Leveraging benchmarking datasets to Identify Energy Efficiency Opportunities in Existing Buildings

Erica Cochran, Flore Marion, Zoe Kaufman, Tim Spencer, Hetal Parekh,
Carnegie Mellon University

ABSTRACT

Energy benchmarking data at a citywide scale is now publicly available in several cities across the US. Such datasets allow us to examine in detail buildings' energy consumption patterns and how individual buildings compare to their peers. This information has the potential to influence investment decision-making and future energy-use.

This research examines the relationship between the physical attributes of buildings gathered through digital mapping sources and building visits, and their energy consumption patterns as acquired through Portfolio Manager, city-reported benchmarking data, and utility meters. Multiple sub-hypotheses regarding the connection between energy use and physical building attributes (e.g. envelope materials, shading devices, etc.) were tested for statistical significance using LEAN and new load dis-aggregation methods developed by an interdisciplinary team to analyze energy use data at various time steps (Kissock and Seryak 2004) .

These cutting-edge statistical algorithms can be applied to any benchmarking dataset available, in order to extract building specific information that will guide energy efficiency decision processes. An example of the resultant findings is that buildings that have less than 25% of their lights on at night, spend on average 32% less on the total lighting, which corresponds to $32,500 savings per year in utility costs for an average 100,000 ft2 office building.

This paper presents the methodologies and results of this new approach, and how it could be used to better target retrofits of existing buildings by particular building attributes or neighborhoods, or used as design guidelines for new construction of buildings within the geographic scope of this research.

Introduction

In the United States and in Europe, buildings account for more than 40 percent of total energy use (EIA 2012). In both cases, governments provide energy tracking and benchmarking tools to help building owners assess their energy performance. In the U.S., ENERGY STAR Portfolio Manager, was developed by the U.S. Environmental Protection Agency (EPA) as an online tool for building owners to voluntary manage energy use in buildings. This tool is quickly becoming the reference standard across the U.S. for building benchmarking, with 14 cities now using ENERGY STAR Portfolio Manager to implement their benchmarking policy. Buildings can receive an ENERGY STAR score ranging from 1 to 100, which compares the building to other buildings nationwide that have the same property type (ENERGYSTAR 2016). A score of 50 points represents median energy performance while a score of 75 points indicates that the building perform better than 75% of its peer group. Those buildings scoring more than 75 points are eligible for ENERGY STAR certification. Since the launch of Portfolio Manager in 1992, more than 27,000 buildings and plants have been ENERGY STAR certified (EPA 2016a).

ENERGY STAR Score is calculated using EUI, and controls for many factors input into Portfolio Manager that are not retrievable in benchmarking data. Although EUI, as used here, could be controlled for building age, use type, and location, ENERGY STAR Score additionally controls for occupancy, number of desktop computers, fuel mix, weather, and operational attributes like schedules and setbacks - a major confounding factor found in CBECS. Portfolio Manager does not release the information about number of occupants or number of computers for privacy reasons. Since factors like occupancy and plug loads can mask the impact of specific building attributes on energy consumption, comparison of two buildings based solely on EUI becomes nearly impossible. These controls make ENERGY STAR Score a useful metric for determining the influence on energy use of specific building attributes. In our dataset, ENERGY STAR Score was more frequently a significant dependent variable in annual data analysis than EUI. While some limitations with regard to the accuracy of the ENERGYSTAR score have been identified by other researchers; it was used in this analysis as it is the indicator currently adopted by many stakeholders (Scofield 2014).

Existing Identified Relationships between Building Attributes and Energy Use

With the increased availability of benchmarking data as well as the deployment of smart meters in the United States, more and more energy data is available publicly and to the building owners; allowing governments, energy utilities and building owners to be informed on energy profiles of buildings, individually or at a city scale. By adding building attribute data to this newly available energy dataset, this research investigates how certain building attributes could be indicators of high energy consumption.

In the past 20 years, researchers investigated whether various building characteristics could be directly linked to energy use with sometimes contradictory findings. The results of the 2003 Commercial Building Energy Consumption Survey (CBECS) shows that era built does affect the Energy Use Intensity (EUI), with buildings constructed between 1960 and 1989 having the highest EUI (EIA 2003). CBECS data also indicates that the newer buildings have lower heating EUI and higher cooling EUI, which may indicate the increased presence of insulation in newer buildings as well the popularization of air-conditioning (EIA 2003). However, in an analysis of annual data in New York, San Francisco and Seattle, David Hsu found no relationship between year built and EUI (Hsu 2014). A 2013 analysis of NYC buildings found that site EUI correlated directly with a building's gross square footage of floor area (City of New York 2014). A 2012 study found that building shape significantly affected energy use (Choi, Cho, and Kim 2012). The study classified new high-rise multifamily apartment complexes in Korea into two categories: "plate type" broad, flat buildings and "tower type" buildings with multiple branches in their floorplan, and found that tower type buildings used 48% more energy in total, but that plate type buildings use 10% more heating energy. Another study found that a 30% window-to-wall ratio (WWR) resulted in a 500 lux condition at the work plane for 76% of the year, and that the addition of on/off daylighting control systems given 30% WWR could reduce lighting energy by 77% and cooling energy by 16% (Tzempelikos and Athienitis 2007). Many recent studies have suggested that energy performance decreases linearly with WWR. Those results might differ because additional factors influence energy use. Some of those factors are difficult to collect without visit of the buildings or discussion with the facility managers, and are not yet often taken into account in the current research, such factors include occupancy schedule, occupant behavior, communication strategy with regard to energy use. As documented, the research correlating building attributes with energy is still limited and additional research is needed to collect more data on the relationship between energy and building attributes. While acknowledging the need to takes this additional factors into consideration in future work, this research focuses on analyzing data already available or easy to collect for the cities and utilities.

Through an interdisciplinary collaboration between multiple universities and industries, this research investigates new data mining and analysis techniques to identify statistically significant correlations between building attributes and energy consumption in existing buildings.

Methodology to Create New Energy Metrics

The team contacted office building owners in Philadelphia and Washington DC to obtain authorization to access and analyze their monthly and interval energy utility data. The utility bills were collected for 38 office buildings that met the benchmarking ordinances criteria either in Philadelphia and Washington DC and therefore had an ENERGYSTAR score. With this information, monthly and interval energy metrics were developed and statistical analysis were conducted for 3 granularity levels to try to find significance between building attributes and annual, monthly or interval metrics. The significant relationships that were identified can be used as a starting point for an analysis of a different set of buildings.

Metrics Based on Monthly Data

Monthly energy data was disaggregated into discrete energy end uses. From the large pool of data sets available, only those buildings were selected for analysis, which were either all electric, or for which both monthly electrical and monthly gas usage data was available. Moreover, buildings with anomalous energy data or occupancy patterns were also removed, leaving a total of 38 buildings in the first phase of analysis after the data cleansing process.

To disaggregate particular loads, LEAN analysis, was used with some modifications (Kissock and Seryak 2004). The LEAN methodology is most commonly used with a portfolio of buildings to distinguish between energy use patterns across the limited number of buildings in the portfolio, pointing to buildings that need the most attention and areas in which each building can improve (Donnelly, Kummer, and Dees 2013). For this analysis, an inflection point between heating-dominated and cooling-dominated seasonal loads was used instead of separate breakeven temperatures to acknowledge residual heating and cooling that occur in reality, often simultaneously, as illustrated in Figure 1.

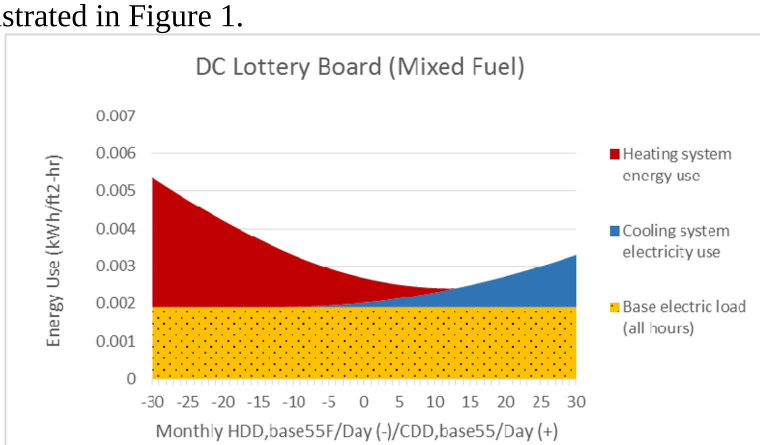

Figure 1: LEAN monthly graph for 1 mixed-fuel building

Another difference is that regression curves, rather than linear change point regression models, were used because individual heating and cooling season data points aligned best with quadratic equations rather than linear equations. For an easier visual comparison, all site energy was plotted on the same axis rather than separating heating and cooling regressions for mixed-fuel buildings based on the fuel type used. Henceforth this type of analysis will be called "LEAN Monthly" and will reference monthly analysis.

Monthly energy metrics must be calculated based on the LEAN-Monthly regressions, such as heating and cooling inflection points, LEAN-Monthly-derived baseload, LEAN-Monthly-derived heating load, LEAN-Monthly-derived cooling load, peak heating energy, and peak cooling energy. Heating and cooling inflection points denote the temperature, corresponding with the degree-day value at which the heating or cooling curve has a minimum.

Baseload is considered to be all energy use below the lowest point on the combined gas and electricity curve, the area of which is considered to be baseload electric use. This baseload also contains some HVAC energy baseload, but this cannot be separated from other baseload end uses in monthly data, and is not weather-dependent. Finally, heating season energy use area is calculated as the area between the heating season curve and the baseload curve, while cooling season energy use area is calculated as the area between the cooling season curve and the baseload curve.

Peak heating load is calculated as the y-value for the monthly energy use curve at the lowest temperature represented in the LEAN-Monthly graph. Peak cooling load is the y-value of the cooling curve at the highest temperature represented. These highest and lowest degree-days per day are constant for all buildings and are representative of the highest and lowest common temperatures occurring within the regions represented.

Metrics based on Interval Electrical Data Analysis (LEAN Occupied Hours)

Interval data allow us to break down the baseload previously identified with the LEAN-monthly methods. This baseload is the sum of a variety of end-uses including significant HVAC electrical use, which continues despite weather variations. This is primarily ventilation, but in some buildings may include significant amounts of cooling energy, particularly in buildings with data centers. In order to test the effect of building attributes on specific end-uses, it is valuable to break down this base load into as many separate loads as possible.

This method used the LEAN analysis methodology in combination with the ECAM tool developed by PNNL to disaggregate the loads. With interval electrical data, it is possible to dis-aggregate night, weekend, and holiday hours in order to better understand how energy use in occupied hours differs from total energy use. This also allows a more accurate understanding of weather-driven loads, as using the average temperature for a month, or even a day, can mask temperature swings which disproportionately contribute to energy use due to lower nighttime temperatures. Figure 2 illustrates how electrical use during occupied hours differs dramatically from nighttime, and how weekend and holiday energy use differ from weekday electrical use.

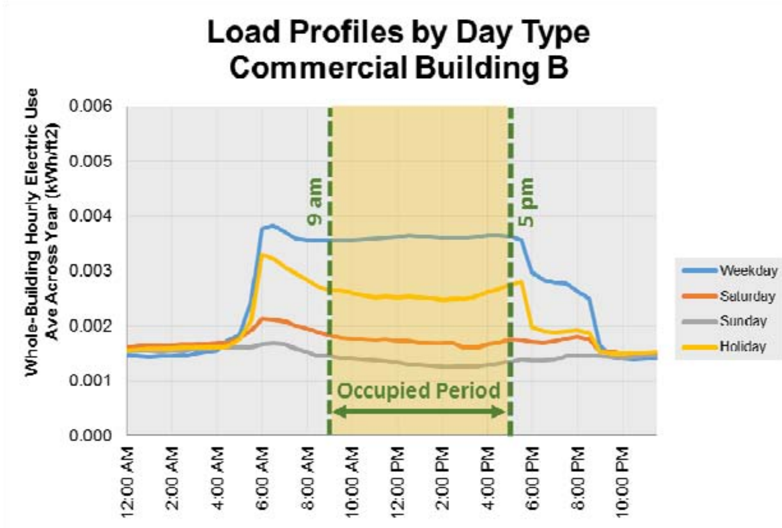

Figure 2: Separating Occupied Hours (ECAM)

Fine grained interval data at an hourly time step or below allows a deeper understanding of how temperature affects energy use, and regression can be done for only hours during which the building is occupied. This dis-aggregation allows us to created additional metrics: Base electric load during unoccupied daytime hours, Heating seasonal energy use during occupied hours, Cooling seasonal energy use during occupied hours, Peak heating/cooling load during occupied hours, Inflection point during occupied hours. A summary of the energy metrics available for statistical analysis of the building portfolio is shown in table 1.

Table 1: Metrics available at various level of details

Granularity	***Annual***	***Monthly***	***Interval***
Energy Metrics	Site EUI Source EUI Electricity EUI Fuels EUI ENERGYSTAR Score	Peak heating load Peak cooling load Overall inflection point Heating inflection point Cooling inflection point Base energy use Heating seasonal energy use Cooling seasonal energy use	Base electric load during unoccupied daytime hours Heating seasonal energy use during occupied hours Cooling seasonal energy use during occupied hours Peak heating/cooling load during occupied hours Inflection point during occupied hours

Building Attributes Data Collection

As stated earlier, the goal of this research is to identify correlation between energy metrics and building attributes. In order to gather data on physical building attributes this research explored a variety of methods. After an initial list of sub-hypotheses was created, a list of data points necessary to test each hypothesis was established. Each of these points was categorized into one of four groups: information available from publicly available geodatabases such as Google Maps and municipal GIS catalogues, information available by driving by the building, information available by an up-close inspection of the building, and information that would only be available by contacting building managers or owners. Ease of information gathering was prioritized, and it was found that a large number of data points needed for each building could be obtained through Google Maps alone.

Following this step, building visits were made to gather information which was not available using online tools, such as the number of glazing layers. Two sets of building visits were done – one visit during the day when the building was in operation, and one during the night in order to find whether and what percentage of lighting was left on during the night or turned off. Buildings which turn off as much lighting as possible during the night may indicate a larger effort to conserve energy.

Building attribute data (including information on building envelope, building systems, shading devices, hours of exposure to sunlight etc.) were collected using virtual and in person site visits, while the corresponding energy data of the same buildings was assimilated through Portfolio Manager and authorized data provided by the utility. The data thus collected was analyzed on three levels of granularity against weather data i.e. yearly data, monthly data and interval data broken down into 15 minute intervals. Each level of analysis presented their own challenges and required a unique methodology, thus each energy interval provides different lessons learned and energy efficient efficiency opportunities.

Statistical analysis linking building attributes and energy metrics

To quantify the energy impact of building attributes, twenty-three sub-hypotheses were formulated and statistical regression were performed for each sub hypothesis. Buildings of similar classifications based on usage, built area, patterns of occupancy and period of construction were thus compared to extract specific valuable (physical attribute or building system) results which can potentially lead to identifying energy efficient retrofit projects. These results relate to building characteristics such as heating and cooling equipment, window wall ratio, façade area to floor area ratio, etc. Because not all levels of energy data are easily available in all regions of the country, this research seeks to provide a replicable method for analyzing any type of data is available within a particular benchmarking region.

After completing the data gathering process, analysis of each building attribute and its effects on the metrics of energy consumption was performed. For preliminary analysis, some variables expected to affect energy use were tested against the metrics using one-way ANOVA statistical analysis with 95% confidence interval. After establishing several important relationships between building characteristics and energy use, post-hoc multivariate tests for each hypothesis were performed using SPSS. Given the sample data set, buildings were able to be separated into sub-groups by up to 3 characteristics, meaning that up to 2 controls could be used depending on the resulting sample sizes. To represent findings from these tests, the data was visualized using box-and-whisker. Often, it was necessary for individual building attributes to be grouped into categories encompassing a percentage of the data points found; for example, wall area-to-floor area ratio was grouped into 3 groups: “0-0.25,” “0.26-0.50,” and “>0.50”. To create controls, building characteristics were treated as binary values for controls—for example, buildings constructed before 1970 and buildings constructed from 1970 onwards.

Particular controls were used for each analysis depending on the attribute at hand. Some controls represent common potential confounding factors such as building age, which were checked initially on the data set at large to determine whether they had a significant impact on the energy metrics and should thus always be controlled for when testing a particular metric. Other controls are attribute-specific; for example, if one is checking for the impact of roof color/material on any metric, one must also control for the number of floors in the building to narrow down impact of roof attributes on only those buildings with high relative roof area whose energy use would be expected to be impacted by the roof. This was done by using sub-groupings determined by the binary controls mentioned above. This methodology may be modified in future work to include factor analysis. In each instance of analysis, it is noted which factors were tested for confounding influence and which were accounted for in the particular analysis.

Statistical tests were run for all energy metrics so that the findings can assist in establishing guidelines based on the granularity of the data available to the researchers.

Findings

Over 238 hypotheses were tested, trying to find significant correlations between building attributes and existing or new energy metrics. The following three sections highlight the significant findings that can assist in decision making for building retrofits using annual, monthly or interval data.

Finding based on Annual Data: Replacing glazing on buildings with dark glass

The sub-hypothesis tested was that darker glass will lead to higher heating energy use and may slightly decrease cooling energy use. Dark glass will also lead to increased lighting loads. The statistically significant preliminary finding confirmed that buildings with dark glass (T-Vis <0.5) have a higher electric consumption than other buildings.

Although dark glass is found most commonly in post-1969 buildings, enough buildings built pre-1970 were available to test annual metrics with both dark glass and non-tinted or slightly tinted glass. Statistical analysis showed that in mixed-fuel buildings built pre-1970, electric EUI was 50% higher in those with dark glass (p=0.014), which could be due to higher lighting loads (Figure 3). If this finding holds true, older mixed-fuel buildings with dark glass may reduce their electricity use by 33% by applying windows without a dark tint.

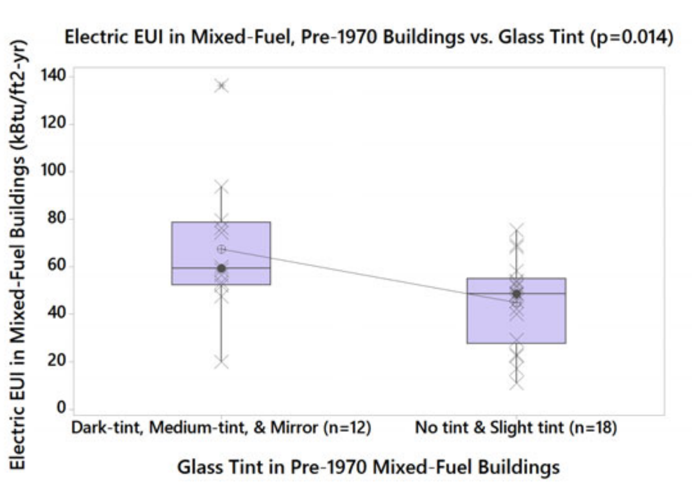

Figure 3: Box plot of comparison of Electric EUI of buildings with dark tint vs light tint in pre-1970 mixed-fuel buildings

Surprisingly, when testing only buildings built in 1970 and after (post 1969), the presence of dark glass (including dark-tint, medium-tint, and mirror glass) also correlates with higher ENERGY STAR Scores in Figure 4 (p=0.028). It is possible that this is due to lower solar heat gain in these newer buildings, assuming that most tinted glass has a lower solar heat gain coefficient than non-tinted or slightly tinted glass. Given the previous finding about electric EUI, however, it is also possible that dark glass is not the major contributing factor, since other variables not considered here could also be linked with the presence of dark glass. It is hypothesized here that lighting loads are negatively affected with the implementation of dark glass, and since older buildings may use less efficient ballasts and bulbs, lighting loads—the largest office building load—could be amplified here.

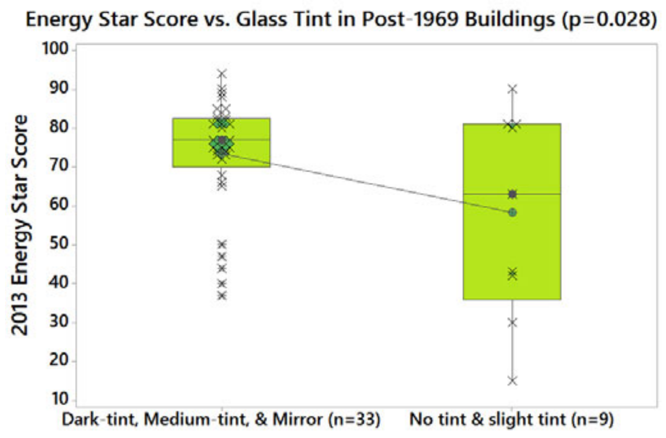

Figure 4 – Box plot of ENERGYSTAR score of Buildings with tinted glass compared to those without

Finding based on Monthly Data: Programming nighttime setback.

The sub-hypothesis tested was that buildings with thermostat setbacks will reduce space conditioning loads in lengthy unoccupied periods, leading to less heating and cooling energy use. The statistically significant preliminary finding confirmed that Buildings with lights on at night have a higher source EUI than others.

When thermostat setbacks are implemented, they are likely implemented for both heating and cooling. This was found to be true when analyzing the data through ECAM, where it was discovered that nearly all buildings with heating setbacks had cooling setbacks, and nearly all buildings without heating setbacks did not have cooling setbacks either. This means that testing for heating setbacks is equivalent to testing for cooling setbacks, since attempting to control for the other would leave nearly no buildings in the data set. If observing all-electric buildings and testing electric EUI or base electric use for the effects of either heating or cooling setbacks, it would be unclear which setback was a greater contributor to the results found.

When heating setbacks were tested against LEAN Monthly seasonal heating energy use, it was found that buildings with heating setbacks use 60% less seasonal heating energy across all temperatures than do buildings lacking setbacks (p=0.009) (Figure 5).

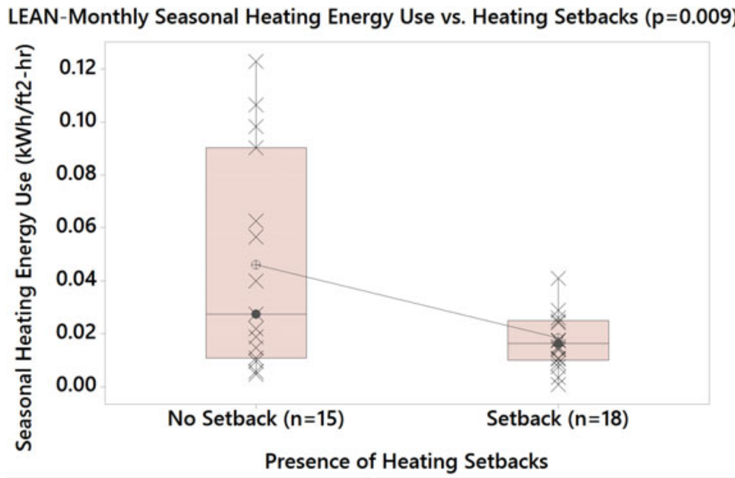

Figure 5: Boxplot of seasonal heating EUI for building without setback compare to building with temperature setback

Finding based on Interval Data: Turning Lights off at Night

Turning off a greater percentage of the lights when the building is unoccupied will lead to significantly lower baseload electric energy use.

The statistically significant preliminary finding confirmed that buildings with only 0-25% of their lights on at night can save 32% of the average total lighting load, as they show a 45% reduction in unoccupied baseload energy use (p=0.027).

When grouping percent of lighting on at night into bins of less than 50% and greater than 50% of lighting on at night, statistical analysis showed that leaving 50-100% of the building's lights on at night was correlated with higher unoccupied base energy use than leaving only 0-25% of the lights on at night as indicated in figure 6 (Since lighting percentage left on was estimated at 25%, no entries fell between 25% and 50%.) This same relationship held true for all-electric buildings only (p=0.049). Although lighting left on at night at first glance should not apply to Sunday daytime baseload, which is the base for "unoccupied baseload" in LEAN Occupied Hours, lighting left on at night is simply a symptom of lighting left on throughout unoccupied hours. This means that the unoccupied baseload included in LEAN Occupied Hours graphs can encompass the lighting left on during unoccupied hours, which is the result of a lack of advanced lighting sensors and controls, or of improper scheduling of the building automation system.

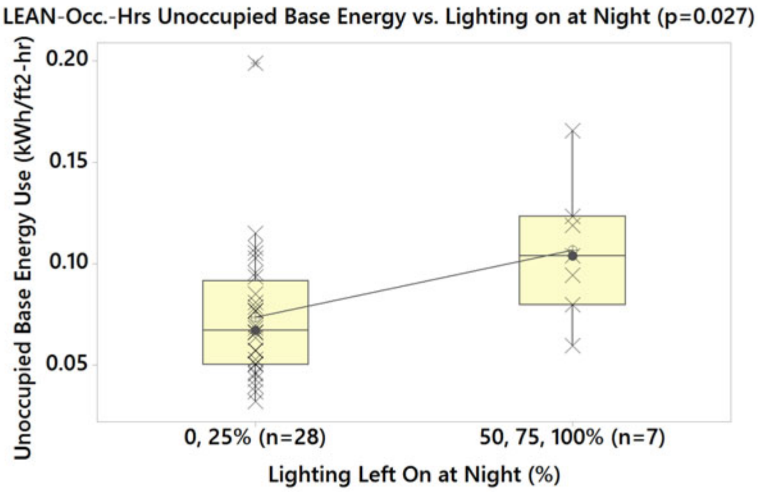

Figure 6 – Boxplots of unoccupied base energy use of building leaving their light on at night compare to buildings that switch lighting off.

Example of quantification of potential savings from turning lights off at night

The above results can quantify the lighting energy and associated costs saved by leaving 0-25% of lighting on during unoccupied hours instead of 50-100% as shown below:

Assumptions:

- Unoccupied hours in an office building are, conservatively, 8pm-7am (11 hours), during which lights could be turned off
- The standard office building is 100,000 ft^2 ((CBPD 2015))
- Cost per kWh in Philadelphia is $0.1496/kWh total for medium to large commercial buildings (PECO 2015)
- The average difference in base energy use between the two groups was 0.033kWh-^{0}F/ft^2-hr for all temperatures, and 61 temperatures are represented on the x-axis (25-85^{0}F, inclusive)
- Dividing by 61^{0}F yields 0.00054 kWh/ft^2-hr
- The number of hours/year this could be implemented is 11 hrs/day * 365.25 days/yr = 4,017.75 hrs/yr
- 0.00054 kWh/ft^2-hr * 4,017.25 hrs/yr = 2.17 kWh/ft^2-yr
- This is 32% of the average annual lighting load for office buildings(EIA 2008)
- Annual energy savings = 2.17 kWh/ft^2-yr * 100,000 ft^2 = 217,000 kWh/yr
- Cost savings = $0.1496/kWh * 217,000 kWh/yr = $32,500 per year

Therefore for a one-time cost of adding advanced lighting sensors and controls (or simply ensuring that more lights are off at night, either manually or through BAS scheduling), huge savings can be achieved.

Conclusion

In this research paper, we described methods where annual, monthly and/or interval data, coupled with ENERGYSTAR Scores, various energy metrics and readily available building attributes, can be used to understand different aspects of building energy use. These new metrics and methods can assist building owners and rebate program managers in targeting buildings that would benefit the most from energy efficiency investment.

To illustrate the methods, we detailed three of the most significant findings that could benefit retrofit applications in the Northeast region, out of the 238 analyses of relationship between building attributes and energy use that were investigated. Those findings are currently being used to help identify buildings that would benefit the most for rebate programs from their local electric utilities.

This research also indicates that the electric utilities hold the data to identify those buildings or the data is public and they could develop application processes that collect this information to help them identify the right candidate buildings.

The findings indicated that utilities in the municipalities studied should target buildings without thermostat setbacks or lighting schedule and assist them in implementing them in order to reduce energy. It also suggest that utilities could invest in building envelope improvement such as replacing dark glass.

Two main limitations exist in the statistical analysis used in this research, one being the sample size and the other being the statistical methods themselves. Often, the sample size was large enough to test a hypothesis, but limitations existed in controlling for more than one factor in the analysis, as the sub-groups simply became too small to achieve significance therefore preventing factor analysis to be conducted.Analysis is currently conducted on a bigger dataset to control for more factors at once and identify potential interaction between building attributes and their effect on energy.

Additionnally, the current effort involves automating the calculations so that the statistical findings can be confirmed with a larger dataset without manually recalculating every hypothesis. Future work includes continuing to add other municipalities to the dataset to find out if the findings are true for a broader dataset while controlling for more factors or applied only to the set of buildings studied..

Acknowledgement

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