of the buildings. Fig. 12 illustrates the 15-minute electricity use patterns of two representative buildings, one with flexible (Fig. 12(a) and Fig. 12(b)), and another with fixed operation schedules (Fig. 12(c) and Fig. 12(b)). The building with flexible operation schedules has the starting and ending of the peak electricity consumption at different times of a day. However, majority of the buildings have a fixed operation schedules with predictable time periods of the peak electricity consumption. A practical approach for the building controllers is to benefit from reasonable building operation schedules. The benefit of using flexible building operation schedules allow to reduce the electricity consumption and benefit from daylight when it is possible. In addition, based on the building occupancy, lighting fixtures could benefit from the occupancy or vacancy sensors. Not all building can use the flexible operation schedules since it requires the building to have programmable building management system (BMS). Therefore, one practical solution for the retrofit of campus buildings need to utilize flexible building operation schedules.

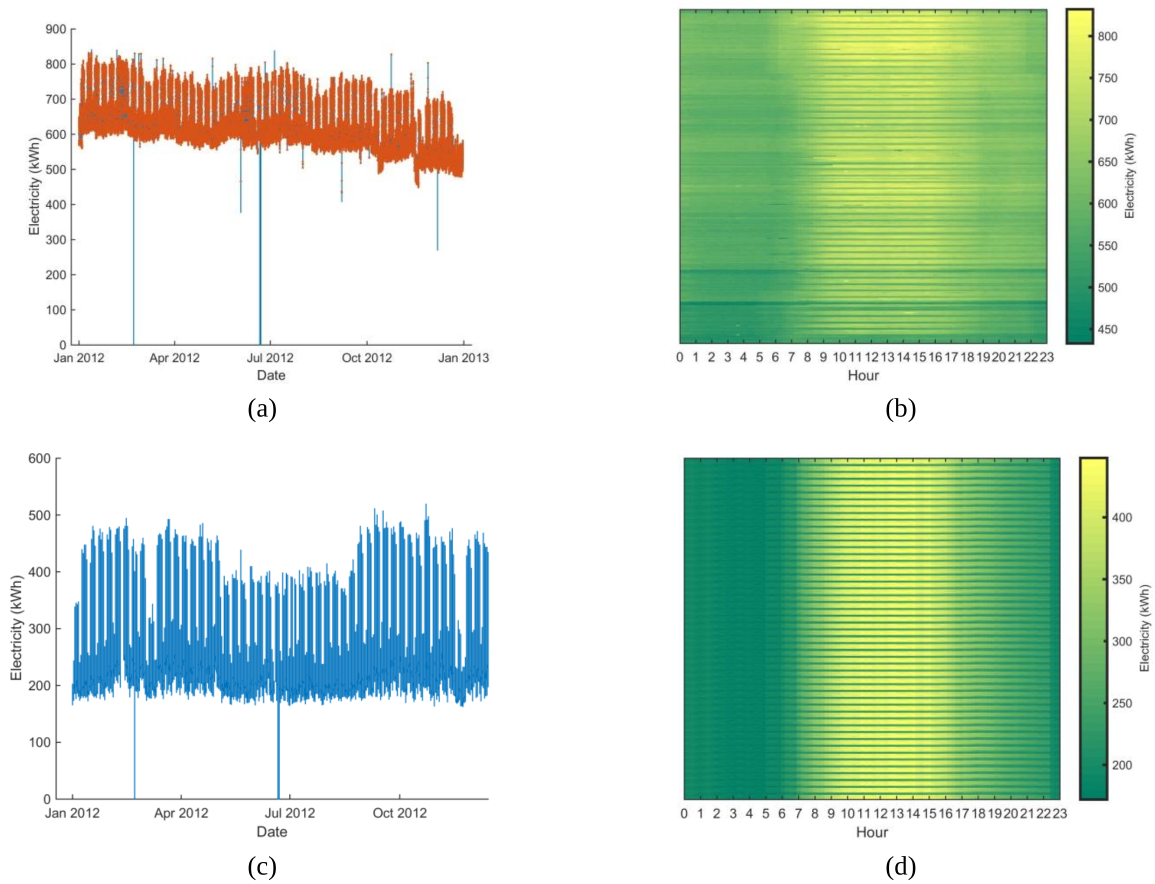


Figure 12. Electricity use patterns of two different buildings, one with a flexible operation schedule and one with fixed operation schedule: (a) hourly interval data, and (b) heatmap for the building with a flexible operation schedule, as well as (c) hourly interval data, and (d) heatmap for the building with a fixed operation schedule

To further understand the variation of the electricity consumptions over time and enable analyses of building retrofit options, it is vital to see how the electricity consumption changes for each building space type. In terms of building principal activity, 83% and 66% of classroom/office and office buildings, respectively, have lower summer electricity to winter electricity consumption ratios with the 95% confidence interval, meaning there is less electricity consumption during summer for these two space types. These lower summer electricity consumption to winter electricity ratios for classroom/office and office buildings may originate from scheduling fewer classes and using more daylight in summer season. Furthermore, 66% of lab mix buildings are within the 95% confidence interval of the summer to winter electricity ratio. Closeness of the mean and median for the summer to winter electricity ratio indicates that there is no significant variation in the electricity ratio for the majority of buildings. Therefore, the results of the electricity use pattern analyses show that there are opportunities to benefit from the plug load management or daylight to reduce the electricity consumption when the building is not fully occupied.

Not only the results of normalized electricity consumptions with the area show no significant changes over cooling and heating seasons, the results of electricity consumptions over multiple years do not suggest substantial changes over years. The local weather data, usually representing the independent variables in the normalization, could show whether the energy use pattern is a function of outdoor air conditions or not. Fig. 13 represents the distribution of CV of electricity consumptions for both studied campuses for five primary space types. All of the space types have a median of CV less than 0.10, representing less than 17.0 kWh/m^2. Among the five primary space types, Residential Facilities have less variation in their energy consumption patterns compared to the other campus building types. This observation contradicts the fact that electricity consumption for the residential facilities should have direct correlation with the university schedule. Therefore, this suggests that the changes in electricity consumption over three years are not significant and for these buildings, electricity consumptions are independent of the outdoor conditions.

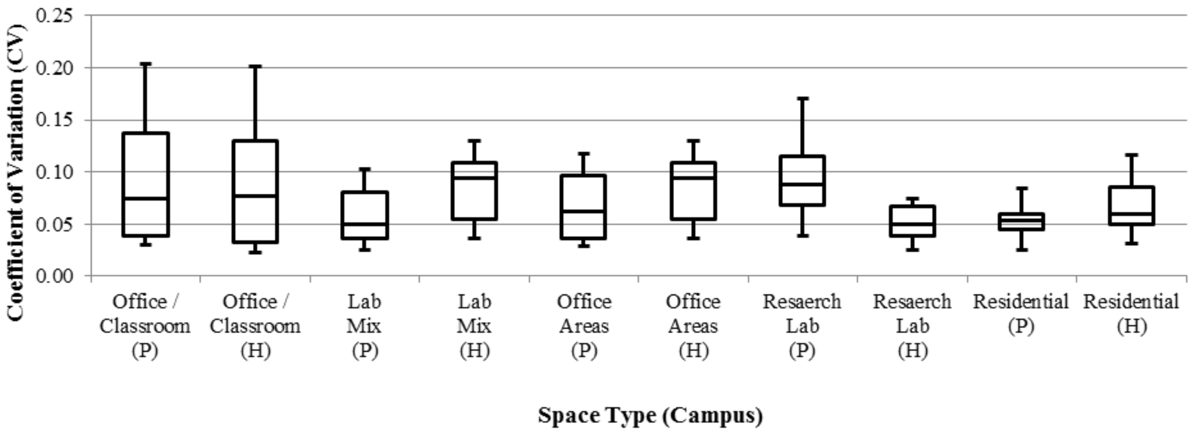


Figure 13. CV of electricity consumptions for different space types for both campuses

Overall, for campus buildings, electricity consumptions are usually available in the form of 15-minute interval data. However, depending on the type of meters and campus energy management strategies, there is a limited availability of steam and chilled water consumptions. Considering the installation cost of the 15-minute sub-metering systems, this study proposes using sub-meters with lower sampling rates to measure daily energy use. Currently, benchmarking efforts do not consider tradeoffs between the level of sampling rate and the implications of such datasets for analyses of building energy use patterns. Based on this study's data collection efforts, it is important to note that it is unprecedented for a campus building energy management system, or even any building energy management system, to simultaneously collect interval energy data for all energy commodities. Majority of the building energy datasets only contain interval electricity consumption. Therefore, the acquired dataset and its breadth / depth are unique.

Overall, for the reviewed campus buildings located in the Northeastern U.S., a monthly steam, daily chilled water consumptions, and 15-minute electric energy consumption could significantly (i) improve the accuracy of the building energy simulations, (ii) provide opportunities to benchmark campus buildings based on their energy use patterns, and (iii) support facility managers and sustainability programs in the efforts to reduce campus energy and carbon footprints.

4. Implications of the energy analyses for calibrated campus energy models

This section demonstrates the benefits of using the developed classification to calibrate campus building energy models. Since the heat transfer through the building envelope and systems is transient, energy simulation tools could capture the dynamic performance of buildings [44, 45]. Energy simulation presumably provides detailed energy end-uses compared to the inverse models. However, the complex nature of the building energy consumption patterns, render the calibration of the energy models very difficult. The aim of this section is to facilitate the calibration process of building energy models using building energy consumption patterns for classification. One campus building at the Penn State campus serves as the case study to create the building energy models and deploy the results to demonstrate the implications of the energy analyses for the calibrated energy models. For this case study, the total energy consumption pattern response of the building is a function of the steam, chilled water, and electricity response to internal and external conditions.

This study suggests creating the baseline building energy model using recommended inputs based on the current standard recommendations. For example, ASHRAE 90.1 2007 recommendations is served as a starting point for the inputs in these building energy models. Actual Meteorological Year (AMY) 2010 from a local weather station is utilized as an input in energy models. The weather data applied to each model is from the same year the actual energy consumption data is being collected. Activity, construction, opening, lighting, and HVAC are additional inputs in the model using ASHRAE Standards 62.1 and 90.1 as guidelines for occupant density, ventilation rate, and internal load estimation. To facilitate the creation of building energy models, it is recommended to use a bulk HVAC system representation. This approach enables annual whole building energy simulation for a large number of buildings within a short period of time, while considering a minimum number of inputs.

Using the steam, chilled water, and electricity consumption pattern classification in this study allows to calibrate the building energy model to meet the requirements of ASHRAE Guideline 14 for monthly CVRSME less than 15% and NMBE less than 5% [46-48]. Fig. 14 compares cooling, heating, and electricity consumption comparisons between the simulated model and actual consumption data. It is vital to note that for buildings with unique energy consumption patterns, e.g. campus buildings, there is a need for additional inputs from walk-through surveys to collect data such as setpoint temperatures and actual lighting density. Steam consumption patterns at the monthly level indicates an externally-load dominated building during winter while the cooling consumption patterns for the chilled water shows a mixed-load dominated. As Fig. 14(a) illustrates the electricity consumption at the monthly level has similar pattern. Overall, use of the building energy consumption classification enables the modeler to create accurate estimation for the building energy consumption.

Comparisons between the simulated and actual building energy consumption patterns shown in Fig. 14 confirm that the energy consumption pattern of campus buildings is unique due to the energy intensive demand and specific need of the building throughout the entire year. The results suggest that there is a need for additional inputs to improve the simulation results. A demonstration of this bulk energy simulation modeling requires consideration of key inputs specially during the shoulder months for the heating and cooling consumptions [17]. For this simulated case study, the electricity and chilled water consumption patterns meet the requirement of ASHRAE Guideline 14, while the steam consumption during the summer requires additional inputs. The electricity consumption patterns show that the model was able to capture the plug and lighting loads. The CHW consumption for this building energy simulation model requires additional inputs during the shoulder months or in July when the building is not fully occupied. Inputs from the zone temperatures and adjusting the building occupancy during July could provide a well-calibrated CHW consumption for this building. This study considered this building to demonstrate the challenges of modeling campus buildings specifically buildings with steam consumption. As Fig. 14(c) illustrates a baseline in the buildings is present during the summer time. In addition, during shoulder months, the zone temperatures were higher than the expected values. Access to the zone temperature during shoulder seasons, zone reheat temperatures for the variable air volume (VAV) boxes, and the laboratory baseline consumption could have provided a well-calibrated model for the steam consumption. Overall, for campus buildings, key features in the calibration of the campus building energy simulations are consideration of (1) specific need for the research laboratories, (2) outdoor air requirements, (3) high steam consumption during the summer seasons, and (4) high chilled water consumption during winter seasons.

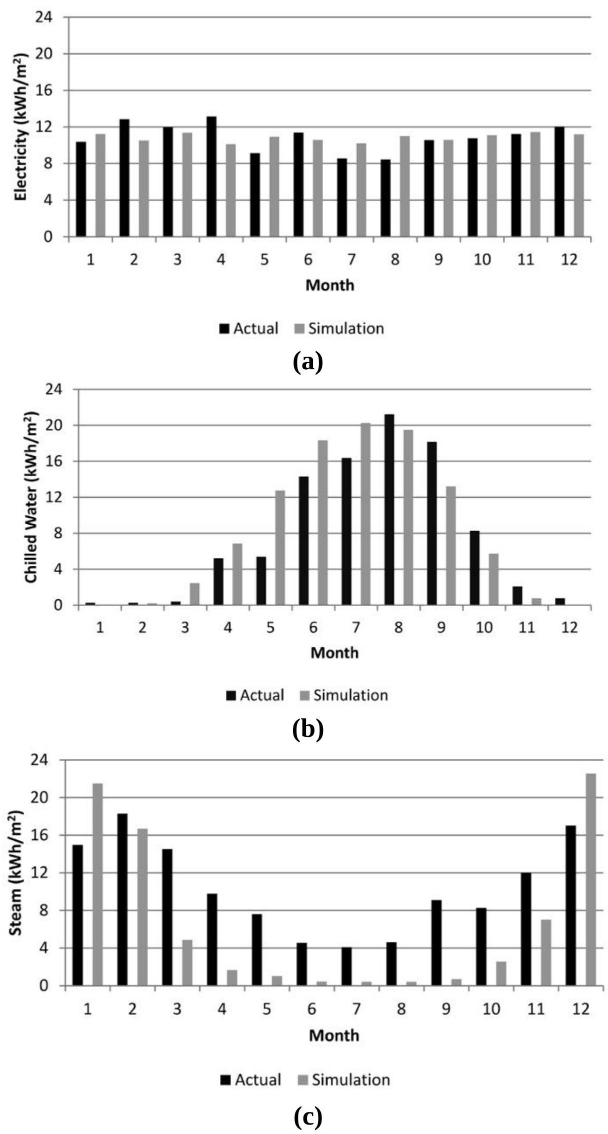


Figure 14. Energy end-uses for cooling, heating, and electricity for one of the simulated buildings: (a) electricity, (b) chilled water, and (c) steam consumptions

Conclusions

Penn State and Harvard campus buildings served as testbeds to develop a building energy consumption pattern classification. The seventy-eight reviewed campus buildings have monthly chilled water, electricity, and steam data. This study developed a building energy consumption pattern classification to categorize buildings based on building energy consumption patterns, rather than describing a building's occupancy type. The outcomes of this classification is to enable performing energy modeling analyses for a building stock, such as a large number of buildings located within an entire university campus or an urban neighborhood. Based on their energy consumption patterns, the reviewed campus buildings are classified into externally-load, internally-load, or mixed-load dominated. The energy consumption of the internally-load buildings is primarily a function of the internal loads and their schedules. Externally-load dominated buildings tend to have an energy consumption pattern that is a function of building construction materials and outdoor condition. This classification has implication for benchmarking, analyzing, and modeling campus buildings.

The normalized steam consumption for the selected campus buildings located in the Northeastern part of the U.S. is highly correlated with outdoor condition. Specifically, 88% of the reviewed buildings are externally-load or mixed-load dominated during heating season. The results of this study also showed that the chilled water consumption of buildings during the cooling season is correlated with the operation of the building management system (BMS). Chilled water consumption for 50% of the reviewed campus buildings are mostly internally-load dominated, rather than externally-load dominated.

This study also assessed granularity of the building energy commodities for benchmarking the reviewed campus buildings or providing recommendations for building energy simulation strategies. Consideration of 10 campus buildings with interval 15-minute steam, chilled water, and electricity consumptions at the Penn State campus enabled this study to assess implication of different level of energy consumption granularity. The results of this assessment for the reviewed buildings suggested that with the consideration of tradeoffs between the cost of measurements and data analysis needs, it is recommended to collect the steam consumption at the monthly level, chilled water consumption at the daily level, and electricity consumption at the hourly level. In addition, this study provided implication of the reviewed energy consumption patterns for the building energy modeling. With the consideration of additional inputs, e.g. zone temperatures and setpoint temperatures especially during shoulder months, the developed framework in this study offers a practical method to create a well-calibrated building energy model. Overall, this study showed the implication of the developed classification for an example of campus building energy simulation. Due to the observed energy consumption patterns of the campus buildings, there is a need to carefully consider: (i) specific need for the research laboratories, (ii) outdoor air requirements, (iii) high steam consumptions during the summer seasons for the zone reheats, and (iv) high chilled water consumptions during winter seasons.

Nomenclature

Symbols		*Abbreviations*	
D	Material roughness coefficients	AMY	Actual Meteorological Year
E	Material roughness coefficients	ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
F	Material roughness coefficients	BMS	Building Management System
h	The external surface heat transfer coefficient [m^2/W]	CBECS	Commercial Building Energy Consumption Survey
I	The total solar radiation incident on the surface [W/m^2]	CHW	Chilled water
R^2	Coefficient of determination	CDD	Cooling Degree Day
ΔR	The net radiation exchange	CV	Coefficient of Variation
T	Temperature [°C]	DOE	The U.S. Department of Energy
		EEM	Energy Efficiency Measure
Subscripts		EUI	Energy Utilization Index
o	Outdoor	FICM	Facilities Inventory and Classification Manual
sol-air	Soil-air	FTE	Full Time Employee
z	Elevation	GFA	Gross Floor Area
		HDD	Heating Degree Day
Greek symbols		HVAC	Heating, ventilation and air-conditioning
		LPD	Lighting Power Density
α	The surface solar absorptance [-]	RECS	Residential Energy Consumption Survey
ε	The surface emittance [-]	VAV	Variable Air Volume

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