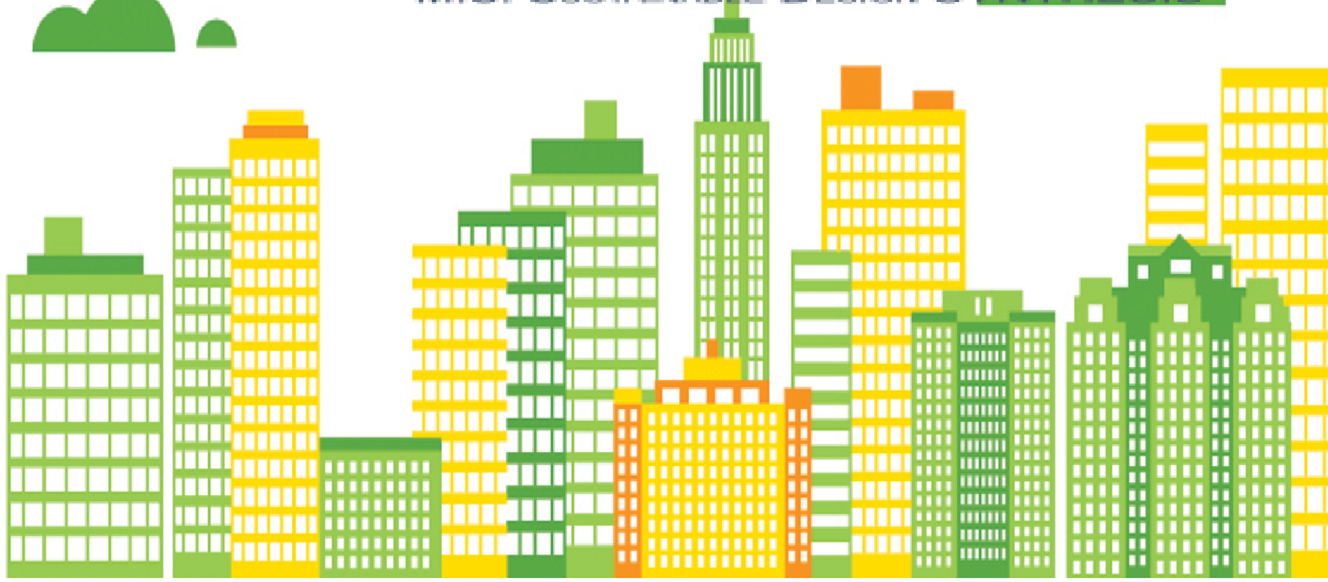
AUGUST 4, 2016

MULTIVARIATE STATISTICAL ANALYSES OF BUILDING ASSESTS AND ENERGY LOADS

M.S. Sustainable Design Synthesis



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Abstract:

To reduce the use of fossil fuels and greenhouse gas emissions for the energy needs of buildings, the Pennsylvania Public Utility Commission (PUC) introduced Act 129 on October 15, 2008 (Pennsylvania PUC, n.d.). This bill sets reduction in electric consumption, and in demand as its main goal. To achieve the maximum benefit, this bill has been implemented in phases:

Phase I: 3% electricity reduction by 2013

Phase II: 2.3% statewide electric reduction, with PECO reducing about 3%, by 2016

Phase III: 4.2% statewide electric reduction, with PECO reducing 5.3%, by 2021

Phase IV: 0.75% average electric reduction (per year), by 2026

Phase V: 0.75% average electric reduction (per year), by 2031

Phases I and II were more geared towards taking advantage of what is called the 'low hanging fruits' of the building industry, to reduce electric consumption and achieve demand reduction. These consisted of easily identifiable building attributes, like lighting or window type and glazing that would provide the maximum impact with minimum of effort. Phase III, on the other hand, would now need to focus more comprehensive measures to create 'rebate packages' under the purview of systems integration, instead of rebates for individual attributes. A higher window to wall area ratio (WWr) would correspond to increased daylit areas and lower seasonal energy bills, but only if this attribute is coupled with the number of glazing layers, specifications of the glazing – visual transmittance (Tvis) and solar heat gain coefficient (SHGC), the kind of shading provided to the interior as well as exterior of the walls, the cooling systems used and its efficiency along with its operation schedule, to name a few. A single attribute would show a relatively less impact on a buildings' energy usage, when compared to a group of attributes and their interconnections. Hence, the rebates for Phase III would have to target not just one attribute, but maybe a multitude of them, to achieve the desired results. (Pennsylvania DEP, 2015).

Phase III of Act 129 begins from the year 2016, and utilities will now face the decision of restructuring rebates again - which rebates to roll forward, which to discontinue and which new ones to create. This synthesis will investigate the link between the <u>process of rebate structuring</u> and the methodology previously developed by CMU that identifies which rebates to target, by analyzing groups of attributes against the buildings' energy bills.

Executive Summary

Carnegie Mellon University, along with CBEI researched on targeting rebate program customers with benchmarking data analytics in 2015. Their methodology uses benchmarking data to analyze energy data and building attributes to analyze cause and effect of energy use intensity. The existing research has utilized regression analyses to determine how buildings utilize energy. Depending upon the level of data available, these analyses can be done on annual, monthly and interval (15-30 minutes) level. Energy use intensity would also vary according to the building type, use, occupancy schedules, and other physical building attributes like roof color, type of layout, window to wall area ratio, number of glazing layers used to even the orientation of the building. For their research, these attributes have been categorized into 3 different types:

1. Attributes relevant for new construction or major renovations

2. Attributes relevant for retrofits in existing buildings

3. Attributes relevant to building operations

The CBEI/ CMU research focused on how individual attributes may affect energy use, and if any recommendations may be made based on patterns and trends identified. However, energy use is not dependent on the performance or characteristics of just one attribute. It would be a collection of attributes that would together impact how a building utilizes energy. Occupied hours cooling seasonal energy use may be affected by building orientation, but it may also be a function of the shape of the building itself, the size of the floor plates, number of floors, even the presence of cooling towers and also the color of the roof. It may also be a function of just certain listed attributes instead of all. This research was undertaken to understand all these complex interrelations between the attributes collected, with the corresponding energy data, and helped in evaluating the causal attributes (attributes which affect energy use and seasonal loads) with the attributes for which rebates are currently available in the market. A rebate analysis has also been conducted within the purview of this research, to analyze this link of the causal attributes with the present rebate structure.

The dataset had a total of 195 buildings. Post cleaning, 116 buildings were in the dataset which had Energy Star Scores. Of these 195, 64 had annual energy data, 52 had monthly energy data and 50 interval energy data. This number is twice as much as the original CBEI/ CMU research, where data on about 25 buildings was analyzed. Energy data of all 52 buildings was analyzed, using LEAN methodology developed by CBEI/ CMU research team, and certain energy data metrics were derived, like total heating and cooling energy use normalized by gross floor area, seasonal heating and cooling energy use (for monthly and interval data) and peak heating and cooling (for interval data), along with total baseload, among other metrics.

Building attributes of all 116 buildings were also then collected simultaneously. Only those attributes which can be easily obtained have been used in this research, since there may be issues about access to the buildings, and time limitations as well. The original CBEI/ CMU database had a total of 32 attributes, of which 16 were categorized as relevant for retrofit measures. These 16 attributes were then used for further analysis against disaggregated energy data, using statistical software (SPSS). There were 3 stages to this analysis. The first stage was where each single attribute was analyzed against disaggregated energy loads individually, using one way ANOVAs, post hoc comparisons using Tukey's test. The results from this stage (attributes which significantly influenced LEAN derived energy data metrics) were then grouped according to the different energy loads – heating, cooling and baseloads. The second stage consisted of performing factor analyses and principal component analyses (PCA), where attributes affecting heating loads were analyzed using SPSS in an effort to identify the attributes that have the most impact on heating. This step was repeated with attributes that affect cooling and baseloads, to identify combinations of attributes that affected the loads the most as well. Stage three involved multiple regression analysis. The attributes identified as having the maximum impact on the three different loads were used as a starting point for the analyses. A total of about 700 statistical analyses were conducted for this research.

The following are some of the results and findings observed from the statistical analysis:

1. Buildings with external shade had higher seasonal heating energy use, increasing with increasing depth of shade, compared to buildings that did not have any shade at all ($p=0.00$).
2. Buildings with external shade had lower seasonal cooling energy use, decreasing with increasing depth of shade till 2 feet, compared to buildings that did not have any shade at all ($p=0.02$).
3. Buildings with window AC units or split heat pumps had higher seasonal cooling energy use, compared to buildings that did not have these units ($p=0.00$).
4. Buildings with cool roofs had lower baseload, compared to building's that did not($p=0.00$)
5. Buildings with cooling towers have a higher Sunday baseload, compared to buildings that don't ($p=0.00$)
6. Buildings with clear glass had a higher baseload EUI, compared to buildings with dark glass ($p=0.08$)
7. Buildings with window AC units or split heat pumps had higher baseloads, compared to buildings that did not have these units ($p=0.00$).

8. Buildings with rooftop packaged AC units had higher heating EUI, compared to buildings that did not have any shade at all (p=0.00).
9. Buildings with cooling towers had higher heating curve inflection points, compared to buildings that did not (p=0.02).
10. Buildings with West and South shading had higher heating curve inflection points, compared to buildings that did not (p=0.02).

Since external shading increases heating loads but is decreases cooling loads, dynamic facades may be the solution to reduce energy consumption for heating. This finding also indicates that further research is needed in external shading and the type of shading that the buildings in the dataset have. This indicates that buildings with window or split heat pumps are also good candidates for further audits and analysis for comprehensive bundles of rebates, since other attributes of such buildings may not be functioning optimally. Also, buildings which had dark roofs had a wide range of disaggregated energy data points, when compared with buildings that had cool roofs and a much narrower range, indicating that these dark roof buildings would be good candidates for further analysis for comprehensive rebate packages.

Acknowledgements

This research would not have been possible without the much needed guidance by Prof Erica Cochran who helped me navigate the world of statistics, making sense of all the results the analyses provided, of Prof. Vivian Loftness for her continuing support in helping me understand and co relate my findings with building science and technology, and Prof Dana Cupkova for her unique insighst into my research project. I would also like to thank Flore Marion for her help in understanding the effects of attributes on building energy.

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Lastly, I thank my parents for their unwavering support that has got me to this stage in life.

1 The Need to Analyze Building Attributes using Energy Data Analytics:

Recent numbers collected by the US Energy Information Administration show an increasing trend in energy consumption (Figure 1). Electricity consumption has being increasing steadily for the past decade. Where it was about 3 quadrillion Btu in 1999, surveys show that by 2012, electricity consumption was around 4.2 quadrillion Btu.

Energy consumption estimates by sector for the United States

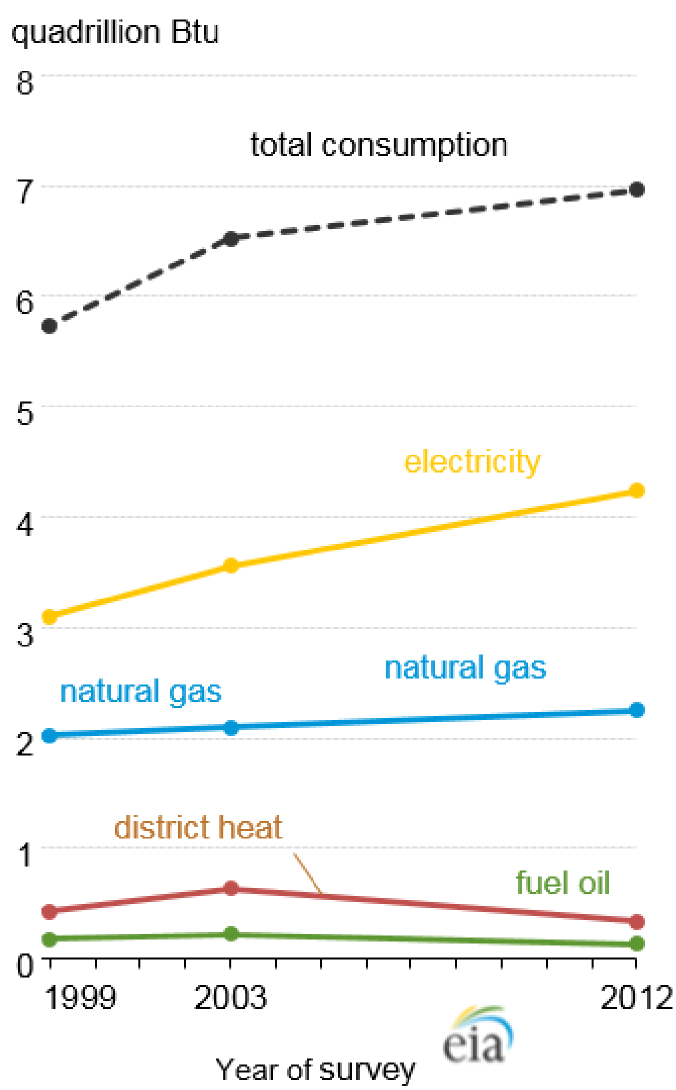

Figure 1: Energy Consumption by Fuel Mix in the US (EIA, 2016)

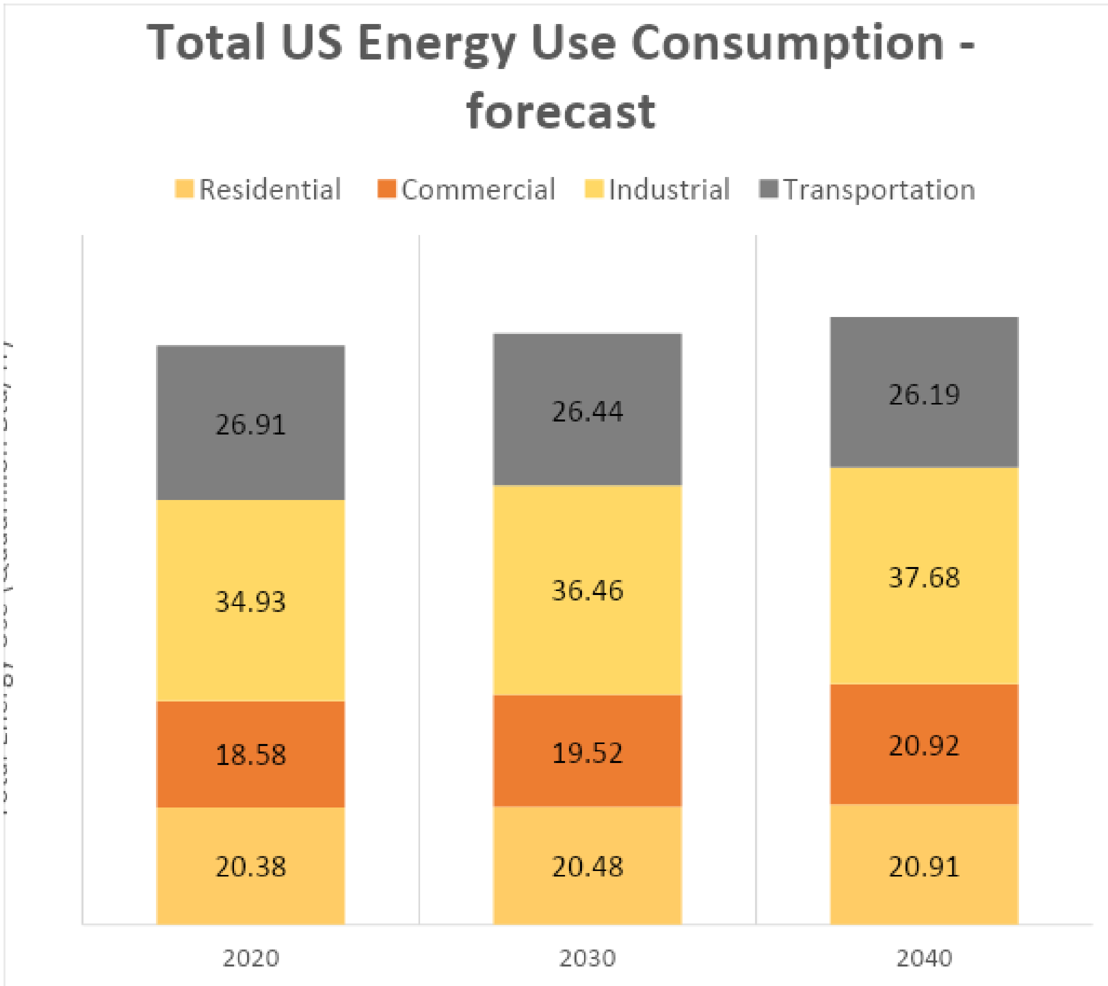

Figure 2: Projected US Energy Usage (EIA, 2015)

Figure 2 provides estimated projections of energy use by sector for the next 25 years, and shows the increasing share of commercial sector from 2020 to 2030. Energy consumption and peak electricity demand, if it cannot be met by the existing operational power plants, is met by using the plants which had not been running due to inefficiencies in generating electricity. To reduce energy consumption, and shave off peak demand, policy initiatives backed by research is now needed.

Energy companies are currently facing pressure to reduce energy consumption. The policy initiative of Act 129 sets goals for energy and peak demand reduction that the utilities have to comply with to avoid being fined. So they provide rebates to buildings to improve their energy efficiency and reduce costs. This has increased interest in figuring out how to help buildings improve energy efficiency by improving assets, and how to incentivize these improvements through policy initiatives. An easy way to understand if a building is energy efficient or not is to analyze its energy bills. Energy data analytics disaggregate the big data into separate loads - heating, cooling and base loads. These loads can depict an inefficiency in the way the building is being heated and/ or cooled by way of graphics. This inefficiency may be due to a number of reasons. For example, if a building is observed to have a very steep curve for cooling load, it may be because the building is old, has single pane glass which allows the 'coolth' to escape outside. The cooling system may be operating for a longer period of time, with no setbacks in place to regulate temperature. Operable windows, which have shading to the internal and/ or external sides will keep the heat away via natural ventilation, further lowering cooling loads. The building may have higher base load, if old T-12 lights are used, or if all lights are switched on at night. Probable causes for higher and/ or steeper heating load curves may be inefficient windows, which have single panes, a high solar heat gain coefficient. It may be a function of the kind of roof the building has, a cool roof will help in reducing heating loads, while a black roof would increase it. Operable windows, which have shading to the internal and/ or external sides will further keep the heat away, lowering cooling loads. But, without a listing of said building's assets, we have no way of knowing what it is that is causing the energy loads to be so high, and the building to function so inefficiently.

Previous research (CBEI, 2016) (Spencer & Kaufman, 2015) analyze individual assets with energy data analytics to identify certain trends and patterns in the dataset of buildings around Philadelphia. Their results were taken up in the policy Phases I and II, with recommendations being made on the basis of these findings, to target particular rebates for the buildings. But Phase III is about combining assets. The first two phases were targeting the 'low hanging fruit', attributes whose impact on energy was easily visible, and which were the easiest to upgrade or update. Phase III focuses on further reducing energy and peak demands, which would be a challenge since the utilities won't be able to provide rebates for individual assets like they did for the initial phases. PECO compares lists to create new rebates, which is not effective for Phase III since they do not look at bundling them together. The lists need to include combinations of rebates, rather than focused rebates targeting individual assets. The existing research focuses only on analyzing attributes with energy data on an individual basis, which is a gap since attributes interact with each other, according to their characteristics and specifications, to affect how much energy a building utilizes to heat or cool. A building, or a set of buildings, may experience high energy usage for cooling because of the presence of single paned windows, but their cooling loads may also be affected by overheated roofs/ ceilings, less or negligible number of operable windows, a high window to wall area ratio, or even an absence of thermostat setbacks. Because of this, even if the building owners were to target a specific rebate, as suggested by the existing research, they may not see a substantial change in energy use. This is not to say that the rebate programs has not reaped dividends, as they have been very successful for the past few years (PUC, 2014). It is this gap in research on these combinations or packages of rebates, which this synthesis will address.

1.1 Building attributes and energy data analysis objectives

Attributes of a building are its features – chillers, cooling towers, number of glazing layers, window frame material, operable windows, roof reflectivity, lighting type, and the like. Previous research (CBEI, 2016) already suggests analyzing these attributes against a buildings energy bills to target retrofit measures. The main premise of that project was to analyze individual attributes with energy data, and identify potential energy efficiency measures. This synthesis will take that work forward, since energy consumption is not just dependent on one attribute, but rather on how various attributes interact and relate with one another in an integrated system, that contribute to the energy load of a building. For example, cooling loads would depend on the window specifications, along with color of the roof, presence or absence of cool roofs, cooling towers and thermostat setbacks. With Phase III of Act 129 about to begin, utility companies now face the decision of developing new rebate packages that would assist in the EDCs reaching their goals. Using the methodology developed previously, this synthesis would use building attributes and energy data analysis to strategically inform selection of candidate buildings for the next set of PECO rebates.

1.1.1 toselection of candidate buildings for the Aim of the Research:

i. Analyze how the various attributes of a building collectively impact energy use.

ii. Understand how this information may be used to help reduce the potential pool of buildings for targeting rebates via further audits

iii. Provide suggestion for utility rebates to target buildings

1.1.2 Scope of work

i. Focus only on buildings which have interval data PECO energy bills, and PECO rebates

ii. To collect attributes of those buildings available in database for the Mid Atlantic Region. The attributes collected are ones which can be obtained by a layperson easily.

iii. Analyze energy consumption of the buildings – load breakdowns

iv. Analyze impact of attributes on energy consumption – quantitative

v. Identify buildings to target for further energy audits to target rebates.

1.1.3 Deliverables

Guidelines for utility companies/ rebate managers to target buildings from its data pool for a comprehensive audit to provide rebates.

1.2 Methodology

To link the analyses of energy data and building attributes to rebate structure, it is necessary to first analyze the existing rebates, and their impact on energy savings versus cost savings. This synthesis can be categorized in two parts. The first part is an analysis of PECO's existing rebate structure, and the second part will be the analysis of energy data with building attributes. The synthesis will conclude with links identified between the methodology for creation of new rebate portfolios and the methodology for energy data analytics with building attributes. The methodology of this synthesis would become a subset of the methodology that PECO to structure its rebates. The 'PECO methodology' for creation of rebates can be explained in three broad steps: planning, verification and final plan approval/ execution (PECO, 2015).

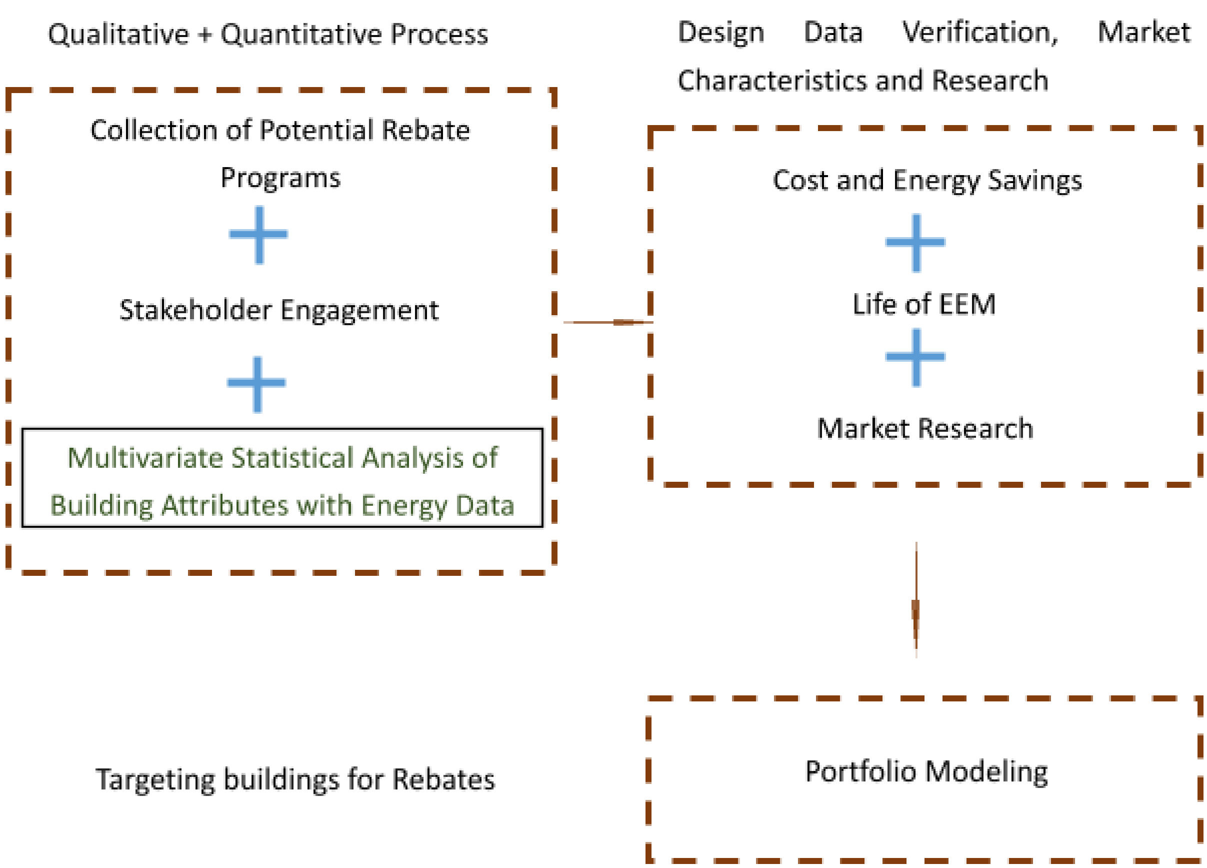

Figure 3: PECO's Methodology for Rebate Structuring

To create new rebates, the rebate managers and utility companies need to identify their target pool of buildings for which they want to create the rebate portfolio. (PECO & DNV GL, Discussion on Rebates, 2015) The creation of new rebate programs for those sets of buildings is done by initially creating a database that has details about the rebate programs currently existing in their portfolio. This database is supplemented by rebates provided by other utility companies, all over the USA. Deciding which rebates are to be continued, are done by comparing the benefit to cost ratio to understand the effectiveness of those rebates, with the number of participants for said rebates over the years. If a particular rebate shows a reducing trend in terms of participation and benefit to cost ratio, it is slowly tapered off, assuming that that rebate has achieved its potential. New rebates are added to PECO's portfolio after conducting meetings with stakeholders – in this case PECO, DNV GL and the building owners – and a qualitative analysis of the benefit cost ratio is also done for the rebates of other utility companies to finalize their inclusion or exclusion in PECO's portfolio. The methodology followed in this synthesis to inform the selection of buildings to target for the creation of new set of rebates would in effect act as an add on or a complement to the already existing methodology already developed.

Quantitatively analyzing building attributes with energy data would help identify potential buildings to target for further analysis via audits, to recommend those buildings rebates. (PECO & DNV GL, Discussion on Rebates, 2016). This new method would take into account the action of climate and surroundings on the attributes of a building, increasing the depth of the database created. The methodology explored in this research would help PECO narrow down its dataset of thousands of customers to a more manageable number of hundreds. These selected buildings can then be audited for identifying areas for which energy efficiency measures may be created. Once this database is created, the rebates need to be assessed on their cost effectiveness and value addition. A market research may also be conducted by PECO for the same.

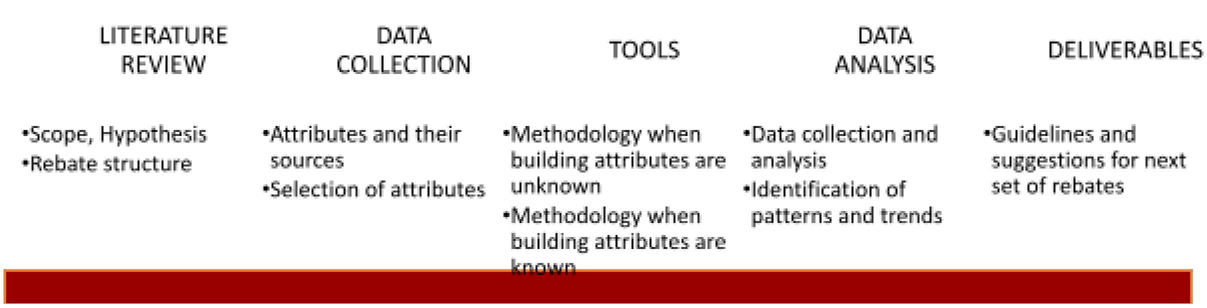

Figure 4: Methodology of the reserach

Figure 4 depicts the methodology followed for the synthesis. Work begins by understanding the need for this synthesis, defining the hypothesis being tested and regulating the scope of work to be done over the course of the semester. Rebates are studied next, with an emphasis on the kinds of rebates provided for the consumers in and near the city of Philadelphia. Analyzing which building attributes are relevant for this study becomes the subsequent step, since they will be linked to the new set of rebates this research would provide as deliverables. The attributes selected need to be such that they can be easily incorporated as potential rebates. Once this list of attributes for analysis is identified, a methodology can be utilized for analyzing building energy data – with and without the attribute list. The energy data analytics would contribute in identifying potential patterns and trends that may be observed in a particular set of buildings which have the same or similar control variables – attributes that are common to certain pools of buildings, like the age of a building, the number of floors, its layout and so on. These trends may be a repetition in the attributes that have increasing collective impact on energy loads of a building that would help in creating guidelines and suggestions for informing the next set of comprehensive rebate packages for Phase III.

1.3 Data Collection: Defining Attributes

The biggest challenge faced here is to define the list of attributes that would be utilized to analyzed energy data against. These attributes can be collected via asset score forms, if the building owners have opted for an asset score rating. These attributes also need to be compared to the current rebate structure. This would help in identifying and comparing the attributes collected to the attributes on which rebates are offered. The database of attributes used for the CBEI project (CBEI, 2016) has them divided according to attributes which would be relevant for retrofit measures, for new constructions or major renovations, and for building operations and facility management. For the purpose of this thesis, data has been collected via:

1. Site visits/ drive bys
2. Google images

Building attribute data for 116 buildings have already been collected, of which energy data has been provided by PECO, the utility company for 52 buildings on interval level. Since the research is focusing on rebates, attributes for retrofit measures for these 53 buildings would be the focus for further analysis with energy data.

A common source of collecting building attributes is through google maps and images, which can be substantiated further with site visits and drive bys that can be conducted during the day and night, to collect and/ or corroborate the collection. A total of 31 attributes were listed, and categorized as attributes relevant for new construction or major renovations (number of floors, building depth and layout, window to wall area ratio, material used for envelope and such), for retrofit measures (window specifications, lighting specifications, HVAC equipment, shading) and for building management (schedules and set points to operate the HVAC systems and lighting systems).

1.4 Selection of Attributes: Listing attributes from all sources to create database

POTENTIAL RETROFIT	DRIVE BYS/ SITE VISIT	GOOGLE IMAGES	REBATES ASSCOCIATED	METRIC
Rooftop packaged AC units		√	√	Total number of units
Rooftop chillers		√	√	Total number of units
Rooftop cooling towers		√	√	Total number of units
Window AC units	√	√		Total number of units
Shading of AC units	√	√		Number shaded units
Number of glazing layers	√		√	Number layers visible

Tinted glass	√	√		Clear vs Dark
Window frame material	√	√		Metal/ Wood frame
Operable windows	√	√		Percent operability
External shading		√		Depth of shading
External shading device type	√	√		Type shading device
Internal shading	√	√		Type internal shading
Roof reflectivity		√		Color of roof
Lighting type	√		√	Type (Parabolic/ Louvered) of light fixture
Lights on at night	√			Percent of lights on at night

Table 1: Selected attributes for energy data analysis

Of the 31 attributes, 15 are selected for further analysis with energy data, due to their suitability for being easily incorporated as rebates. It is easy to bundle HVAC equipment, window and envelope specifications in a package. It would not be so easy to restrict the attributes collected for new construction or major renovations to be provided as rebates, since they are a function of architectural design and activity or use of the building type, which utility companies would have very little control over. Thus, it was decided to use these 'un marketable' attributes as controls for obtaining more accurate results of the analysis of energy data with retrofit able attributes for energy efficiency measures. Table 1 lists all the attributes selected, along with the sources from where they are collected. A separate column has been made, that marks which attributes have a rebate associated with them at present, by PECO for phases I and II.

1.5 Tools and Methodology of Analysis

Analysis of buildings can effectively be done in two ways: when only the energy data is available, and when both energy data and building attributes both are available. The tools to analyze data for both ways differ, and so does the methodology followed.

When building attributes are unknown, that is, only energy data is available to analyze, depending on the level of energy data – annual, monthly or interval, we can utilize different tools to analyze them:

1. Annual Data analysis: Annual data may be analyzed by comparing Energy Star Score, Site EUI, Source EUI, Electricity EUI and Fuels EUI of different buildings, which have similar gross floor area. This level of analysis will allow researchers to narrow down the pool of buildings for which they feel rebates are necessary to reduce energy consumption. Only those buildings that perform poorly on an annual level, or have a poor Energy Star Score, would then be studied in detail on the monthly and interval level.

2. LEAN Monthly Analysis: Energy use can be disaggregated into heating, cooling and baseloads on a monthly basis. The method used to do this is called LEAN analysis (also known as regression analysis), and that provides information on the peak heating and cooling loads, overall inflection point, the heating and cooling inflection points, base energy use and seasonal energy usage for both heating and cooling season.

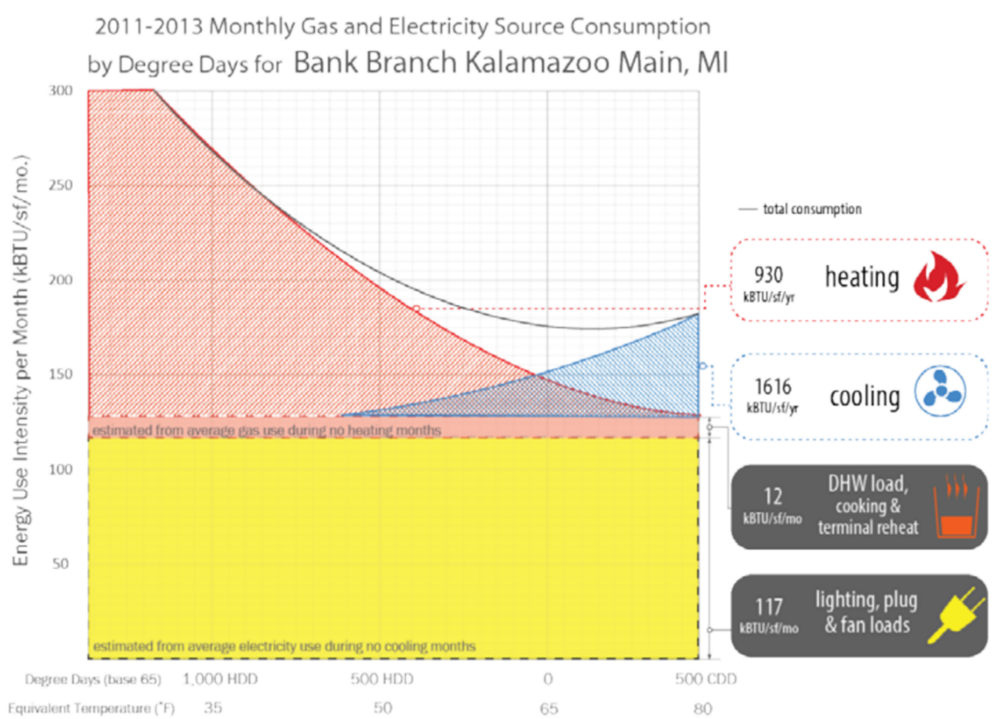

Figure 5: LEAN Monthly analysis, Hsu and Wang, 2014

Figure 5: LEAN Monthly analysis, Hsu and Wang, 2014 detail out methodology used for conducting LEAN analysis on monthly energy data, and it is further explained in the chapter on

Data Analysis Methodologies utilized for Energy Data Analytics:

3. LEAN Interval Analysis: LEAN interval analysis provides information on energy usage during occupied hours, on weekdays. So in addition to the data points parsed out from annual and monthly level data analysis, base electric loads during occupied and unoccupied hours, seasonal energy use for heating and cooling for occupied hours and peak energy loads along with their inflection points are also known. The methodology followed is the same as for LEAN monthly. The only difference is that instead of energy use intensity being plotted against degree days, outside air temperature is used, since this data is on an interval level for each day.

When building attributes are known, that is, information on building attributes has been collected as well, statistical analyses can be used with energy data analytics to understand how building assets may be improved to reduce energy costs.

1. Descriptive Statistical Analysis:

The simplest form of analysis, this can be performed for analyzing the effect of attributes on annual data. Buildings which have similar gross floor area but different Energy Star scores can now be analyzed to understand why this variation may occur. Bar charts or histograms, line charts and box plots may be utilized to observe trends between attributes and annual energy use that may not be visible at first glance.

2. ANOVA/ MANOVA for LEAN monthly/ Interval:

This method is more sophisticated, in that it uses software like SPSS or MS Access to analyze building attribute data with month or interval level data points of energy loads and peak loads. This is in addition to the descriptive statistics that is explained. This type of analysis is beneficial when a number of attributes are to be collectively analyzed against energy use and loads.

A number of tools were debated upon, to run these regression and statistical analyses:

1. MS Excel – LEAN Monthly and Interval Analysis
2. Energy Star Portfolio Manager – Annual Data Analysis
3. SPSS – Descriptive and Statistical Analysis (80% complete)

2 Analysis of Rebate Structures and their Effectiveness:

To obtain a greater context on the energy efficiency measures taken for the state of Pennsylvania, the Database of State Incentives for Renewables and Efficiency (DSIRE) was mined for data. DSIRE was established in 1995, and is operated and maintained by the N.C Clean Energy Technology Center, N.C. State University, with fund support from the U.S. Department of Energy[1]. Utilities which have a consumer base of more than a 100,000 customers are listed here with their rebate programs. This database allows a person to search for programs on the basis of technology (EEM/ Renewable Energy), category of program (financial incentive/ regulatory policy), type of program on offer (Appliance efficiency standards/ Corporate Tax Credits/ Energy Efficiency Resource Standards and so on), the implementing sector (Federal/ State/ Local/ Non Profit/ Utility), sectors (Residential/ Non Residential/ Others). It also allows us to search for programs by state. Pennsylvania, for example, has a total of forty nine programs for energy efficiency and/ or renewables for the commercial sector. To understand the hierarchy of rebate programs in the U.S, the federal and state level rebates have been touched upon briefly:

2.1 Federal Rebates

From the DSIRE list of rebates, it was found that Pennsylvania has five programs available on the federal level. These programs are financial incentives, provided to consumers in the commercial sector for implementation of energy efficiency measures and the application of renewable energy sources. Two of these programs are administered by the U.S. Department of Agriculture, and the rest by the U.S. Internal Revenue Service, the U.S. Department of Energy and the USDA Rural Utilities Service. The incentive type also differs accruing to the program. The Department of Agriculture has one loan program and one grant, while the U.S. DoE is a loan. The USDA Rural Utilities Service is a grant provided to consumers and the incentive provided by the U.S. Internal Revenue Service is a corporate tax deduction. All of the five programs provide incentives for energy efficiency measures like geothermal electric, solar thermal electric, solar thermal process heat, solar photovoltaics, wind, biomass, hydroelectric, fuel cells using non-renewable fuels, landfill gas, tidal, wave, ocean thermal, daylighting and fuel cells using renewable fuels, among other technologies. Please refer to Appendix A: Federal Rebates - DSIRE for more information.

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[1] http://www.dsireusa.org

2.2 State Rebates

There are six rebates offered on the level of the state of Pennsylvania, i.e. it is the state which is the implementing sector. These are also financial incentives, provided by two different agencies - the Pennsylvania Department of Environmental Protection, and the Department of Community and Economic Development. There are just 3 programs – a program for targeting small businesses, a program for high performance buildings and a third for promoting the use of alternate sources of energy. These programs are offered as loans, and also as grants by the two agencies. For more information, please refer to Appendix B: State Rebates - DSIRE.

2.3 Utility Level Rebates

Utility level rebates gained popularity after Act 129 was created. Act 129 is a legislation that was enforced to reduce electricity consumption, and it has been rolled out in phases, with the third phase about to begin this year. It directs the seven largest EDCs of Pennsylvania to reduce demand and consumption by formulation of energy efficiency and conservation plans (EE&C), which can be availed by their consumers. It directs utility companies which have a customer base of a minimum of 100,000 to reduce their electric sales, as well as electric peak demands. Table 2 lists the reduction goals that these utilities have to achieve. A failure to comply with the stated goals and to meet with the specified targets would result in the utilities being fined up to $20 million (PUC). The act was targeting energy reduction till the year 2013, initially. The PUC would evaluate the effectiveness of the programs once every five years after 2013, to analyze if the programs provided by utilities are cost effective relative to the benefits they provide, added and otherwise. The utilities, and for the purpose of this research, PECO, have created and introduced rebates under the purview of the goals stated in Act 129.

Phase	Year	Reduction	Goal
Phase I	2011-2013	Peak Demand and Consumption Reduction	Electricity savings of upto 3% (compared to that of 2009-2010), peak demand savings of upto 4.5% (compared to that of 2007-2008)

Phase II	2013-2016	Consumption Reduction	Electricity Savings from 1.6-2.9% (2009-10 consumption) – an aggregated savings of 3.3 million MWh
Phase III	2016-2021	Energy Conservation and Peak Demand Reduction	State average reduction of 5,710,487 MWh (on basis of 2010 standards)

Table 2: Act 129 and its phases

Appendix C: Utility Rebates - DSIRE lists rebates offered by all the utilities that qualify to be on DSIRE list. Since the buildings are located in the Mid Atlantic Region, more specifically in and around Philadelphia, this synthesis would focus on energy efficiency measures (EEM) provided by PECO. Initially known as the Philadelphia Electric Company, PECO provides programs and rebates for residential and business consumers, and has had quite a few programs in the market for commercial sector from 2010. PECO targets its customers with the various rebate programs it has, for upgrades in lighting, HVAC equipment and commercial appliances.

2.3.1 Rebates: Analysis of Incentives provided by PECO, and their effectiveness

PECO files its annual and quarterly reports for the rebate programs it offers with Pennsylvania PUC. It outsources the preparation of these reports to Navigant Consulting Inc, which analyses all the data available on the rebates – money spent, money saved, energy saved and the demand reduction. Navigant also verifies the data collected by PECO and presents corrected values in its reports. A big drawback of these reports is that they do not have a consistent format for displaying their results, nor do they maintain a record of which rebates have been discontinued since which year.

Rebate Programs	**2010-11**	**2011-12**	**2012-13**	**2013-14**	**2014-15**
Smart Lighting Discounts Program	✔	✔	✔	Phase II	

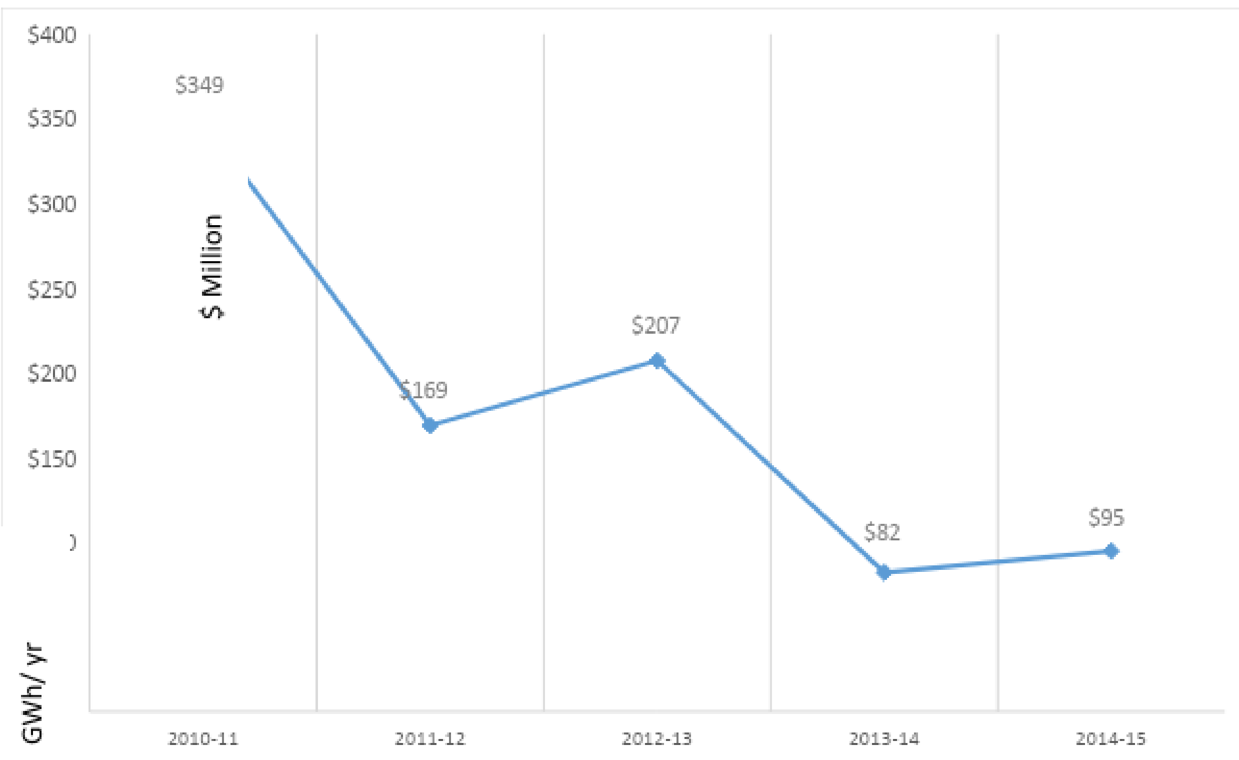
Smart Appliance Recycling Program - CI	✔	✔	✔		
Smart Equipment Incentives-C&I	✔	✔	✔	✔	✔
C&I Conservation Voltage Reduction			✔	✔	✔
Commercial Smart A/C Saver		Phase I		✔	✔
Smart Business Solutions				✔	✔
Smart on site				✔	✔

Table 3: PECO Rebates for Commercial Sector

Table 3 lists all the rebate programs introduced in the market since 2010. The table also depicts which programs were discontinued and which were created new.

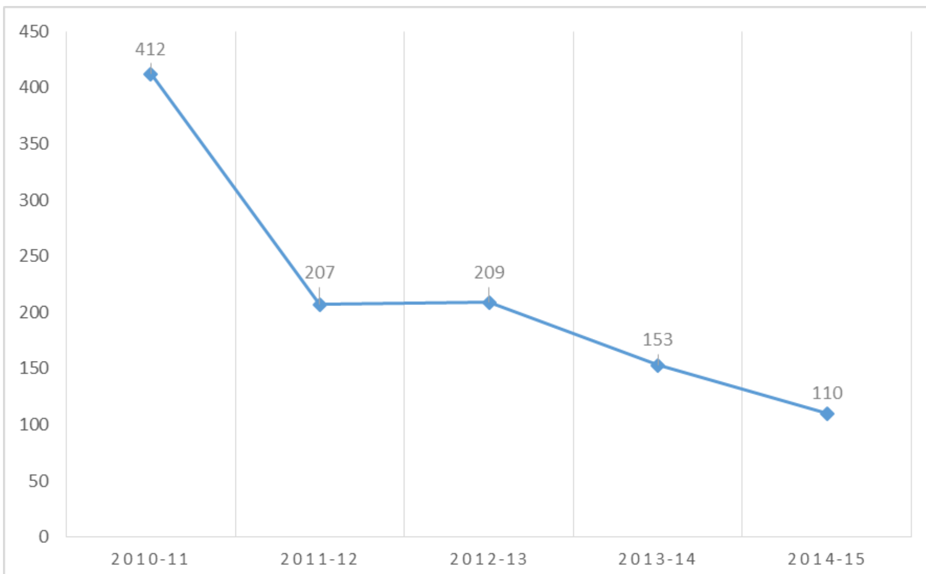
The EDC defines Total Resource Cost (TRC) as the summation of all administrative costs – costs associated with processing of rebates, tracking them, general and clerical costs, the EDC costs (which are expenses incurred by the EDC), the management costs – expenses for managing the programs and major accounts and the participant costs, which are defined as the 'costs for the end use customer'. TRC benefits are based off the verified gross energy savings, and they are the summation of 'avoided supply costs, including the reduction in costs of electric energy, generation, transmission and distribution capacity, and natural gas valued at marginal costs for periods when there is a load reduction' (Annual Report, PY 3, Navigant). The effectiveness of any rebate program may be ascertained by dividing the benefits by costs incurred, to obtain the benefit to Cost Ratio. If this ratio is more than 1, the program was successful. If it is less than 1, it is indicative of a not so successful or failed program. Benefits, costs and energy saved were then analyzed on a year to year basis, for the commercial sector.

Figure 6: Rebate Benefits in $ Millions



The trend observed in Figure 6 is that while the first program year (2010-11) experienced huge benefits, to the tune of about $350 million, it dropped steeply to about $170 million in the next year. A probable reason for this may be that the rebates introduced in the first program year were availed by residences more than commercial sector. It was from 2011-12 and 2012-13 (program years 2 and

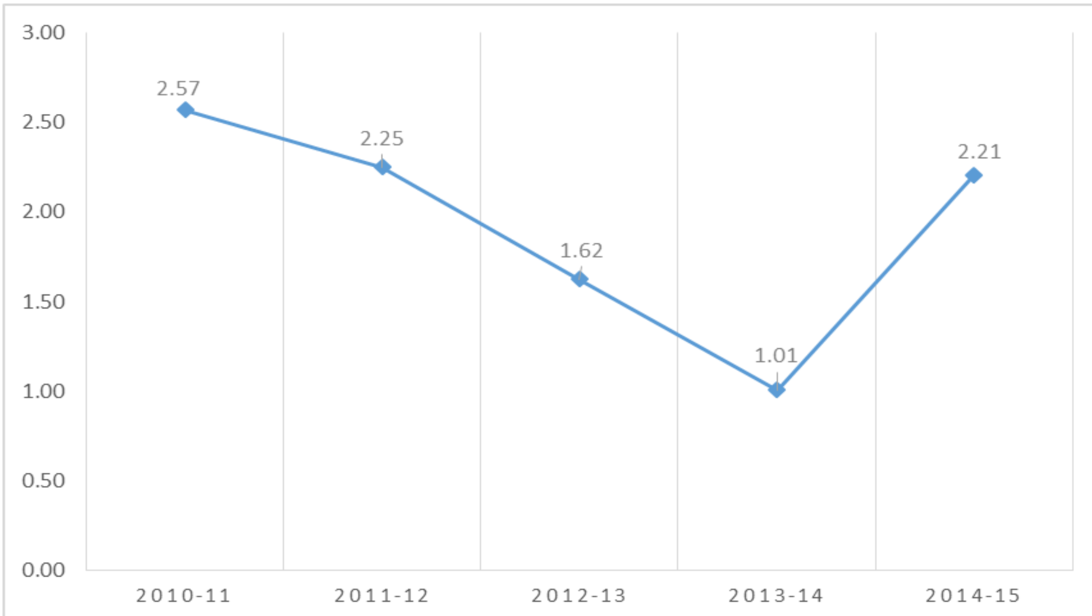
3 respectively) that the share of the residential sector decreased comparatively, as more commercial building owners started participating in the rebate programs. Another drop is observed when phase II ended and phase III began (from 2012-13 to 2013-14), because certain rebate programs were phased out, while new ones were introduced. The reports state that EDCs and utility rebate managers did not spend enough time on propagating these new rebate programs, and hence the reason why the benefits dropped in Phase II. The surveys undertaken by Navigant report that majority of the consumers had no idea about the programs, while some felt that the rebate programs were not helpful to them, since the financial incentive would just about cover the cost of



the simulation studies and audits the consumers have to undertake to be eligible for the rebates.

Figure 7: Reported Energy Savings in GWh/ yr

Figure 7 compares the energy savings across all the five program year, from 2010 to 2015. It corroborates the analyses of the benefits and other findings, as the pattern of decreasing energy savings is clearly visible. Since the inception of the rebate programs, energy saved in GWh/ yr has dropped almost four times. This downward trend points to certain problems in the rebate world. But these values are for the commercial rebates all combined together. A subsequent and further detailed analysis was done to identify any trends or patterns in the rebate programs themselves, over the years, which can be useful in obtaining a probable answer for the apparent decline in energy savings.

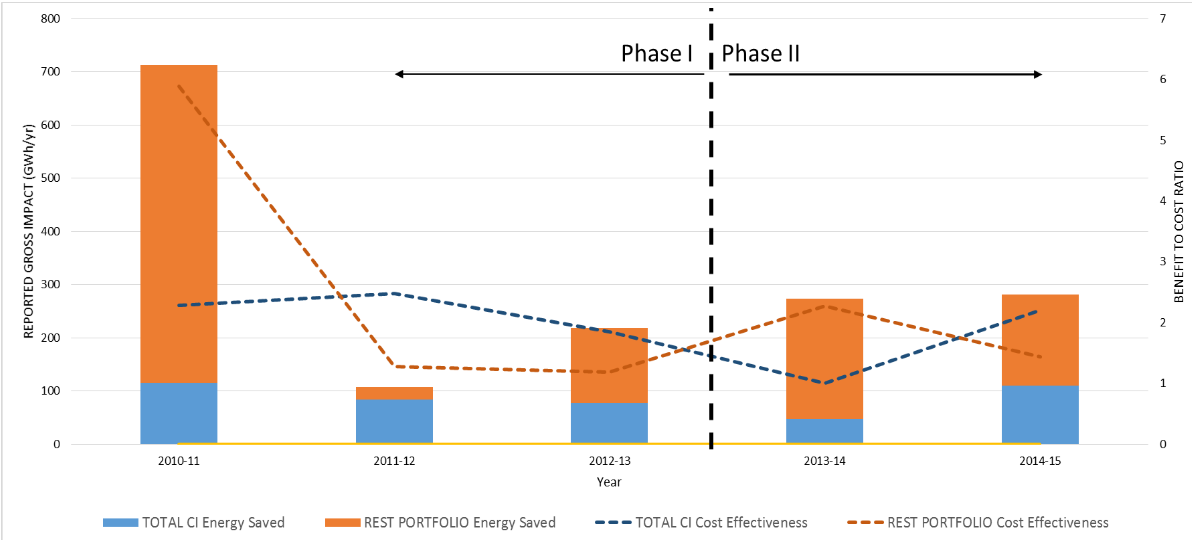


8: TRC Benefit to Cost ratio

ɜ 8 does show that the rebate programs collectively have been a success during Phase I and ɜ II, but comparing them within the phases, their effectiveness is declining, as is seen with the ıing energy savings. So in addition to analysis energy savings by rebate programs over the five , a third variable of Benefit to Cost ratio is also added to the charts.

Energy Savings by Rebate programs

ːe programs are not just created, they need to be pitched to customers as well. PECO and DNV GL conducts meetings with its customers to target rebates for particular buildings as well. That is how PECO creates new rebates as well. Both PECO and DNV GL have expressed a need for a solution that would help them narrow down their list of buildings to target for rebate programs. To avail most of the recent rebates, PECO requires the buildings to conduct an in depth energy audit of their facilities, to identify potential areas for upgrade. The rebates they provided for the first year (2010-11) consisted mostly of lighting upgrades, and new programs were inducted into PECO's portfolio from the year 2011 onwards.



A probable reason for the steep decline observed from 2010-11 to the next consecutive years, as seen in Figure 9 could be the fact that the share of the commercial sector was not clear in the first program year (2010-11). The first year of introducing the rebates, they were not classified as residential, commercial or government, nonprofit and institutional, but rather as rebates for residential and nonresidential sector. So shares of maybe the nonprofit or institutional sectors could have easily been counted towards the commercial sector, unreasonably inflating the values for that year. Unfortunately, details of the number of rebates availed and their sectors are not known, so it is impossible to figure it out. Figure 9 gives an inkling that this may be the case, since we can see the number of consumers for

Figure 9: Performance of Rebate Programs: Commercial v Rest of the Portfolio

the commercial sectors are roughly consistent throughout the years, except when Phase II began, and some rebates were discontinued and others were introduced.

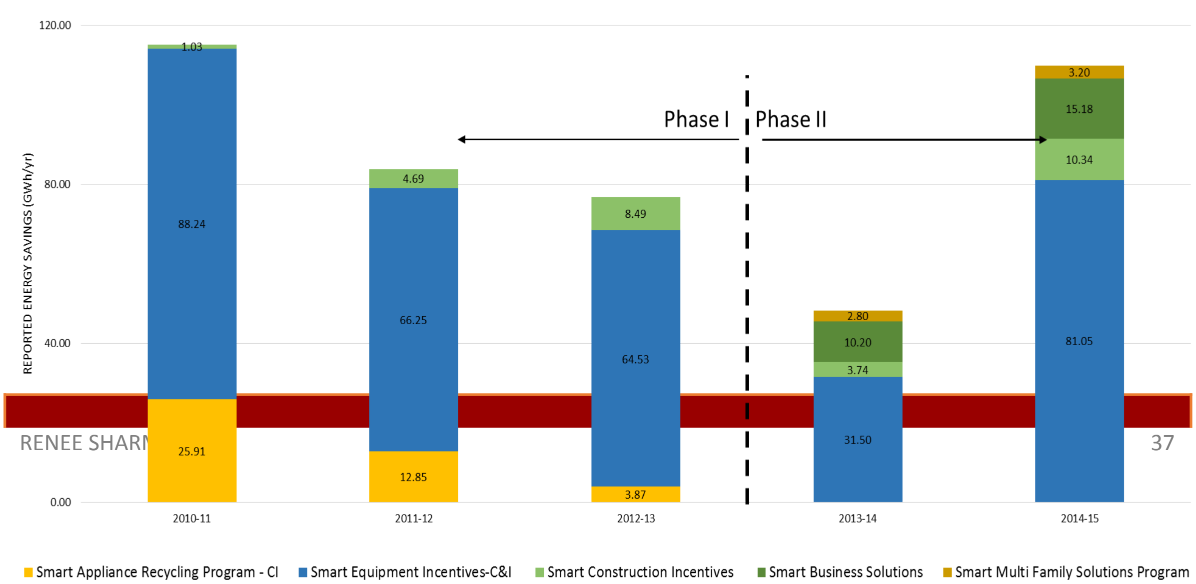


Figure 10: Energy Savings according to Rebates by Program

Figure 10 provides an estimate of the proportion each rebate program had for each program year. *Table 3* gives an exhaustive list of the number of rebate programs offered, but the author found that the following 5 rebates have been consistent throughout the years, with substantial savings, costs and benefits associated with them that they can be analyzed:

1. Smart Appliance Recycling Program
2. Smart Equipment Incentives
3. Smart Construction Incentives
4. Smart Business Solutions
5. Smart Multi Family Solutions

With the beginning of Phase II, the Smart Appliance Recycling Program was discontinued, and it contributed to about one fourth of the total energy saved in 2010-11. Smart Equipment Incentives, as stated earlier, shows consistent performance, since retrofitting a building is the smartest and the quickest, with less capital investments involved. Smart Construction Incentives is yet to find a strong foothold in the commercial sector, but Smart Business solutions is gaining popularity, since a lot of the building owners are small time business owners/ renters as well.

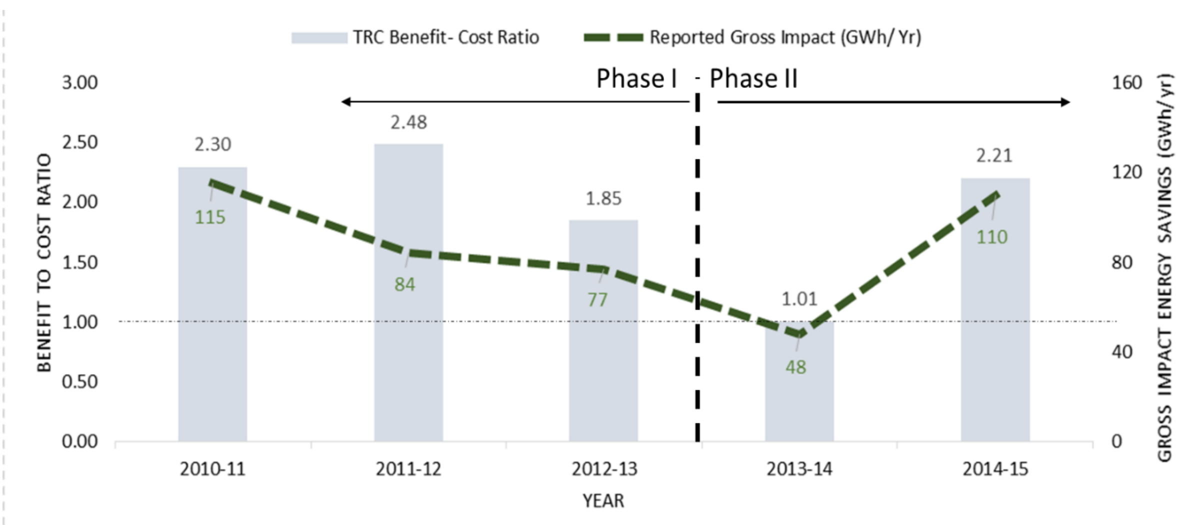


Figure 11: PECO Rebate Savings

When just those 5 rebate programs are scrutinized, a more promising picture emerges. The surplus data is removed, and only those rebates which are definitely for the commercial sector is analyzed. Figure 11 has three datasets on its axes. The Y axis is the time in years to track changes, while the X axes are Benefit to Cost ratio on the left and energy savings to the right. Where the befit to cost ratio and energy savings are closer together, that is where the program has been worthwhile and successful, the farther away these two data points are, the less effective the programs have been. So while the year 2013-14 has had less mount of energy saved, it has still been very successful, since the difference between the ratio and total energy saved is not large – that year, PECO managed to save a lot of energy for less aunt of money spent.

With the apparent success of the set of rebates for phases I and II, PECO has begun the task of creating the next set of rebates. They referred to their previous reports that Navigant Inc has been responsible about creating on PECO's performance in rebate world, which is then filed with PUC. Navigant also conducted surveys to explore more about the pros and cons of the rebates. The biggest issues that the responders had was the incentives were not sufficient enough for the consumers to avail the rebates, since the amount would just barely cover the cost of the building owners complying with the pre requisite conditions to avail the rebates (PUC, 2015). To cover up these problems, PECO has come up with a new plan to restructure the new set of rebates for Phase III, on the basis of the following 4 guidelines:

1. Provide energy saving and management solutions
2. Involve and engage stakeholders – building/ property owners – to come up with comprehensive set of rebates for their buildings.
3. Provide said stakeholders with the comprehensive rebates, along with solutions for demand reduction.
4. Continue engaging the stakeholders in continuing to constantly evolve the rebate structure for the individual properties.

With the implementation of Act 129, the EDC's and utility rebate managers introduced different rebates in the different phases. At the start of Phase II (2013) some rebates were discontinued and some rebates were newly introduced. When the rebate programs began, they were geared towards the residential customers, with just a rebate program on lighting being available for the commercial sector. The rebate for lighting was then meshed with the Smart Business Solutions and Smart

Equipment Incentives rebate. The following list enumerates programs and rebates provided for the business sector at present:

PECO Smart Equipment Incentives:

These incentives are offered for incorporating energy efficient design and equipment upgrades in existing projects. They are usually offered on lighting systems and types, and on equipment and/ or systems used for heating, ventilation and air conditioning of a building – variable speed and frequency drives, which are the fans and pumps utilized in the air handling units in any HVAC system. PECO provides a listing of what they consider acceptable types and systems to receive this rebate, but at the same time are flexible enough that owners may use specifications other than what is listed on their audit sheet, provided they can show a significant reduction in energy usage.

PECO Smart Construction Incentives:

This incentive is particularly for all new construction projects and/ or major renovation projects to incorporate energy efficient measures. For the utility company and third party managers handling the rebates, major renovations would encompass a complete overhaul of entire buildings systems like HVAC or lighting.

PECO Smart Business Solutions:

This incentive by PECO is targeting small business ventures that would like to reduce their energy use and save money, but cannot put in much capital investment for the energy efficient measures which are costly. Thus, this is provided as an option for retrofitting, incentives, where (50-60% of upgrades) are in lighting and electric hot water, among others. Since this incentive is for small business owners, the utility recognizes the fact that they may not have funds to conduct an energy audit, to identify which systems need to be upgraded, and so include a free on site energy analysis as well.

PECO Smart On-Site:

Smart On Site solution is provided for installing Combined Heat and Power (CHP) plants, and their equipment. There are about 7 projects which have availed this incentive option, but the plants are not yet operational and so no savings have been reported as yet.

PECO Smart A/C Saver:

This incentive has currently been discontinued. PECO would optimize A/C operation to reduce energy demand from June – September.

PECO Smart Gas Efficiency Upgrade/ PECO Smart Natural Gas Conversion:

These rebates were for buildings owners who wanted to increase the energy efficiency of their heating systems, as well as to promote natural gas as a fuel to heat buildings

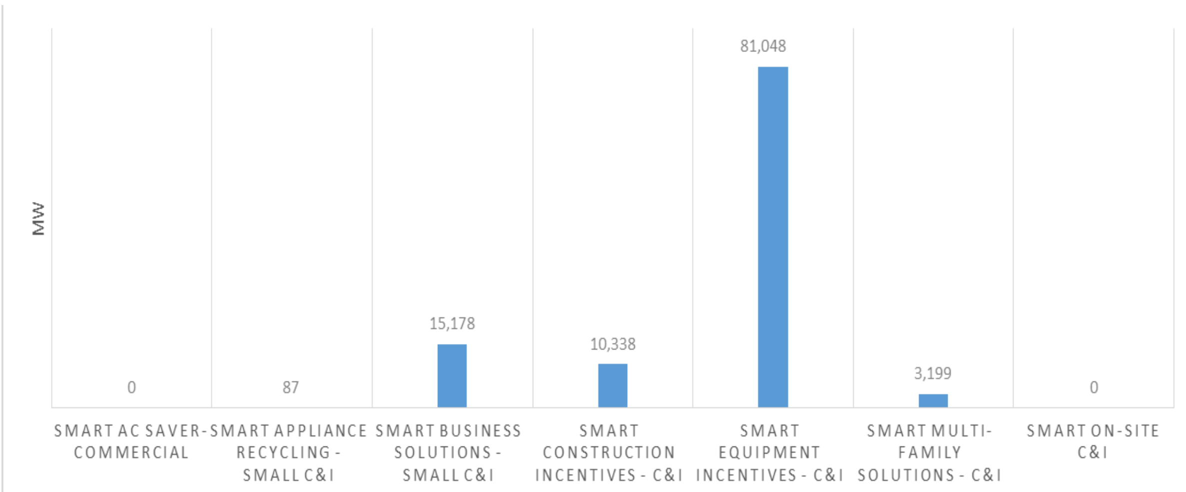
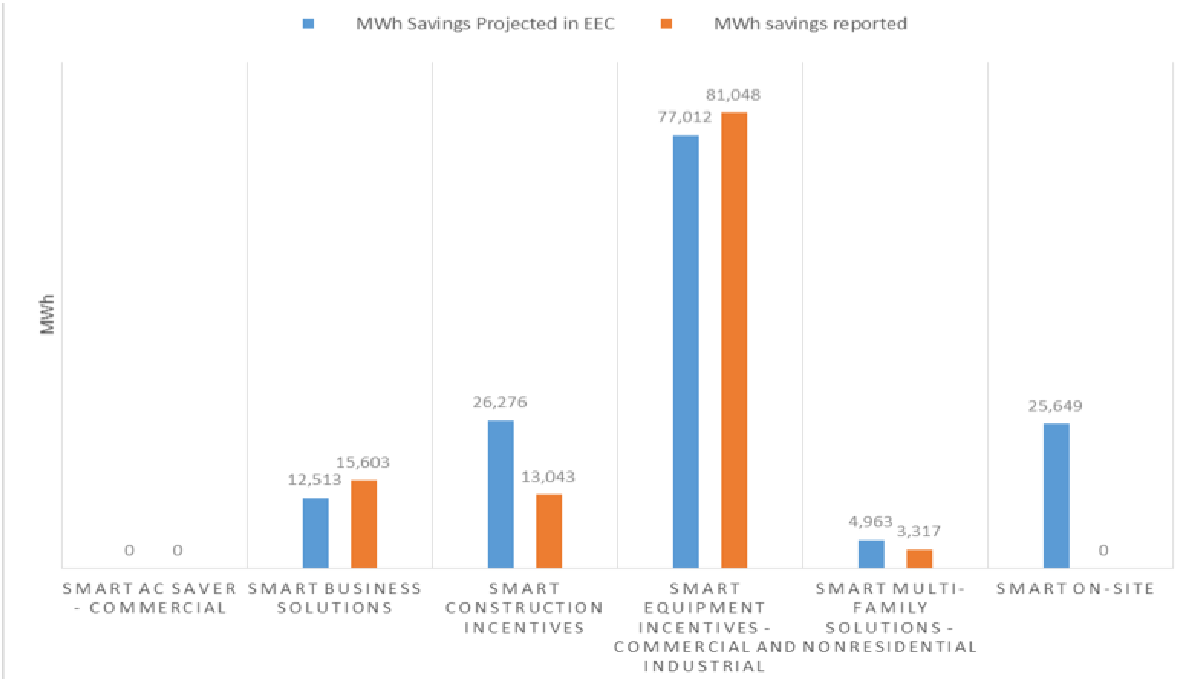


Figure 12: Reported Gross Impact (MW) on Energy for 2014-2015, PECO

Figure 12 reports how many megawatts of energy were saved for the year 2014-15 by PECOs rebate programs. Smart equipment incentives was extremely popular, since the rebates provided in this program provided maximum impact in energy savings. The rebates for retrofitting an existing building (Smart Equipment Incentives) has been extremely popular with the consumers for the past



year, with about 80% of the consumers opting for it.

Figure 13: Energy Savings (MWh/yr) per program in Commercial Sector for 2014-2015; PECO

Figure 13 provides an overview of the apparent success of the rebate programs. It is a comparison between the projected and reported energy saved, in MWh/ yr. Apart from Smart Construction Incentives and the Smart On Site solutions, the other rebates – for retrofits of big and small businesses – has been successful. The failure of Smart Construction Incentives to achieve their targeted goal of energy savings has been attributed to problems in creating awareness about them in the public arena, and the fact that the construction of new buildings takes time, which does not usually integrate completely with the timeline specified by the rebate managers for the owners to complete the process of obtaining the rebates. There has been no reported energy savings for the Smart On Site solutions since no CHP plant is at present operational.

Once we start comparing the energy savings with the amount spent on those rebate programs, a different picture emerges. These costs include all the expenditure an EDC and/ or rebate manager company had to do to create awareness about the programs, any infrastructure costs, costs of audits being offered, and so on. In other words, these were the total resource costs. Smart Equipment Incentives show a consistent performance since through this rebate PECO achieved more energy savings with less expenditure, but Smart Business Solutions does not fare so well, since the expenditure exceeded the budget by a $1000, which is almost double than what was initially projected.

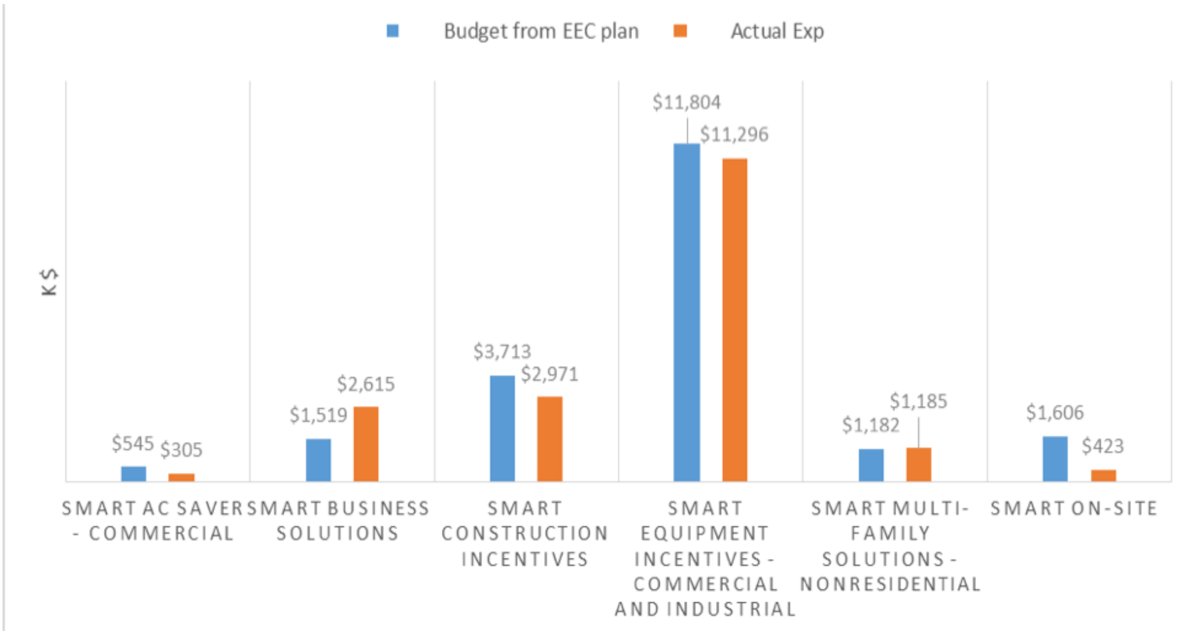


Figure 14: Expenditure ($1000) per Program for Commercial Sector for 2014-2015; PECO

2.4.1 Lighting

Lighting has been one of the most popular rebates, but is no longer offered as a separate rebate program.

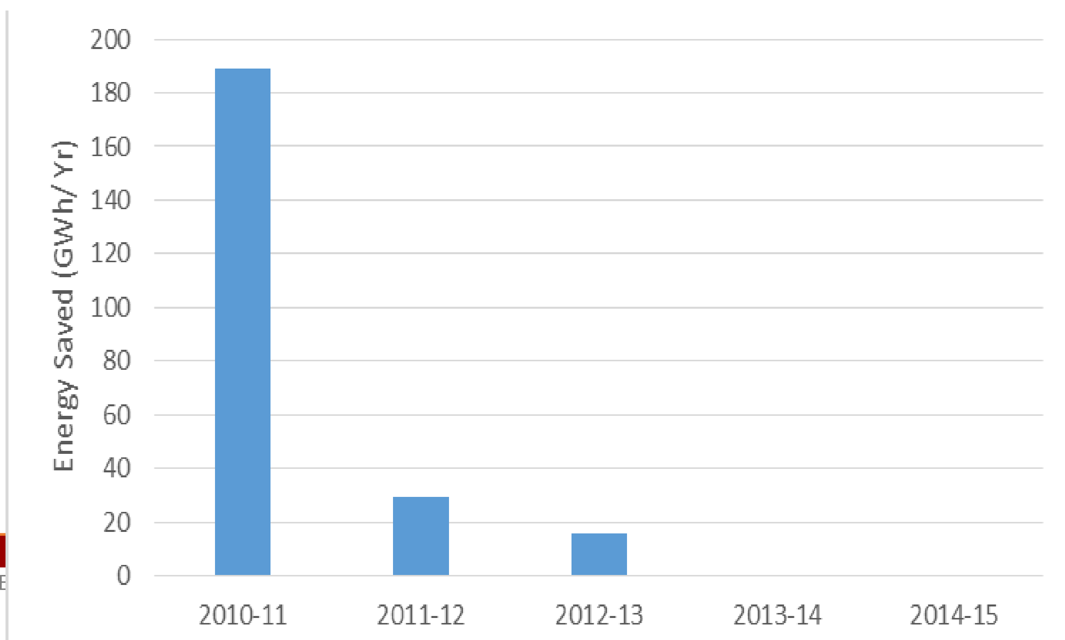


Figure 15: Lighting Rebate Energy Savings

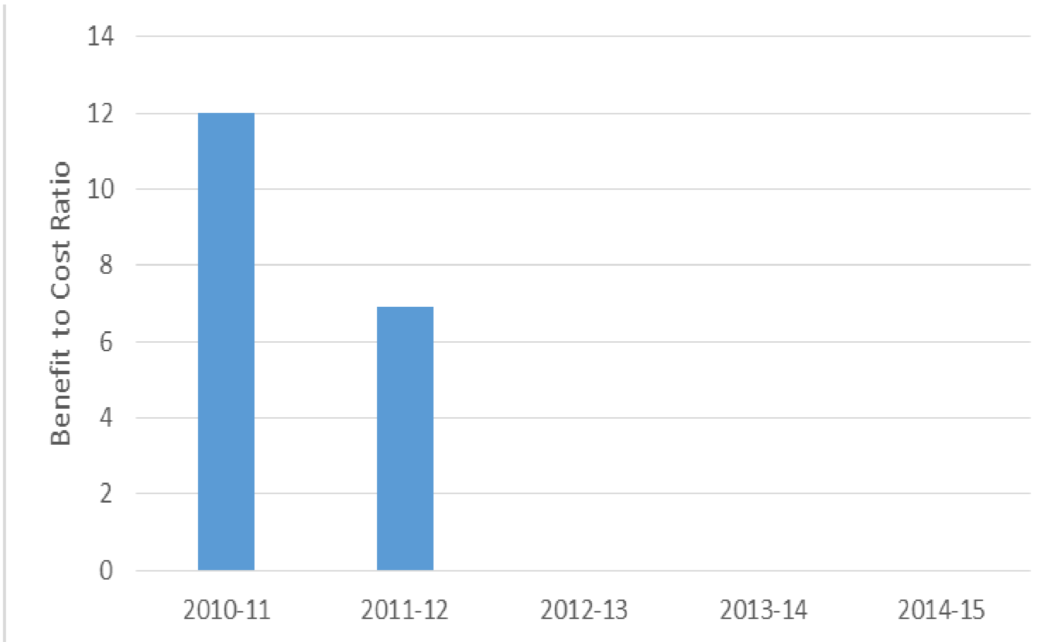


Figure 16: Lighting Rebate Cost Benefit Ratio

One of the earliest rebate programs was the replacement of old inefficient T12 lights with T 8 or T5 lights. This rebate was the first one introduced since energy and cost savings in lighting are most easily and quickly visible. Figure 15 depicts that the biggest effect in lighting rebates has been seen in the first year, when about 185 GWh/ yr of energy was saved, which dropped steeply to about 30 GWh for 2011-12. Figure 16 provides the benefit to cost ratio of the rebate, which validates the fact that lighting rebates were very successful. This program was discontinued in Phase II, and lighting rebates are now offered as a bundle with other rebates through different programs.

2.4.2 HVAC Rebates

Rebates specifically for HVAC have not been specified, but in fact are bundled in with other rebates:

1. Smart Equipment Incentives
2. Smart Construction Incentives
3. Smart Business Solutions
4. Smart On Site Solutions

A point to note here is that these categories do not consist entirely of incentives for HVAC. They are bundled with other incentives as well. Hence, these graphs are not indicative of the effectiveness or success of HVAC rebates, but rather a qualitative assessment of HVAC rebates offered. While detailed information on benefit to cost ratio and energy saved by utilizing just the HVAC rebates is not known, the numbers may provide us with an overall picture. The graphs have been depicted in Comprehensive Rebates in Figure 17. A point to note here is that these categories do not consist entirely of incentives for HVAC.

2.4.3 Envelope Rebates

Rebates or incentives on envelopes have as yet not been offered by PECO. This may be a missed opportunity that could have reaped enormous dividends.

2.4.4 Comprehensive Rebates

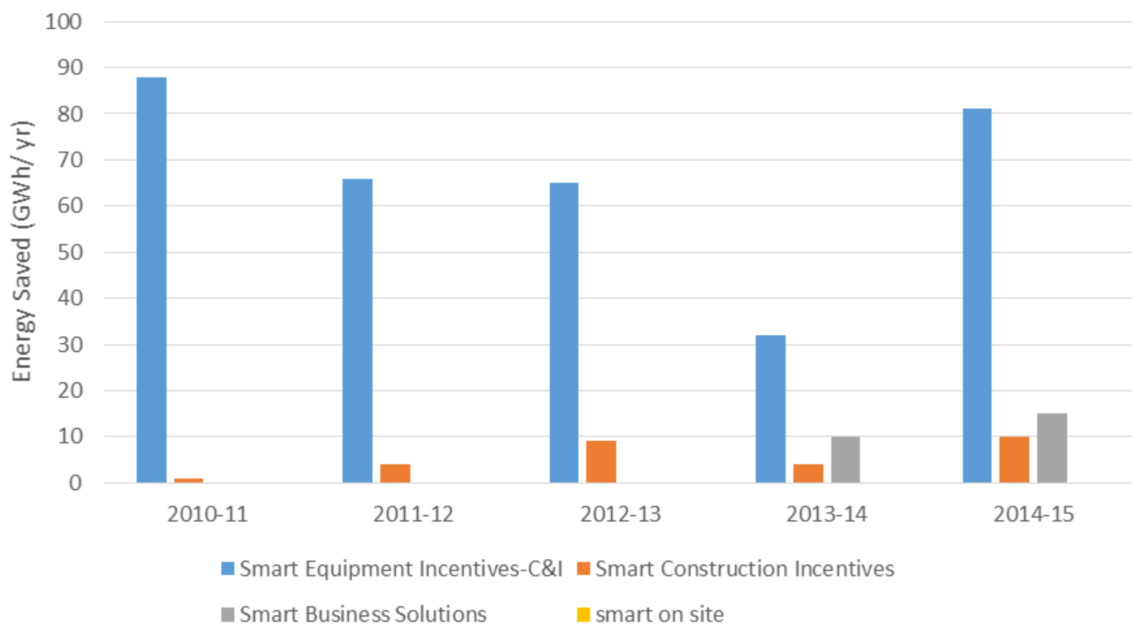


Figure 17: Comprehensive Rebates Energy Savings

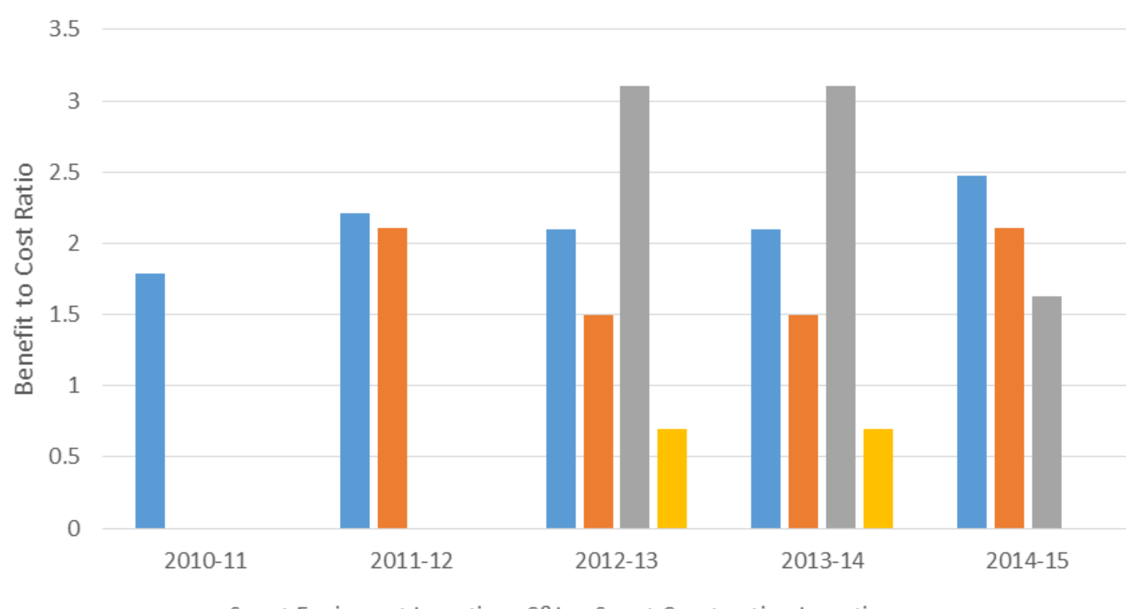


Figure 18: Comprehensive Rebates Cost Benefit Ratio

Comprehensive Rebates have been offered by PECO in 4 different categories:

1. Smart Equipment Incentives
2. Smart Construction Incentives
3. Smart Business Solutions
4. Smart On Site Solutions

Figure 17 Provides information on energy savings of these comprehensive rebates, and Figure 18 depicts how successful the rebates have been via a benefit to cost analysis. Smart Equipment Incentives program has a fairly consistent performance in terms of energy saved and the benefit to cost ratio. It was during the change to Phase II that this program recorded less energy saved, which may be accounted to the fact that the rebate could have been modified, when Phase I ended and Phase II began.

2.5 The Next Step in Rebate Structuring:

The way PECO is structuring rebates for the next phase follows a five step procedure, as detailed in

Figure 19. The first step is conducting an in depth analysis of the existing and potential energy efficient measures and the costs associated with them. This step would also involve engaging the building owners and obtain their perspective to finalize a plan of action. The next step would then be to verify the data collected on the measures. A database was developed of all the measures that can be utilized for the residential and commercial sectors. An example of the data available for selection purposes would be 'technical savings/ measure (kWh/kW), incremental cost/ measure, expected measure life, retail rates and avoided costs'. This is combined with market research that would provide the best options to be put forth by taking into account current practices and local climate conditions. Results from past studies would be applied for market data – 'customer segmentation, building functionality/ stock/ type and benchmarking other EE portfolios' – and leveraging opportunities available. Step 4 – Portfolio Modelling – is a combination of the previous two steps, where the objectives for EEM for a building would be defined, targets specified and plans and budgets developed. This would cumulate to a final plan, which is the last step in the entire development process.

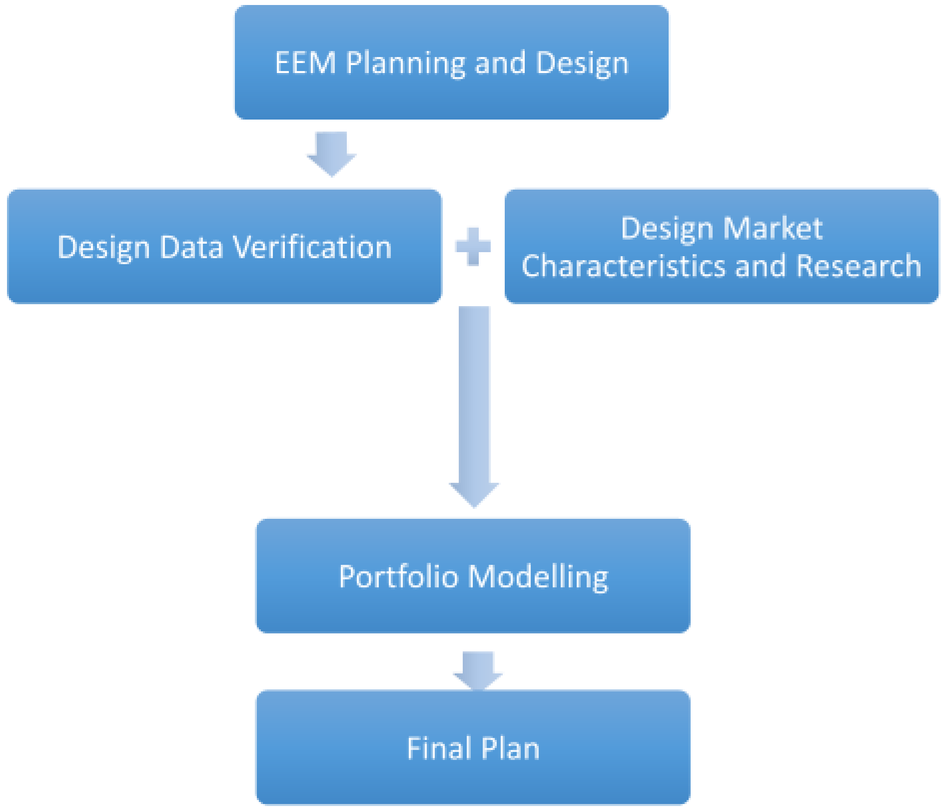

EEM Planning and Design
Design Data Verification
Design Market Characteristics and Research
Portfolio Modelling
Final Plan

Figure 19: Plan Development Methodology, adapted from PECO Phase III EE & C Plan (PECO, 2015)

The first step, where potential programs can be designed, developed and analyzed for their suitability, is where this synthesis will act as a supporting tool, in addition to the process developed by PECO. The process developed by PECO to create new sets of rebates includes the analysis of probable rebates, and then comparing them with the potential savings that may be obtained from them.

This process has been broken down to three broad levels:

1. Identifying probable measures:
   Compilation of all the EEM and other demand reduction measures. The applicability of the selected measures can then be used to analyzed

2. Quality screening:
   Those measures which are:
   a. A current requirement for complying with the building code
   b. Not relevant to local climate conditions
   c. not quantifiable in terms of savings or cost impacts,

   are removed from the selection. The remaining rebate and EEM/ programs then go through a screening for quality, which would focus on technology, market availability and popularity, audience acceptance and popularity, and other value added benefits that may be provided.

3. Economic Screen:
   This is the last level, wherein the programs remaining after the qualitative screening are analyzed for their lifetime benefits vs their costs. It is not necessary for all the measures to pass this particular screen, but the portfolio itself needs to have a positive benefit to cost ratio.

While phases I and II focused on easier retrofit options, phase III builds upon the previous 2 phases to develop a 'more comprehensive and customer centric portfolio of energy solutions' (PECO, 2015). PECO plans for 5 EEMs and 3 demand response programs. Of the 8 programs, 4 programs are targeted to customers in the commercial sector:

1. Low income EEM – this program would target small corner store commercial centers which are a part of multi family residences/ apartments
2. EEM programs for small and large commercial properties
3. Promotion of, and installation of CHP plants in small and large commercial properties
4. Electric demand responses for small and large commercial properties

These programs would have a set of solutions that would be tailored to the customers taking part in PECO's Phase III plan. The demand response programs would be in effect specifically for the months from June to September, when electric demand would be the highest. Participants from the commercial sector via the direct load control (DLC) and demand response aggregation (DRA). While the former would be geared small commercial properties, the latter is for the large commercial properties. The plan outlines 4 different ways for customers to avail of the EEMs: providing discounts for energy efficient products, working directly with PECO for EEMs through direct install or appliance recycling and installing energy kits, working indirectly with PECO – through allies and third parties – to incorporate rebates for EEMs like retrofits and design and building management consultations, and lastly through an initiative where the customers would themselves craft their own rebates and EEMs, for approval by PECO. PECO's phase III rebates are expected to be structured in such a way that they would be comprehensive in nature, when addressing the energy needs of a building. The document further states the intention of the utility company to achieve 5% energy savings on average (on the basis of 2009-10 energy consumption). The total investment specified in the report is about $430 million stretched over the years from 2016 to 2020.

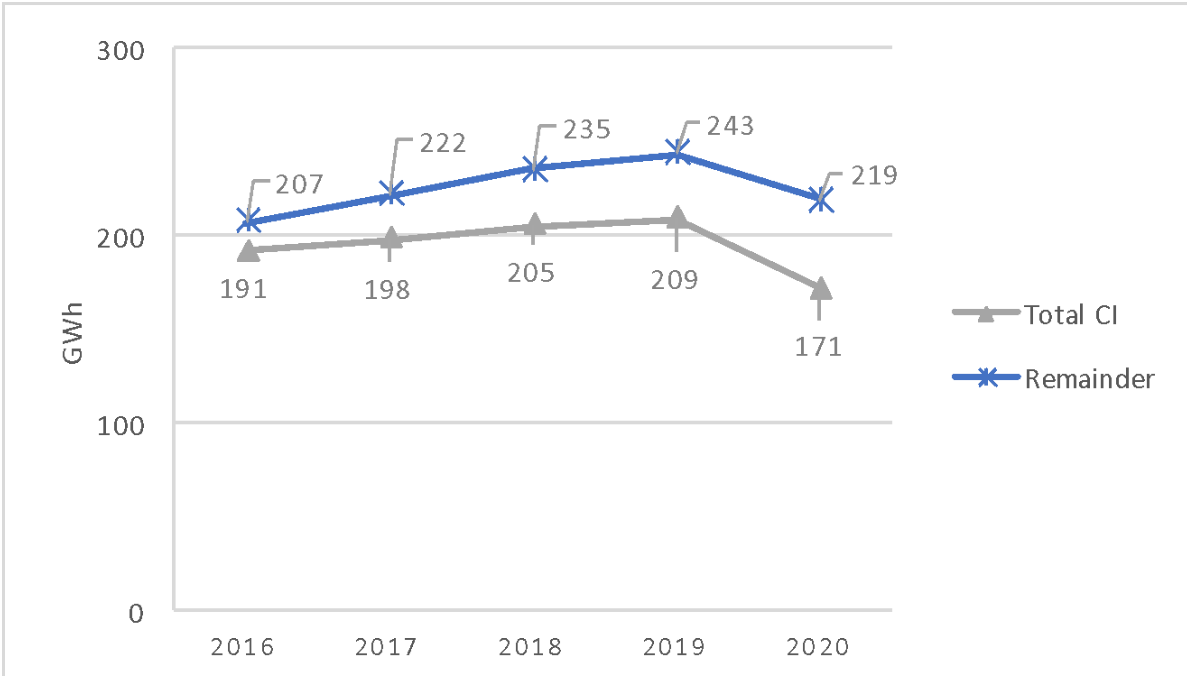


Figure 20: Projected Energy Savings for Phase III

Figure 20 projects energy savings that PECO hopes to achieve for phase III for the commercial sector. The commercial sector savings form a big portion of the entire portfolio, with about 48% of the entire portfolio in 2016.

Seven milestones have been set forth, to achieve the targets specified, by PECO. They are:

1. A minimum of 5% energy savings shall be achieved on the basis of the forecasted number of about 1963 GWh of energy saved in 2010.

2. 2% of the utility company’s yearly revenue, or $85.5 million annually, with a cap of $427.7 million shall be the investments for energy savings and demand reduction

3. Government, educational and non profit sector shall provide a share of minimum 3.5 % of the energy saved in the entire portfolio.

4. Low income program shall generate about minimum of 5.5% of the total energy saved in the entire portfolio.

5. 15% of total energy shall be saved at the minimum for each year

6. 161 MW of demand reduction savings shall be achieved from 2017-2020

7. A set of comprehensive rebate program pathways shall be set up, so that customers from all sectors can avail them.

3 Data Analysis Methodologies utilized for Energy Data Analytics:

The methodology utilized for the statistical analyses conducted under the purview of this research involved using annual, monthly and interval data to parse out disaggregated energy loads. The Annual data was in the form of EUI and Energy Star scores of the buildings in the dataset. Monthly level utility bills, and 15-30 minutes interval level energy data are using to disaggregated energy consumption into heating loads, cooling loads and baseloads. These terms are explained further in the following subsections.

3.1 Annual

The city's benchmarking ordinance makes it imperative for buildings with gross floor area above 50,000 square feet to report their energy use via Portfolio Manager. This information is publically available. The entire dataset contains of 970 such buildings. This list was then mined for buildings whose Energy Star Score was higher than 98 and lower than 2, since these would be outliers, and can be ignored. Energy Star scores a lot of building types – banks, courthouses, hospitals, schools, offices, retail stores, wastewater treatment plants, worship facilities and the like. To focus the scope of work, only office/ commercial buildings were selected from the remaining pool of data, to maintain consistency in analysis. Office buildings has a typical function and activity associated with it, which is not similar to other building types like a school or a hospital. Their workings differ dramatically. They have different occupancy schedules, they would be operated differently, and their design would be different too. All these affect how these buildings would utilize energy, and so this problem was removed by selecting just office buildings. Buildings which housed data centers were also removed from the dataset, since data centers are very energy intensive buildings – due to the load on energy to keep the places that house the servers cool. The last filter applied was the age of the buildings. Only those buildings which were built after 1930. That brought the dataset down to 60 buildings. Energy bills of the past 3 years were collected, to obtain EUI. Once the bills had been collected, site and source EUI's were calculated. This is a metric that can be analyzed against the Energy Star scores, and EUI's of buildings with comparable Energy Star Scores can also be analyzed.

3.2 Energy Star Score:

This is the most easily available metric for buildings above 50,000 sqft. A relevant point to note is that this score is just a result of the Portfolio Manager tool. Having this score does not necessarily mean that the building is Energy Star Certified, so energy efficient in any way. The score is a range of 1-100, and the score of an average US office building is 50. That is, if a building's energy data has been entered in Portfolio Manager, and it is as energy efficient as an average US building of that particular type, then the score of that building would be 50. A building is considered more efficient if its Energy Star Score is higher. The CBEI research found that about 70% of the buildings in the selected pool have an Energy Star score of 50 and above. Of these 70% buildings, about 50% have an energy Star score of 75 and above. One big advantage of using Energy Star scores as a metric to analyze attributes is that it controls for a lot of factors like plug loads, occupancy schedules, fuel mix and also the weather. The only problem is that the public does not have access to this information, due to privacy concerns. In certain ways, Energy Star Score is a much better metric to use than EUI, for comparison amongst buildings, as EUI does not take into account the factors listed above.

EUI: Site/ Source/ Electric/ Fuel Mix: Calculating all four types of EUI allow us to test attributes in detail, and accord cause and effect correctly to the attributes. Site EUI is the amount of energy utilized by a building (at site) per sqft. Source EUI also includes the amount of energy needed to generate and distribute that energy, along with transmission and distribution losses that occur. Electric EUI is the same as Site EUI for buildings that do not use natural gas, propane or district steam for heating purposes, and so Fuel EUI was coined as a term to represent energy use intensity (per unit area) for all energy apart from electricity.

3.3 Monthly Data

This is the most commonly available energy data from the utility companies for buildings. Annual data is solely a function of energy use intensity which is per unit area, but monthly level data would also account for energy use fluctuations based on temperature changes. It would, however, not account for occupancy scheduling.

The first step was cleaning the data, and removing those buildings which utilize fuels other than electricity for heating, to maintain consistency within the dataset. This was already done the previous year for the CBEI project, and the same methodology has been adopted for cleaning the monthly energy bills for new buildings inducted into the dataset. One method was that if an extremely high or low reading was recorded for a month, then it could be discarded by assuming that reading as an outlier. Outliers can be defined as data higher than 1.5 times the third inter quartile range (or alternatively, lower than 1.5 times the first quartile range). Buildings which had interval data were rolled up to get monthly energy data values. Then the monthly energy use values are divided by the number of days, to obtain Energy Use Intensity per day.

LEAN analysis was developed by (Kissock & Seryak, 2004) to observe how energy use varies with fluctuations in weather. This method is especially useful if trends are to be observed across the dataset collected. Seasonal energy use, peak loads and baseloads are parsed out by plotting energy use intensity per day against normalized degree days. Certain modifications were made to the analysis, to adapt it for the CBEI project, as detailed in their project reports:

1. Degree days are used instead of average outside temperature. Degree days may be a better representation, because there may have been days which needed more cooling, and there may have been days which needed more heating. Variations can also be observed in temperatures across a single day as well. If the energy use data point are for occupied hours, then outside air temperature can be used as an independent variable, but if regression is to be done for monthly level data, it would be more prudent to use degree days. The monthly energy use intensity is normalized per day, according to the days in a month, so the degree days would need to be normalized according to the number of days in a month as well. Also, since a month would have both heating and cooling degree days, it becomes necessary designate a month as heating dominated or cooling dominated. Months that are heating dominated would have the heating degree days as the independent variable, and vice versa. Months which have about the same number of heating and cooling degree days were neglected, due to complications that arise upon analyses.

2. (Kissock & Seryak, 2004) developed their method of analysis by using the 2 point change model.

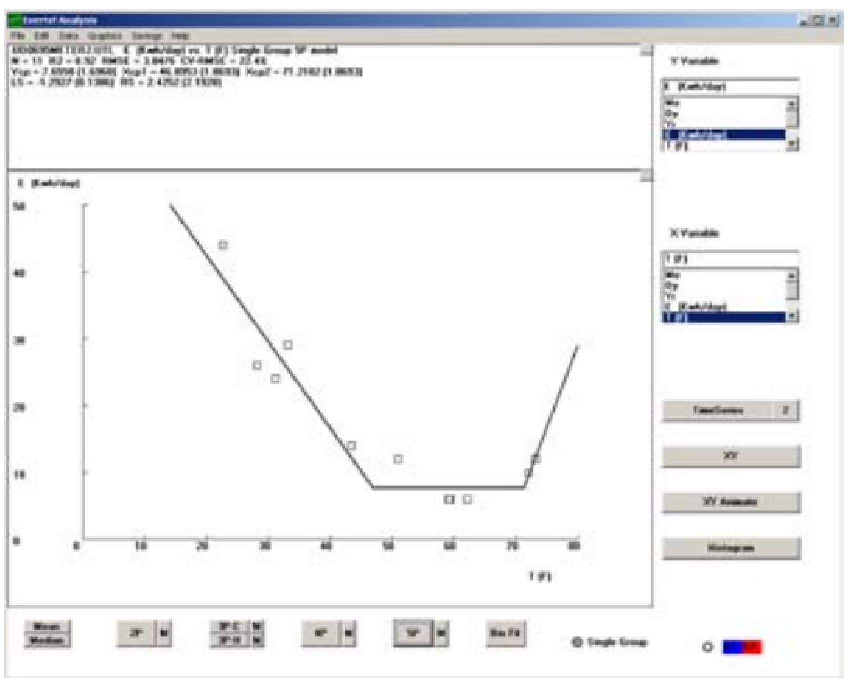


Figure 21: LEAN - 2 Point Change Model by Kissock & Seryak, 2002

It is assumed that the baseload would be the bottom line, and the area under the curves above the baseload would be heating and cooling energy use. This may be a bit misleading, since there are some system components like ventilation systems that would be running continuously, regardless of whether there is one person occupying the buildings, or fifty. It would also not be affected by temperature changes. There may also be areas in the graph that represent that cooling is no longer needed in a building, but that would not be feasible, at least till the heating season starts. Thus, inflection points are used to signify seasonal changes in heating and cooling energy use.

3. Instead of straight lines, polynomial curves to the order of degree 2 are used

4. For buildings using fuels other than electricity for heating, site EUI is plotted on the same axis for making easier comparisons with other buildings

5. (Kissock & Seryak, 2004) had developed the analysis by using production loads, since they were analyzing energy consumption in factories. These are not used for monthly level analysis and are substituted with occupancy loads for interval level analysis.

3.4 Interval Data

The methodology employed to analyze interval data is similar to the ones used for monthly level data analysis. The monthly energy use intensity values by day are then again divided by 24 to get Energy Use Intensity per hour for LEAN Interval analysis. The only difference is that instead of degree days, outside air temperature is used as in the independent variable.

3.5 Building Attributes Data Collection

To re-emphasis the reasoning of selecting the list of attributes mentioned in Table 1, it was imperative to choose those attributes for which data may be easily available. Not all buildings would have an Asset Score form filled up, and access to the mechanical room or the boilers, chillers, cooling towers, packaged rooftop AC units and such may be restricted. This is a limitation of this research since all the attributes collected have been obtained from site visits and drive-bys, along with Google images.

At the same time, not all of the buildings in the database can be used for analyzing building attributes, due to the availability of the level of data needed. It is very easy to obtain annual level data (Energy Star Scores, site EUI) for analysis, but not all property managers allow access to their buildings utility bills. The dataset had 116 buildings, and because energy bills were obtained for just half of them, the dataset was reduced to 60 buildings. The next step was to analyze the energy bills of these 60 buildings, and some had missing data points. Ultimately, the dataset was reduced to 52 buildings which had monthly and interval level data.

4 Summary of Energy Data Analytics with Building Attributes

The first part of the analysis was disaggregating the energy bills into heating, cooling and base loads. The methodology for LEAN analysis was utilized, and most of the analyses has already been done for the previous studies. LEAN charts for the new buildings were created with the help of two colleagues, and the original dataset was updated. The charts use color coding to represent the proportion of energy or electricity (for an all electric building) with the yellow bands signifying base energy use, red curves for heating seasonal energy use and blue curves for cooling seasonal energy use. Please refer to (Spencer & Kaufman, 2015) for more information on the LEAN analyses.

The LEAN charts allow a quick preview of electricity as a proportion of base/ plug loads, heating loads and cooling loads of a building. The EIA defines baseload as 'the minimum amount of electric delivered or required over a given period of time at a steady rate' (EIA Glossary, n.d.). For a building, the baseload would be the amount of energy needed to operate the bare minimum essentials over the course of a year (Belshe, 2009). For the purpose of this research, baseload is categorized into four different sections. Since the buildings are all offices, it was assumed that they would be completely unoccupied on Sundays and/ or holidays. Saturdays would have some office workers in the building, for some time. Baseloads for Sundays and Saturdays would differ from the weekday baseloads since the building would be fully operational the entire time people are working.

1. Sunday/ Holiday Baseloads – for the lowest electrical demands.
   This baseload would represent the lowest electrical or energy demands of a building since only the bare minimum equipment needed would be operational. These include all the security lighting installed in the building, basic ventilation and exhaust fans, some fans and pumps to maintain the minimum thermal conditioning or boiler and furnace loads, and some AC units with air handlers for minimum air conditioning, elevator loads and plug loads from the office equipment, refrigerators, water coolers and computer processors. Philadelphia needs heating more than it does cooling. Switching of the HVAC systems in buildings on Sundays and holidays may lead to pipes freezing during the harsh winters. Also, in winters, the system would require less energy to heat a building from 50 F to 70 F, rather than from, say, 10 F. The same goes for summers, when cooling the building from, say, 80 F to 75 F would be less energy intensive than from 90 F or above, and this range is called a beadband. The deadband – the range of temperature where the building systems are neither heating nor cooling – is larger.

2. Saturday baseload – when some workers are in the building

The baseload on Saturdays would be a bit higher than the Sunday baseload since the buildings would have some occupancy. Some owners do not turn on the air or thermal systems, but in addition to all the systems running for Sundays/ holidays, local lights would be functional, the building would be ventilated and the deadband for heating and cooling would narrow down. Since the buildings will have some occupancy, the elevators would be functional and not just on standby, the same with plug loads – they would increase as people switch on office and desktop equipment to work.

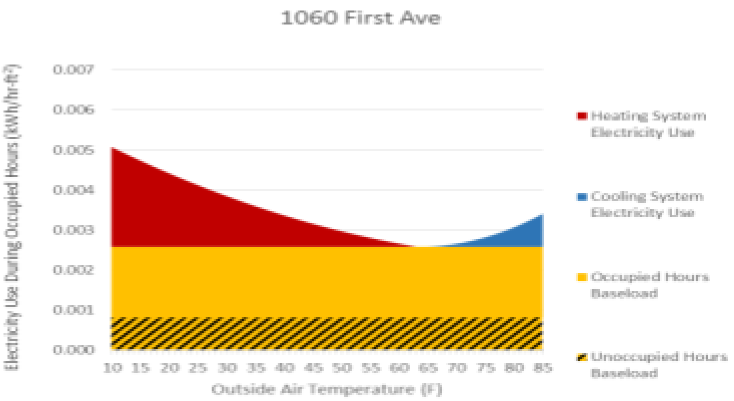
3. Weekday Baseload
   All systems and equipment are fully functional in the week, during office hours. Baseload would differ from that of the weekends since the entire building would be heated and/ or cooled.

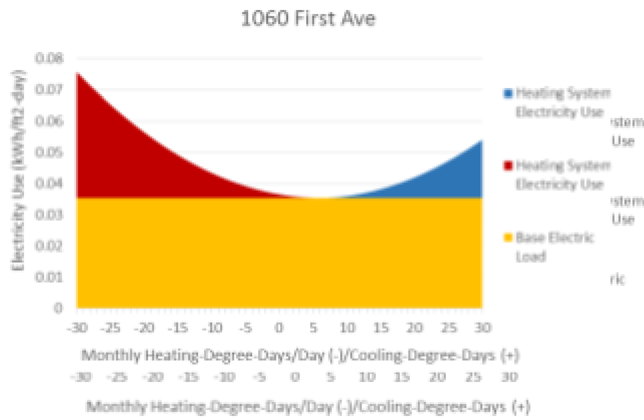
4. Weeknight Baseload
   On a weeknight, the baseload may be the same as the weekday baseload in the worst case scenario, when all the HVAC and lighting systems are functional, or like the Sunday baseload in the best case scenario where just the emergency lights and basic HVAC systems are operating.

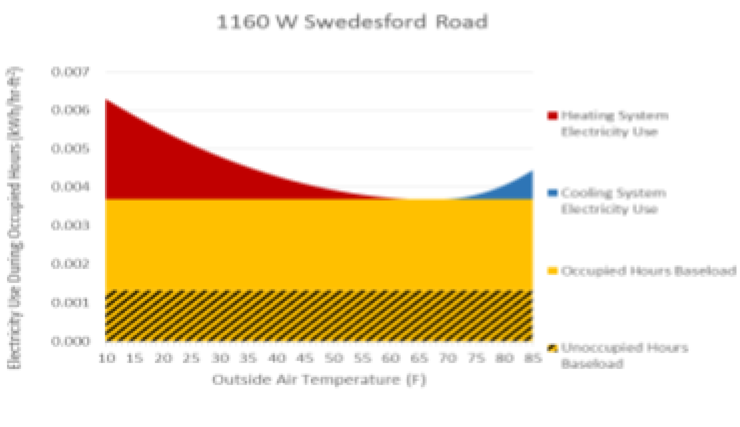
5. Cooling Loads
   Loads from the equipment needed to provide cooling to the different spaces of a building are classified as cooling loads. These may be from air handlers; rooftop packaged units, energy or heat recovery ventilators, humidifiers, and so on. These are weather dependent loads and increase with an increase outside air temperature, based on occupancy or work hours.

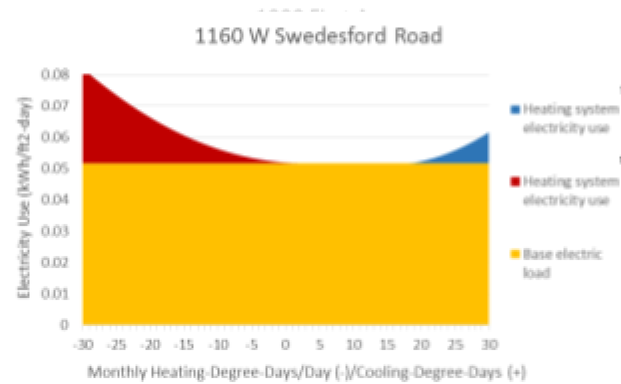
6. Heating Loads
   Loads from equipment needed to provide heating to the different spaces of a building are classified as heating loads. Heating may be air or water based, forced air or radiant systems. Air based systems are more energy intensive than the water based systems (US DOE, n.d.). This is because water is more efficient in storing warmth, due to the fact that it stores more heat due to enthalpy. Because of this fact, radiant systems are more energy efficient than the forced air systems due to no duct losses (DoE, 2016).

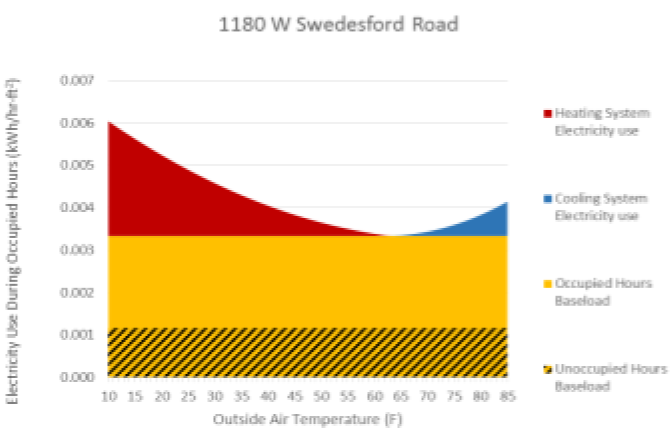
The LEAN charts for the new additions to the dataset were created by the author and two of her colleagues collectively. The existing LEAN monthly and LEAN interval derived data points for the original set of buildings were updated. The next three pages contain LEAN month and LEAN interval charts for the new buildings.

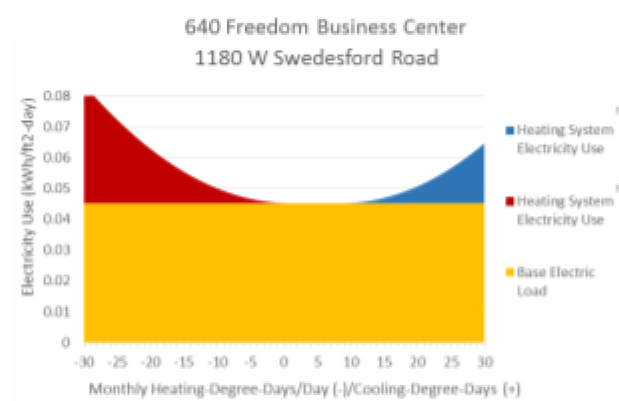

1060 First Ave
Electricity Use During Occupied Hours (kWh/hr-ft²)
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload

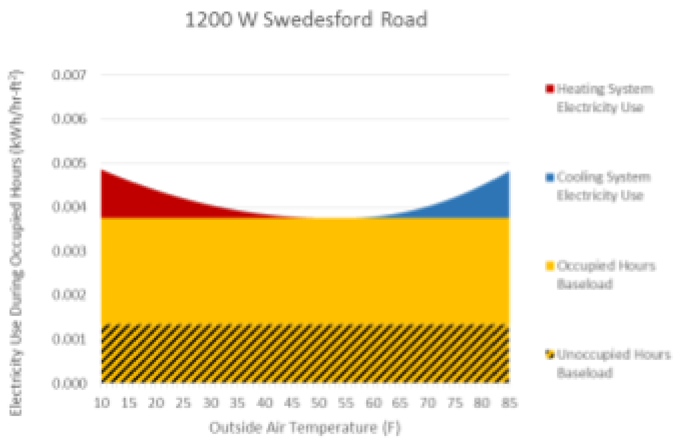

1060 First Ave
Electricity Use (kWh/ft2-day)
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Heating System Electricity Use
Heating System Electricity Use
Base Electric Load

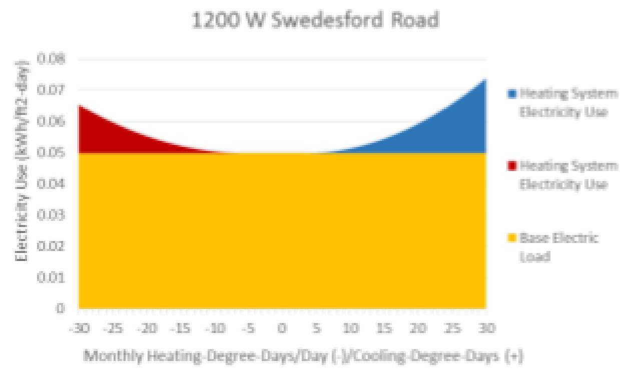

1160 W Swedesford Road
Electricity Use During Occupied Hours (kWh/hr-ft²)
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload

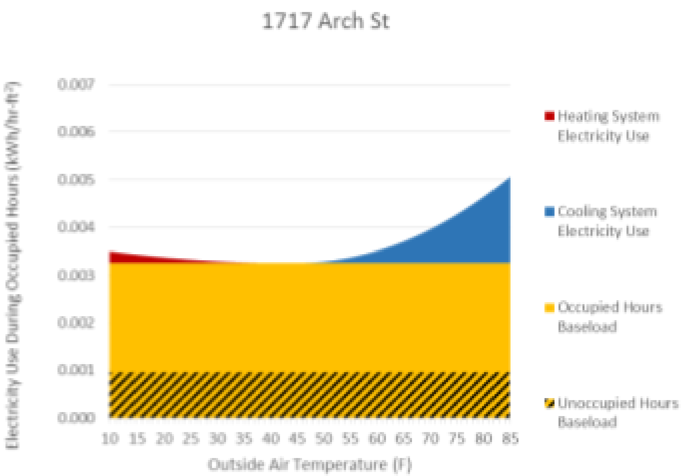

1160 W Swedesford Road
Electricity Use (kWh/ft2-day)
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Heating system electricity use
Heating system electricity use
Base electric load

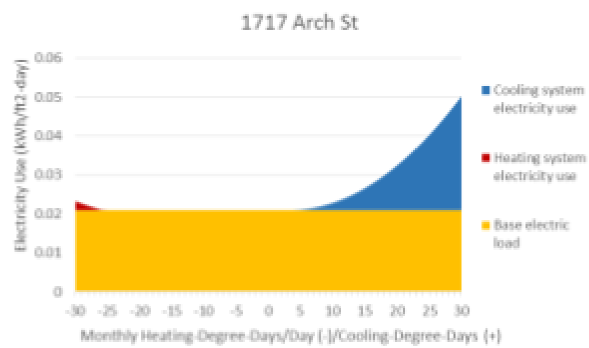

1180 W Swedesford Road
Electricity Use During Occupied Hours (kWh/hr-ft²)
Outside Air Temperature (F)
Heating System Electricity use
Cooling System Electricity use
Occupied Hours Baseload
Unoccupied Hours Baseload

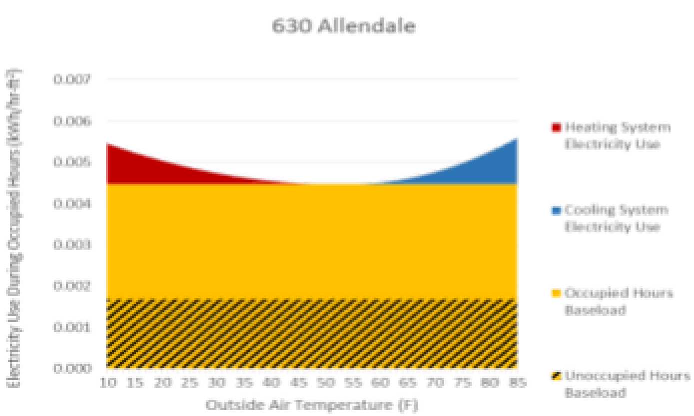

640 Freedom Business Center
1180 W Swedesford Road
Electricity Use (kWh/ft2-day)
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Heating System Electricity Use
Heating System Electricity Use
Base Electric Load

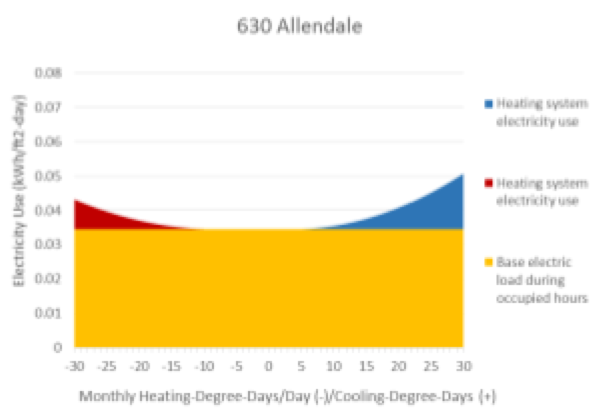

1200 W Swedesford Road
Electricity Use During Occupied Hours (kWh/hr-ft²)
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload

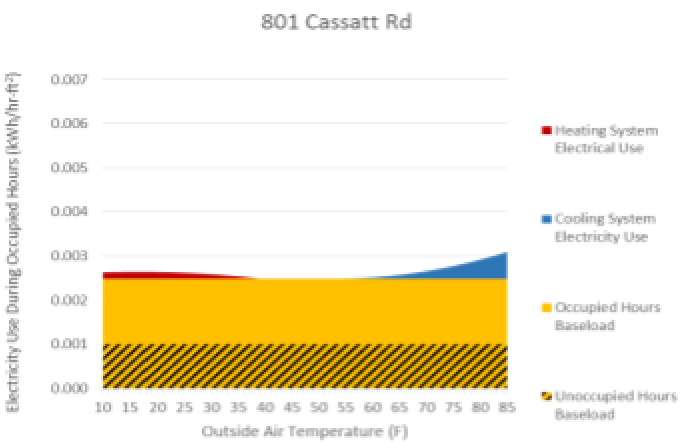

1200 W Swedesford Road
Electricity Use (kWh/ft2-day)
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Heating System Electricity Use
Heating System Electricity Use
Base Electric Load

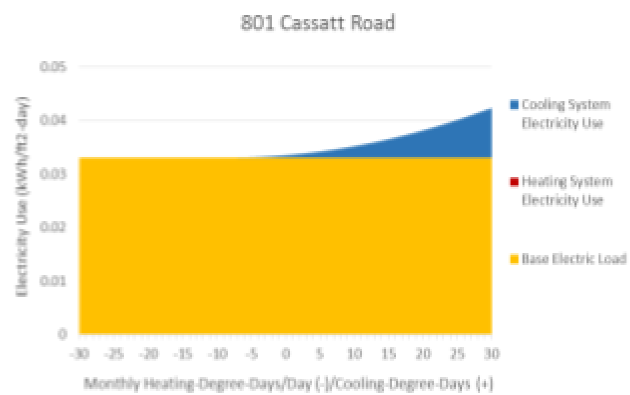

1717 Arch St
Electricity Use During Occupied Hours (kWh/hr-ft²)
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload

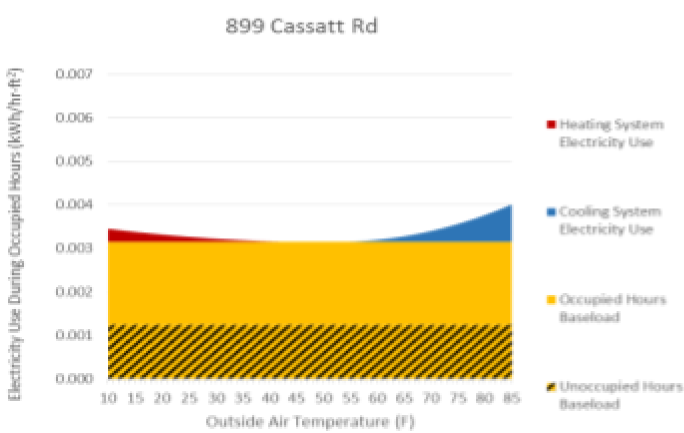

1717 Arch St
Electricity Use (kWh/ft2-day)
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Cooling system electricity use
Heating system electricity use
Base electric load

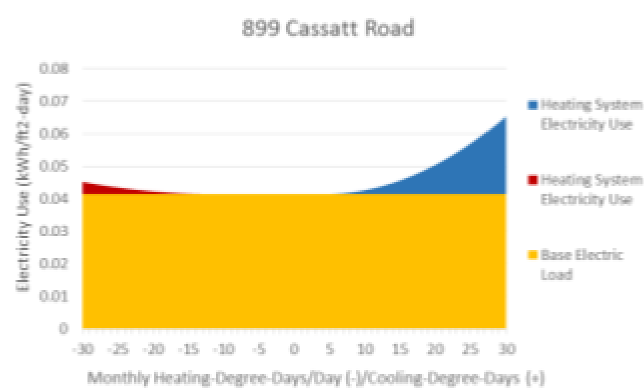

630 Allendale
Electricity Use During Occupied Hours (kWh/hr-ft²)
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload

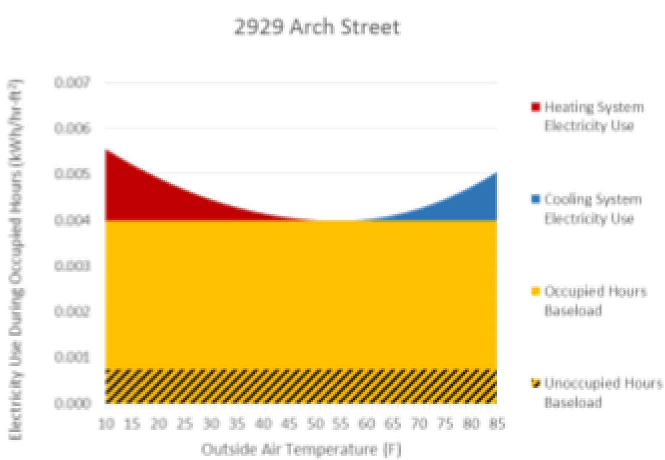

630 Allendale
Electricity Use (kWh/ft2-day)
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Heating system electricity use
Heating system electricity use
Base electric load during occupied hours


801 Cassatt Rd
Electricity Use During Occupied Hours (kWh/hr-ft²)
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85
Outside Air Temperature (F)
Heating System Electrical Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload


801 Cassatt Road
Electricity Use (kWh/ft2-day)
0.05
0.04
0.03
0.02
0.01
0
-30 -25 -20 -15 -10 -5 0 5 10 15 20 25 30
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Cooling System Electricity Use
Heating System Electricity Use
Base Electric Load


899 Cassatt Rd
Electricity Use During Occupied Hours (kWh/hr-ft²)
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload


899 Cassatt Road
Electricity Use (kWh/ft2-day)
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
-30 -25 -20 -15 -10 -5 0 5 10 15 20 25 30
Monthly Heating-Degree-Days/Day (-)/Cooling-Degree-Days (+)
Heating System Electricity Use
Heating System Electricity Use
Base Electric Load


2929 Arch Street
Electricity Use During Occupied Hours (kWh/hr-ft²)
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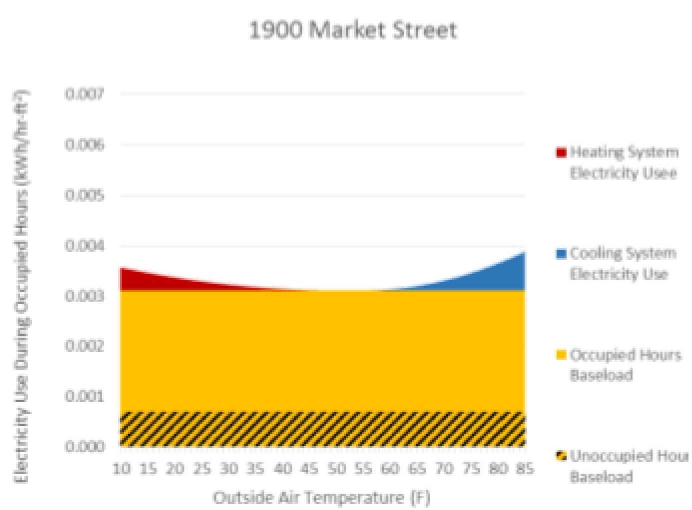
0.006
0.005
0.004
0.003
0.002
0.001
0.000
10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85
Outside Air Temperature (F)
Heating System Electricity Use
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload


1900 Market Street
Electricity Use During Occupied Hours (kWh/hr-ft²)
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85
Outside Air Temperature (F)
Heating System Electricity Usee
Cooling System Electricity Use
Occupied Hours Baseload
Unoccupied Hours Baseload

4.1 Impact of Load Breakdown on Attributes:

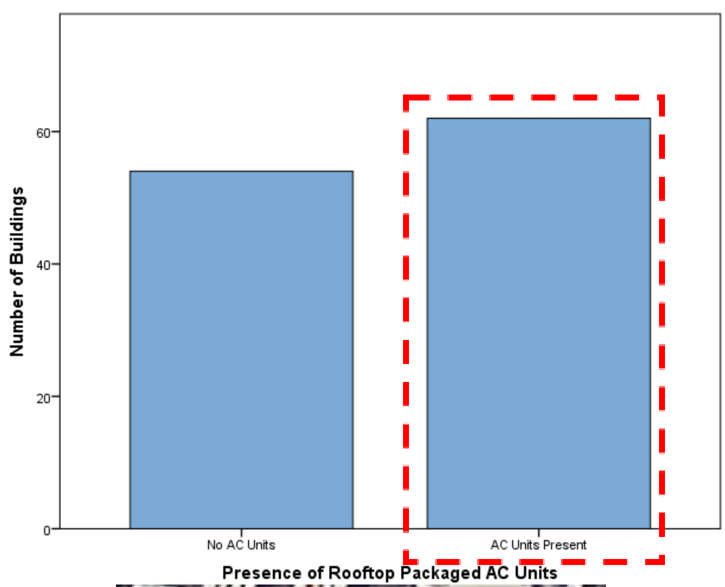
As mentioned previously, the total number of buildings in the dataset is one hundred and sixteen, for which attribute information has been collected. Of these one hundred and sixteen buildings, fifty two were analyzed against a delimited set of building attributes. The other seventy four were not analyzed since their energy data was not available. Analysis of Variance (ANOVA) are conducted when it is necessary to compare variability between groups to the variability within each group (Pallant, 2013). ANOVA for this research is used because the independent variables have two or more than two groups within, and the analysis was performed in SPSS. All the building attributes collected are the independent variables. The metrics (which are the different energy loads) parsed out from LEAN analysis are the dependent variables. The significant results are discussed in the following sections according to the twelve building attributes as well as according to disaggregated energy loads. The underlying reason for some of the findings observed and mentioned in the subsequent sections may be due to underlying factors that have not been explored, or because of attributes that have not been collected for this research. These probable factors and uncollected attributes have been mentioned in the sections below.

4.1.1 Rooftop Packaged AC Units

Packaged air conditioning units have a separate unit that houses the different parts of an air conditioning system, like fans and coils. The cool air is circulated inside the building via an air handler, through the ductwork (Burgess, May 2014). In the dataset of fifty two buildings, there were only eleven that did not have rooftop packaged AC units. This may be because of the costs associated with setting up and operating a packaged unit is comparatively less than a central cooling system (Bhatia). One way ANOVAs were run to understand how they would impact energy consumption. One of the main advantages of having a packaged AC unit is the decentralization of the cooling system equipment. Each unit would serve a limited area in a building, unlike a central cooling system. In the former case, certain units may be switched off after hours, if need be, but in the latter case, the central cooling system would need to function in the background to condition parts of the building after work hours, with only the air handling units not functioning in areas which do not need to be conditioned.

Figure 22: Aerial Image of Rooftop Packaged AC Units

The most relevant finding obtained with them was that buildings that utilized more rooftop packaged AC units had less seasonal heating energy use (p=0.001). These packaged units would be operational in selected areas only, after hours, and would use less energy because of that. Buildings which had rooftop packaged ac units also had significantly lower weekday baseloads when compare to buildings that did not (p=0.02).



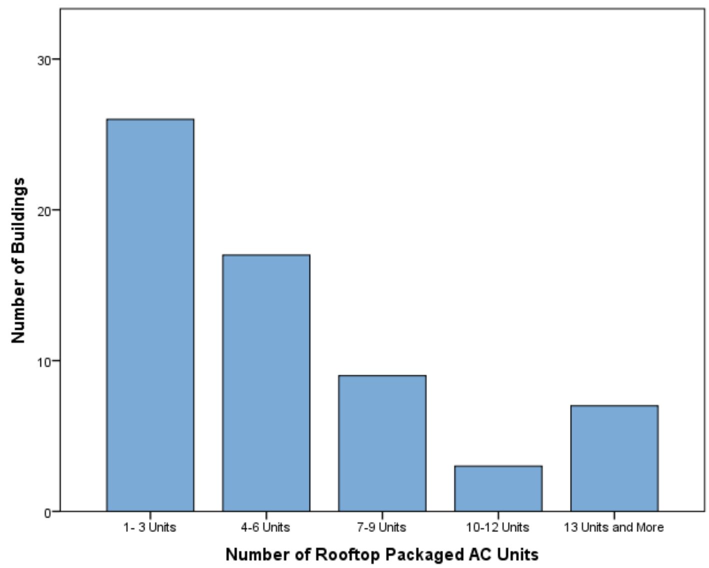


Figure 23: Number of Buildings which have Rooftop Packaged AC Units

Figure 23 is a histogram that provides information on the number of buildings in the dataset that had rooftop packaged AC units. Of the one hundred and sixteen buildings in the entire dataset, fifty four did not have these units, while sixty two did. Also, of these one hundred and sixteen buildings, only fifty two buildings had energy data available from the building owners and PECO.

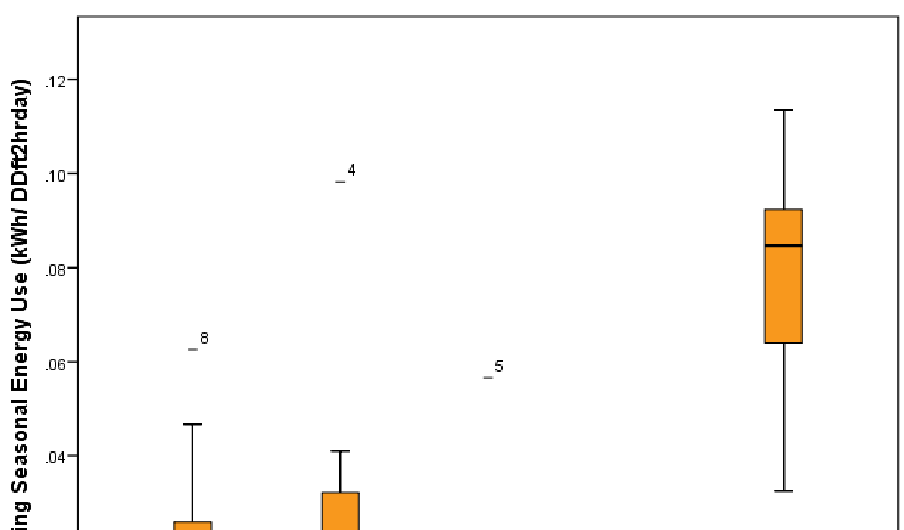


Figure 24: Buildings that utilized rooftop packaged AC units used less seasonal heating energy use (p=0.002)

Figure 24 depicts the trend that **buildings with rooftop packaged AC units show less seasonal heating energy use (p=0.00)**. It may not be because of the presence of the AC units, but may also be due to the presence of other attributes that work together with rooftop packaged AC units that results in lower heating energy. Buildings with rooftop AC units may have more insulation in the construction assembly, an attribute this research did not account for. Heating loads would also be reducing if the buildings have thermal breaks, another attribute for which information was not collected. Most of these buildings in the dataset also had double paned windows, which could act together to reduce heating loads. Buildings with rooftop packaged AC units are generally small in terms of gross floor area and number of floors, which may account for less energy. This trend indicates that buildings with rooftop packaged AC units are good candidates for further analysis, to figure out which attributes are working in tandem to lower seasonal energy consumption.

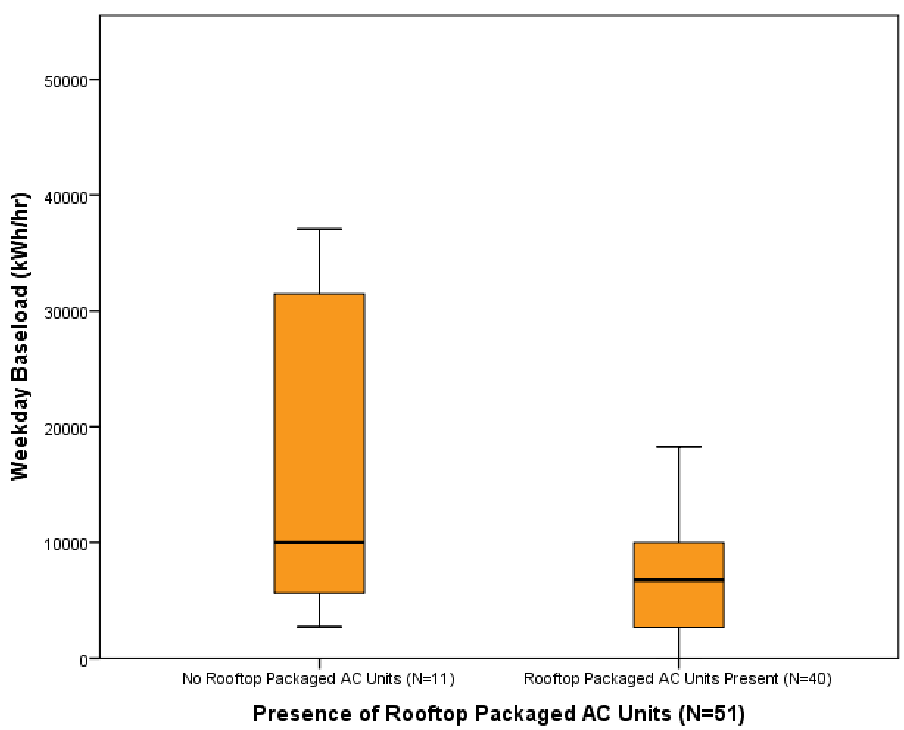


Figure 25: Buildings which had rooftop packaged ac units experienced lower weekday baseloads when compare to buildings that did not (p=0.04).

Figure 25 shows that **buildings which had rooftop packaged ac units experienced lower weekday baseloads when compare to buildings that did not (p=0.04)**. The figure also depicts the wide range of baseload value for building without rooftop packaged AC units compared to the more compact range of baseload values for buildings which have these units. The median baseload for such buildings is a little higher than for buildings which do have them. This trend is again indicative of using these buildings for further analysis. These findings do not necessarily mean that buildings should invest in rooftop AC packaged units more, but rather that buildings which do have these AC units have other attributes that are working in tandem to help reduce baseload and seasonal heating energy consumption. These underlying 'causal' attributes are not known, since they have not been collected for this research. These trends and findings all act as indicators

4.1.2 Rooftop Cooling Towers

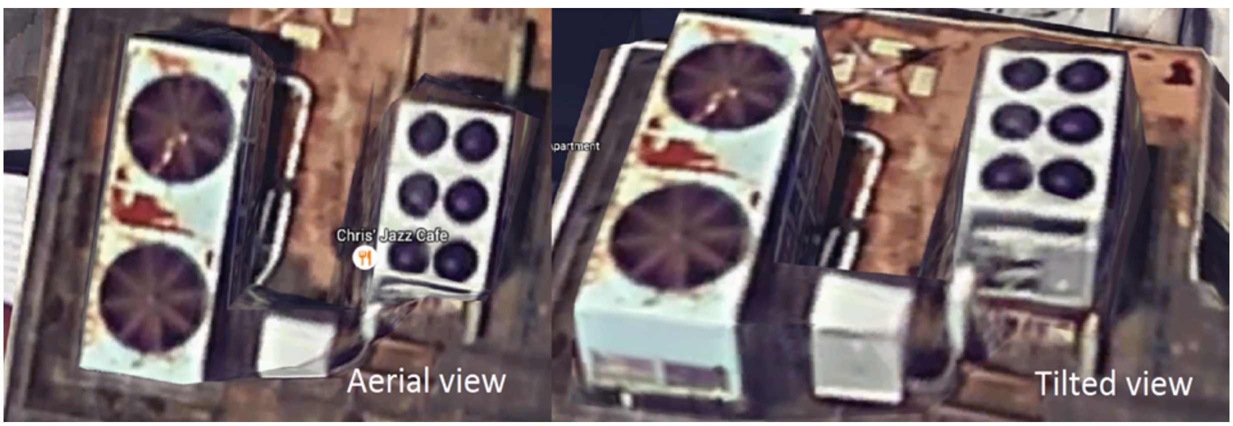


Figure 26: Rooftop Cooling Towers

Figure 27: Number of Buildings with Cooling Towers, out of one hundred sixteen buildings

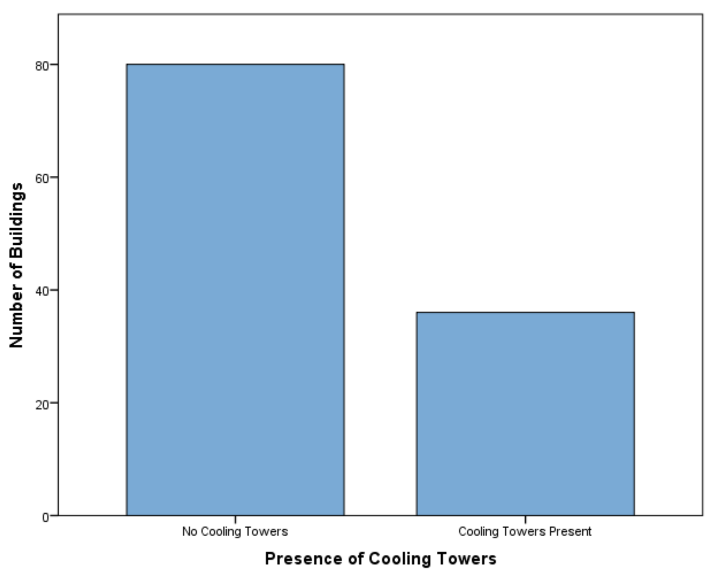


Figure 27 provides numbers of buildings having cooling towers for all one hundred sixteen buildings. Of these one hundred and sixteen, only fifty two buildings in the dataset had energy data. Of these fifty two, seven buildings had cooling towers on their roofs. Cooling towers are used in air conditioning systems of a building, to remove heat from a space and reject it to the surroundings outside. The removal of heat is through evaporative cooling, where water is used to extract heat from water to the outside air (CTI, n.d.). Since the towers use water to remove heat, they are considered more environmentally friendly, and also energy efficient. The efficiency is clearly visible, when the presence of cooling towers as an attribute is analyzed against energy data metrics. Another trend observed was that buildings with cooling towers also had high energy consumption for heating (p=0.001). Cooling towers work with chillers to provide air conditioning to a building, by moving chilled water around the spaces to be cooled. Such a system, would need central heating for the winter months, and radiators are used to heat up individual spaces. Since temperatures in Philadelphia and the Mid Atlantic region drop to 30 F (US Climate Data, n.d.), the heating system would be functional after working hours, to bring the temperature inside the building up from 30 F to around 50-60 F. Buildings with AC units would have less detailed or defined thermal zones, therefore wasting seasonal energy use to maintain comfort temperatures.

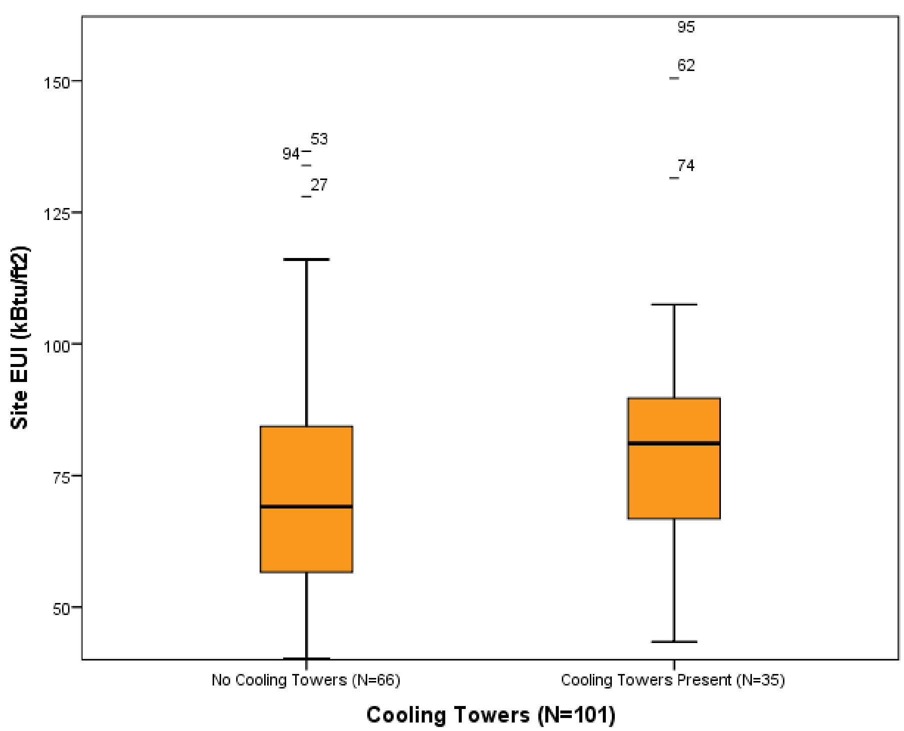


Figure 28: Buildings with cooling towers have a higher site EUI than the buildings that did not have cooling towers (p=0.05)

Figure 28 depicts that **buildings which have cooling towers have a narrower range and higher median of site EUI (p=0.05)**. The buildings which do not have cooling towers may also include buildings which do not have a cooling system apart from window AC units. No information was collected to list the number of window AC units buildings in the dataset had. It may that buildings using these units would have installed them in certain areas only, and not for the majority of the building space, which would affect energy consumption. The tight range of site EUI for buildings is desirable as there would be less variability in energy consumption through the year. The tighter range may also be because buildings having cooling towers may also have cooling setbacks in place, which would help in regulating temperature after work hours and the energy consumption related to it. If certain buildings have workers who prefer coming into work early, or leaving late, the building would need to cool for a certain set period of time before the setback kicks in.

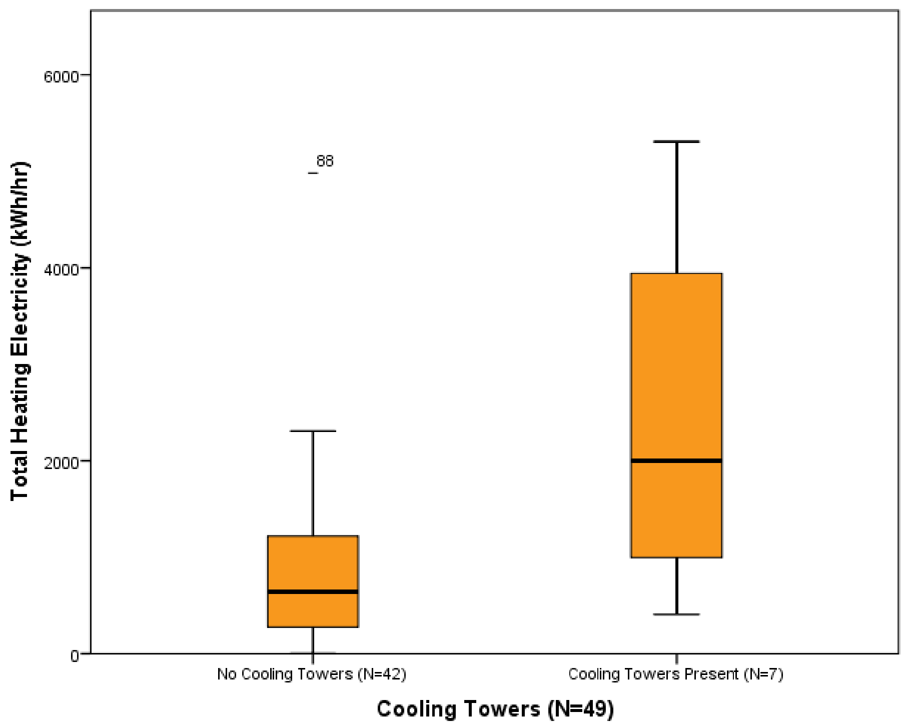


Figure 29: Buildings with cooling towers also had high energy consumption for heating (p=0.001)

Figure 29 depicts that **buildings which have cooling towers also showed high total heating electricity use than buildings which did not (p=0.00)** The range of heating electricity for these buildings is also widespread. Since the graph measures total heating electricity instead of energy, it may also indicate that either the heating system is not performing efficiently, or that gas fired heating is more suitable in terms of energy efficiency than electricity. This finding indicate that the pool of buildings with cooling towers are good candidates for selection for further analysis for reducing heating loads.

4.1.3 Heat Pumps/ AC Units – Split and Window Units

Figure 30: Window AC units

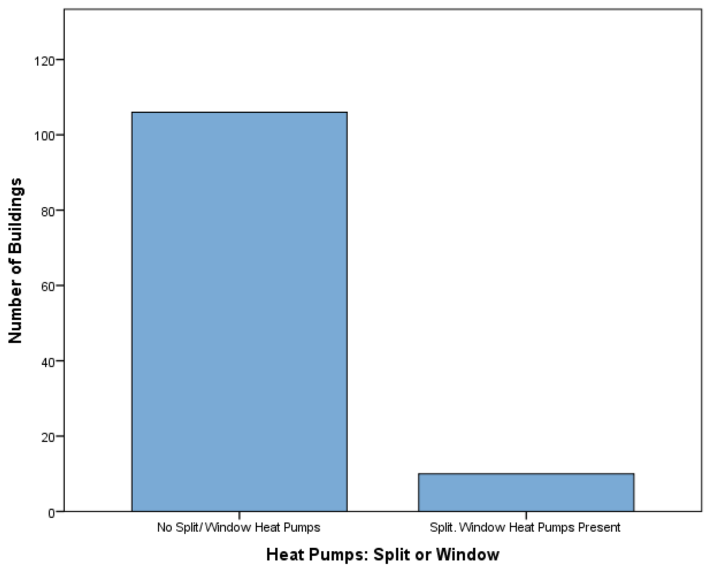


Figure 31: Number of Buildings which have Window or Split Heat Pumps

Figure 31 provides information on how many buildings in the entire dataset had split or window heat pumps installed for heating and cooling purposes. Most buildings in the dataset have either rooftop packaged AC units or cooling towers, with about fifteen buildings out of one hundred and sixteen having split or window heat pumps to condition interior spaces. Window or split air conditioning units in the smaller dataset also are not much. Out of fifty two buildings, only six had them. These buildings were built before 1970s, with single glazed clear glass windows and wood framing.

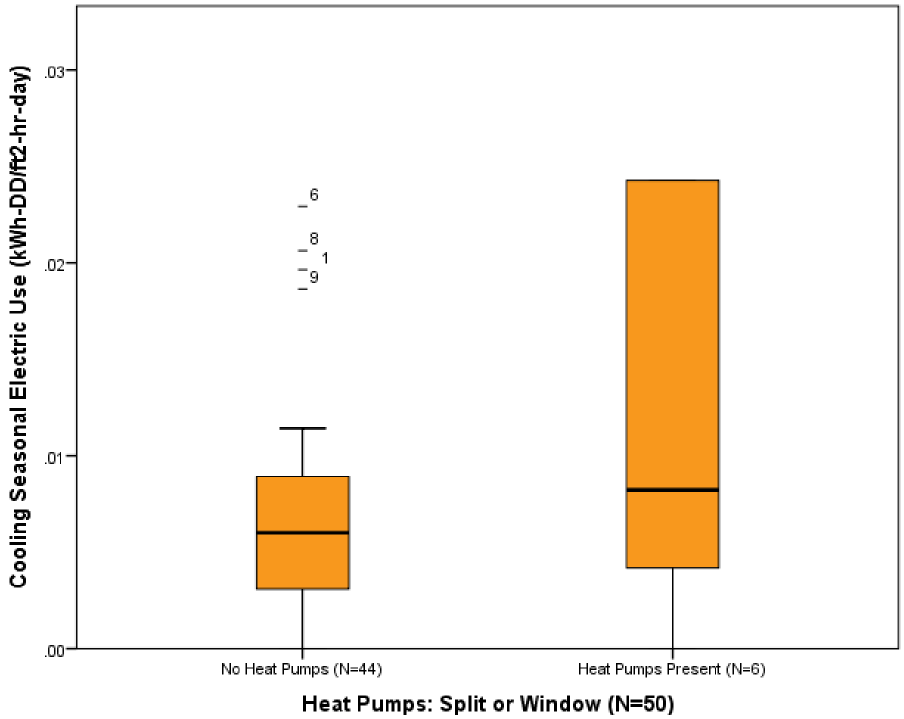


Figure 32: The buildings with separate AC units had higher cooling seasonal electric usage (p=0.005)

Figure 32 depicts that **buildings with heat pumps had higher seasonal cooling electric use when compared to buildings that did not (p=0.00)**. The spread of seasonal cooling electric use values for buildings with these heat pumps too is very vast, indicating that the systems and/or attributes of these buildings are not performing as they were intended to. AC units are supposed to give the occupant more control over thermally conditioning their spaces. The wide range of values for seasonal cooling electric use may be due to occupant negligence, or because the units themselves are cheap and inefficient when compared to more recent ones in the market, again attributes for which no information has been collected. Since these buildings also had clear single paned glass, they must have high solar heat gain during the summers, which would also increase seasonal cooling energy use. Another problem with the dataset is that the data collected grouped split heat pumps and window AC units together, which is incorrect since their functioning is different. Window AC units would not heat, and buildings which have window AC units would need a central heating system. On the other hand, split heat pumps do heat the space, and so a secondary heating system would be optional.

4.1.4 Shaded Cooling Equipment

Figure 33: Aerial view of cooling equipment shaded by adjacent tall building

Air conditioning systems work by dumping excess heat absorbed from the interior spaces of a building to the outdoor surroundings. This can be achieved by evaporative cooling in the case of cooling towers, or through the condenser unit in packaged or window/ split AC units. To categorize this attribute, buildings which had walls enclosing the cooling towers or rooftop packaged units on the roof were classified as having shaded cooling equipment. There were 22 such buildings observed in the dataset. The question that arises is, will shading these units provide a more efficient way to sink the extracted heat to the surroundings or not.

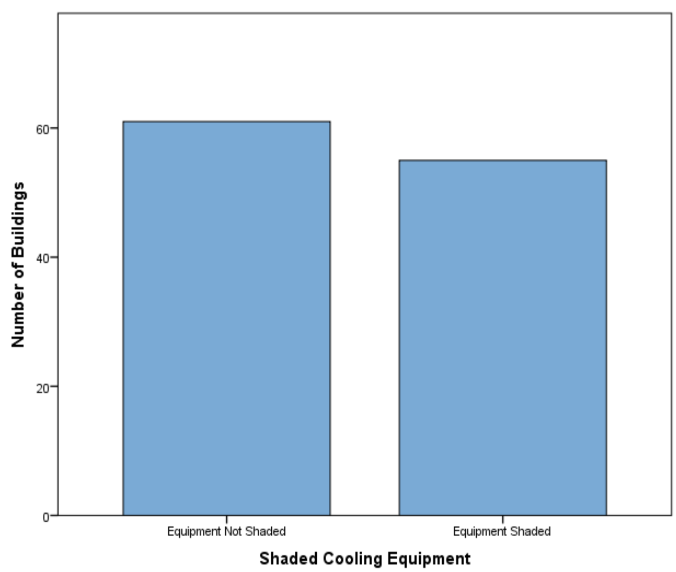


Figure 34: Number of buildings with shaded cooling equipment

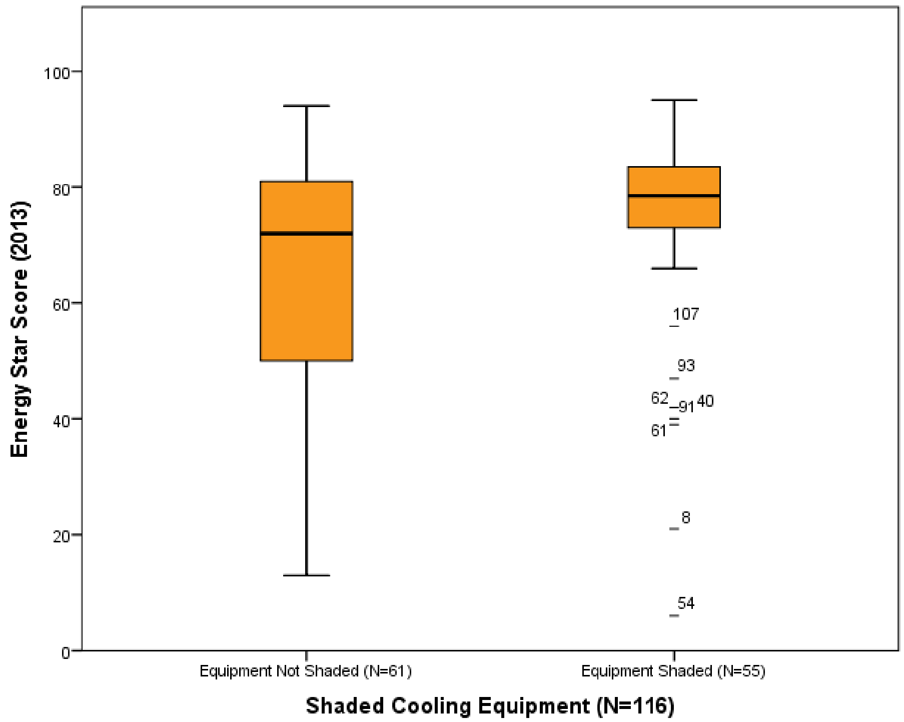


Figure 35: Buildings that had a wall shading a majority of the cooling equipment on the roof had higher energy star scores than buildings which did not (p=0.026)

No statistically significant trends were observed to validate the theory of shading cooling equipment to reduce energy loads, but Figure 35 shows that buildings that had a wall shading a majority of the cooling equipment on the roof had higher energy star scores than buildings which did not (p=0.026)

4.1.5 Single vs Double Glazed Windows

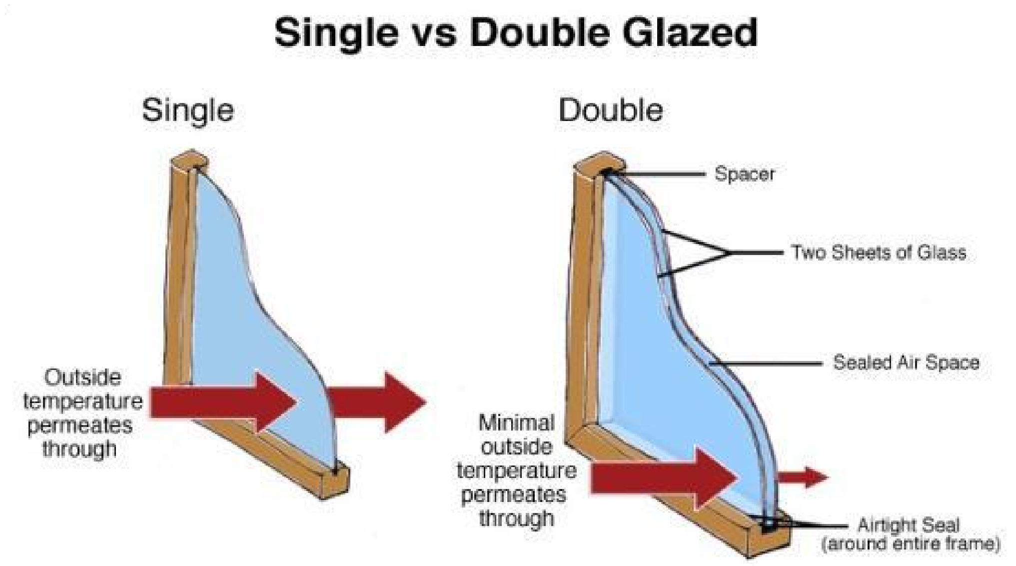


Figure 36: Advantages of Double Glazed Windows over Single Glazed Windows

Previous research (CBEI, 2016) hypothesized that buildings which are double glazed would have lower seasonal energy loads. The double layers would limit heat transfer from the outside to inside the building during summers, and from the inside to outside the building during winters. This research attempted to understand the impact of double glazed windows on energy consumption, but dataset consisted of buildings with double glazed windows, with just five buildings having single glazing. This hindered in obtaining any significant results.

4.1.6 Dark vs Clear Glass

Windows were also categorized according to tint, and of the 52 buildings in the dataset, 9 buildings had clear glass windows. Buildings which have dark glass would hypothetically utilize less energy for cooling, but the ANOVA results are inconclusive for seasonal electricity use as well as baseloads.

Figure 37: Image of Clear Glass

4.1.7 Operable Windows

To categorize buildings on the operability of windows, it was decided to keep the threshold at 30%. So buildings which had less than 30% operable windows were classified as buildings with non operable windows. Of the total fifty two buildings in the dataset, only 5 buildings have windows that are operable. Because of the reduced sample size, the trends observed were not significant. More research is needed, with an increased dataset that includes more buildings with operable windows, to arrive at any conclusions about the influence of operable windows on energy loads.

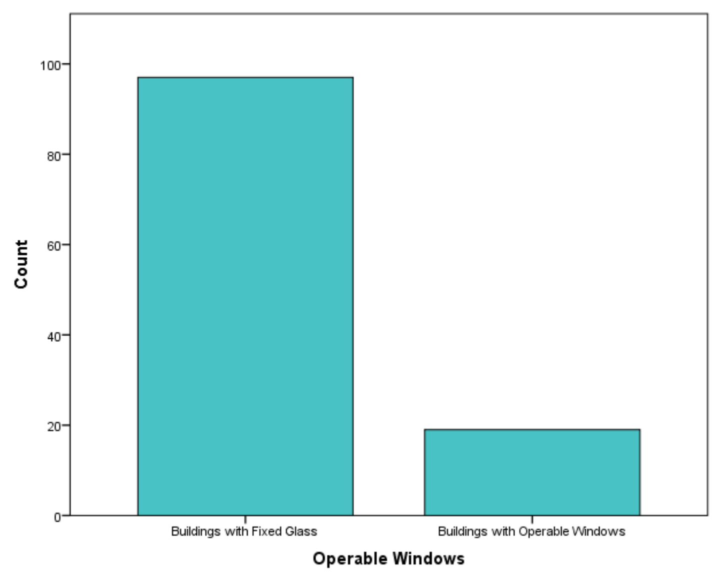


Figure 38: Number of buildings with fixed glass windows

4.1.8 Presence and Depth of External Shading – N/S/E/W

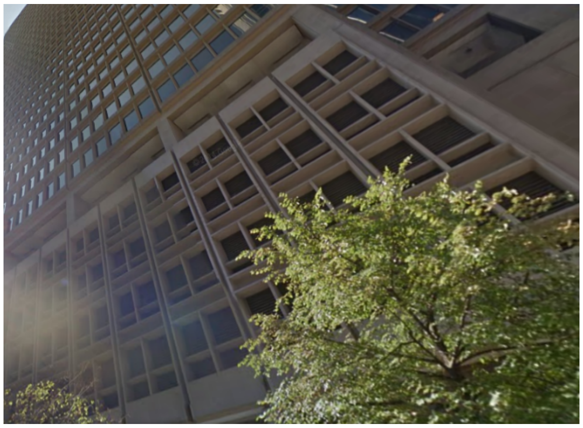
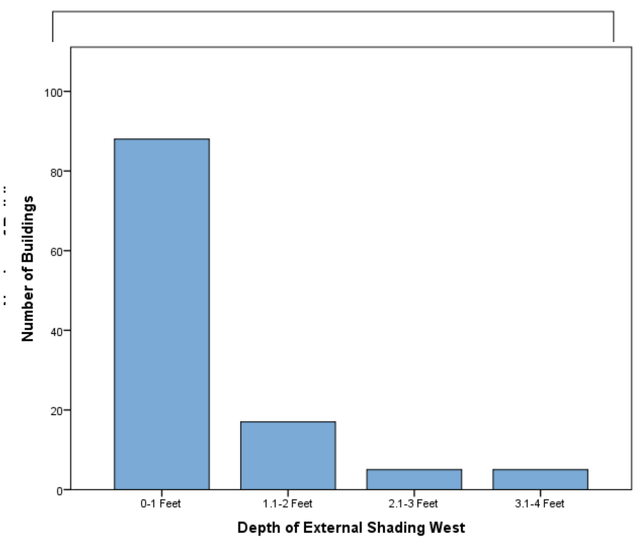


Figure 39: External shading of buildings in dataset

Previous research (CBEI, 2016) could not achieve any significant results due to limited data available. For this research, the data was re-categorized as buildings which had external shading to East, West and/ or South and buildings which were unshaded. North shading was left out since there is negligible incident solar rays to the North, when compared to the other cardinal directions. Of the fifty buildings, 12 buildings had shading towards East, West or South. It was observed that buildings that had external shading to the South, East and West had increasing seasonal heating energy usage. ($p=0.00$). The more the depth of the external shade, the more energy the building used for heating, since the incident solar rays would not be able to strike the building façade, and so the building would not be able to gain solar heat.



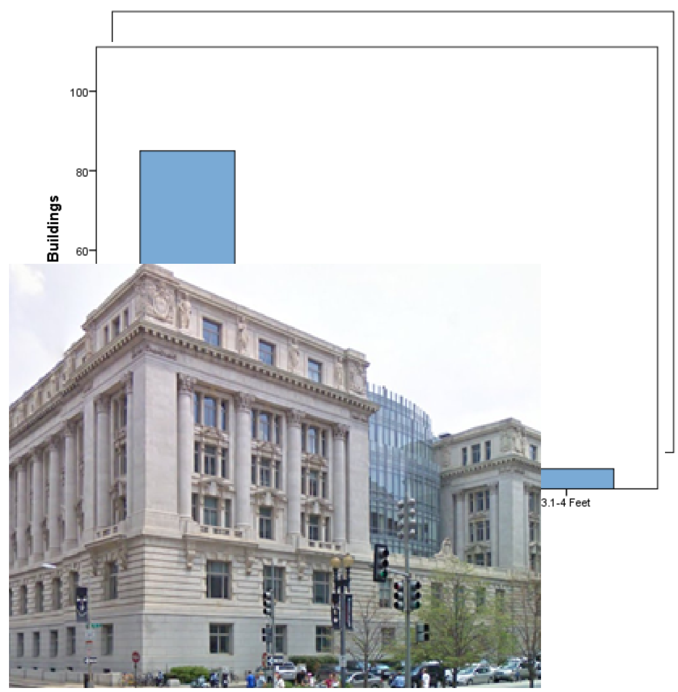


Figure 40: Number of buildings that have external shading on the North, South, East and West facades

Figure 40 consists of four histograms, all depicting the number of buildings in the dataset of 116 that have shading. The histograms have been divided according to direction for the purpose of counting how many buildings have shading to a particular depth, while the histogram representing presence of external shade has been created for East, West and South directions combined, as explained earlier in this section. Of the 116 buildings, there are only about twenty which had shading of some sort, to some extent. Of these twenty buildings only 14 – 16 had energy data available.

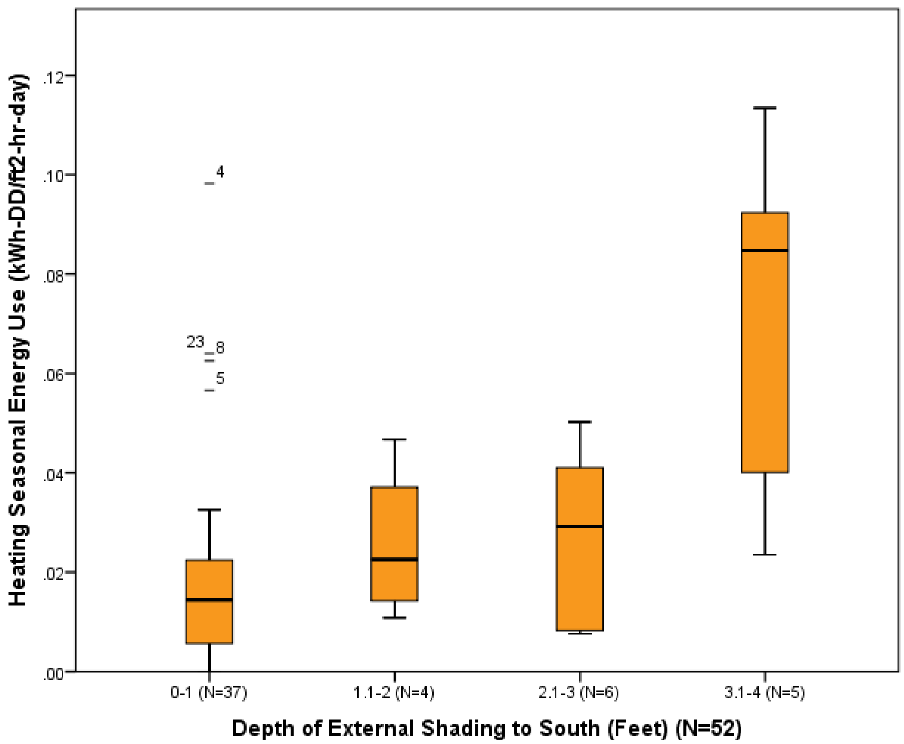


Figure 41: Buildings that had external shading to the South had increasing seasonal heating energy usage than buildings which did not (p=0.00)

Figure 41 represents the finding observed that **increasing depth of external shading results increasing seasonal heating energy use (p=0.00)**. A probable reason may be that the correct type of external shading is not being used on the correct façade/ orientation. A horizontal overhang on the

East would not help, since the rising sun has a low angle of sunrays and would not be blocked by the overhang.

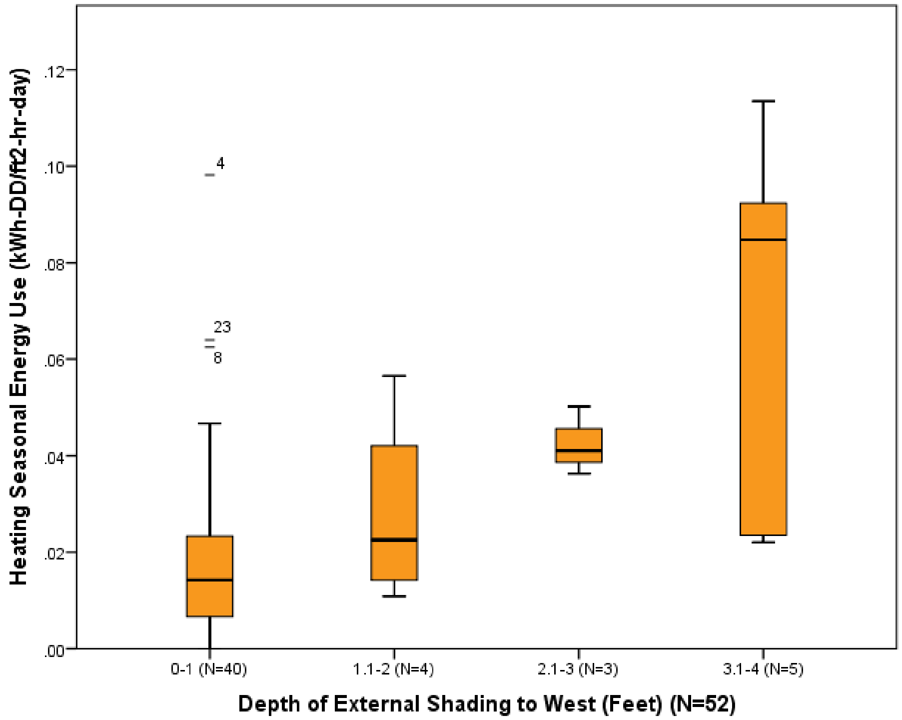
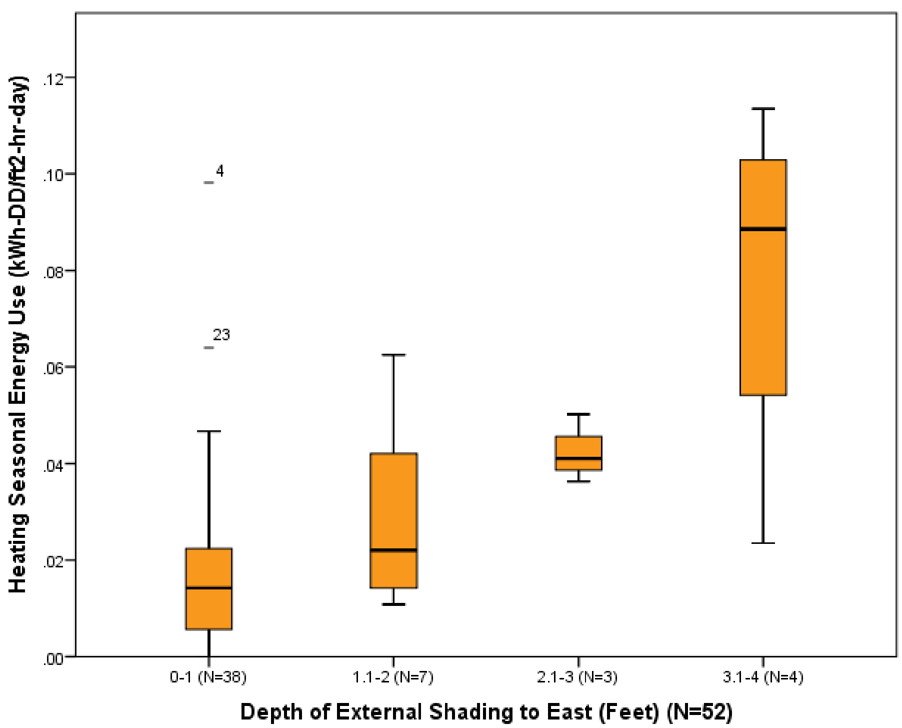


Figure 42: Buildings that had external shading to West had increasing seasonal heating energy usage than buildings which did not (p=0.00)



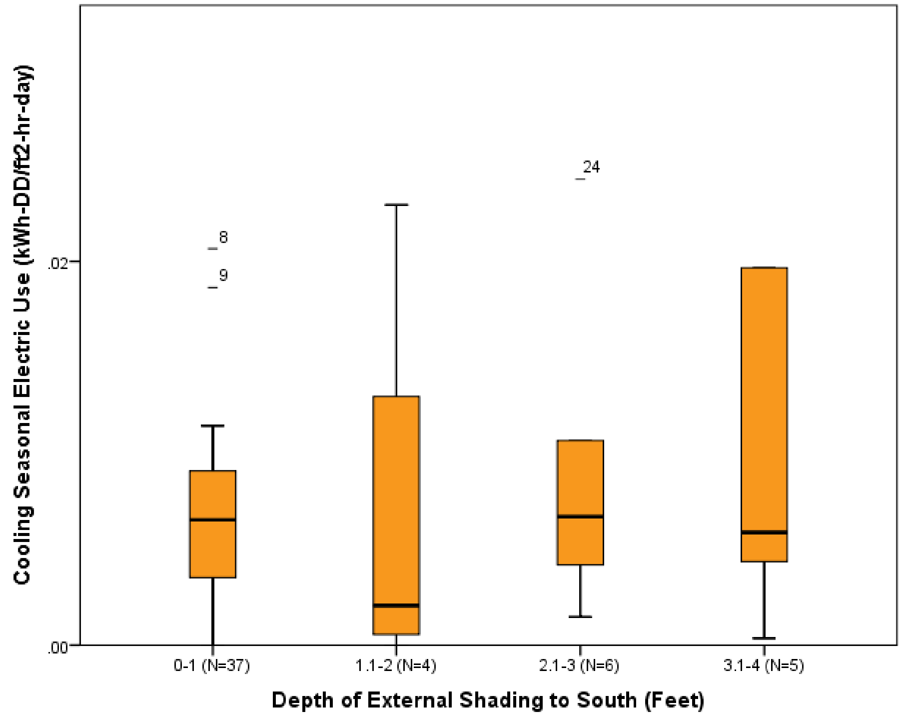


Figure 43: Buildings that had external shading to East had increasing seasonal heating energy usage than buildings which did not (p=0.00)

Figure 44: Buildings that had external shading to South had decreasing seasonal cooling electricity usage than buildings which did not (p=0.02)

Figure 43 shows similar trends as observed in Figure 41. The major difference in both these charts is that median seasonal heating energy increases steadily as depth of external shading on the East façade increases. There is not much of an appreciable increase between external shading of depth 1-1 -2 feet and 2.1-3 feet in Figure 41. The trend followed in Figure 42 resembles for depth of external shading to East.

Figure 44 shows that **increasing depth of external shading does reduce seasonal cooling electric use of buildings, when compared to buildings that do not have shading (p=0.02)**. The trend observed was that while seasonal cooling electric use reduces drastically when buildings are shaded, but that seasonal cooling electric use rose when depth of external shading increased. A probable reason for this slight increase would be because external shading is maybe not being done correctly, which is visible in the statistical analyses. The overall trend observed for seasonal cooling electric use is that external shading decreases it, validating the supposition that external shading is not being treated the way it was supposed to. Further analysis of the kind of external shading did not reveal any significant findings.

4.1.9 Internal Shade Type

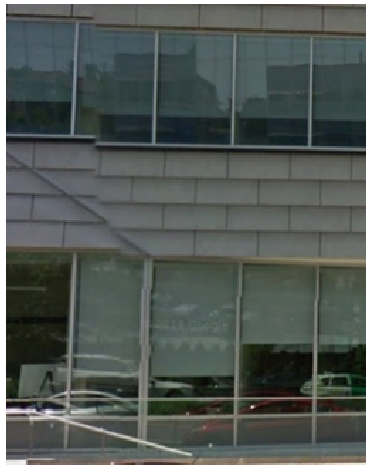


Figure 45: Internal Shade Type

Previous research had hypothesized that internal shading would decrease seasonal cooling energy use, since the shades would limit solar heat gain through the windows (CBEI, 2016). The problem with this hypothesis was that all buildings in the dataset had internal shading. Upon closer inspection, it was found that internal shading present could be divided into two separate categories – one where the shading is through venetian blinds and the other where the shading is through cloth sashes on a roller. It was found that only 3 buildings had sashes as an internal shading mechanism, instead of venetian blinds, and as such is insufficient data to analyze the effect of venetian blinds on energy loads.

4.1.10 Cool vs Dark Roof

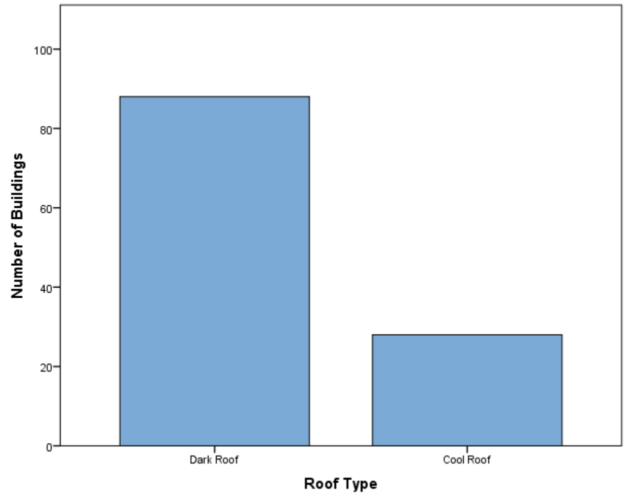


Figure 46: Cool vs Dark Roofs

Figure 47: Number of Buildings with Dark Roofs and Cool Roofs

Philadelphia introduced a new legislation in May 2010, that mandates all new commercial roofs to be cool roofs or green roofs (City of Philadelphia, 2010). The Oak Ridge National Laboratory and the DOE both have cool roof calculators available online, and estimate about 20% of energy savings for a 100,000 sqft office building with around twenty floors. To translate these savings for cooling energy loads, the dataset was analyzed with respect to dark vs cool roof, Figure 47 shows that out of one hundred and sixteen, there are about eighty five buildings which have dark roofs, and around thirty five buildings with cool roofs. Out of these one hundred sixteen buildings, energy data is available for just fifty two, and of those fifty only twelve buildings had cool roofs.

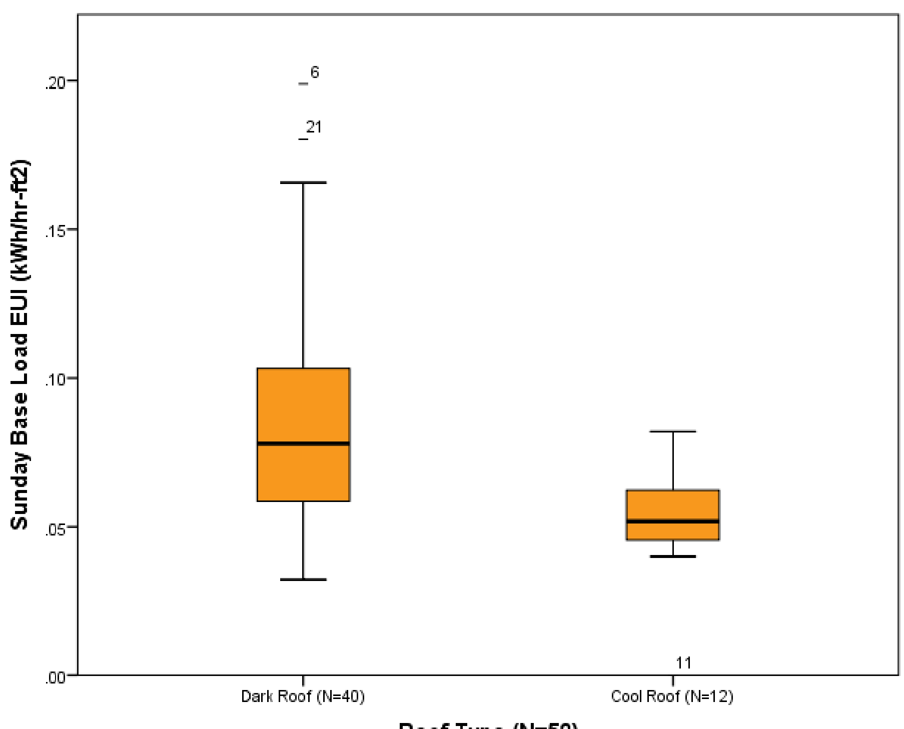


Figure 48: Buildings with cool roofs had lower Sunday/ Holiday baseloads per unit area than buildings with dark roofs (p=0.004)

Figure 48 depicts that **buildings with cool roofs had lower Sunday/ Holiday baseloads per unit area compared to buildings which had dark roofs (p=0.004)**. The lower baseloads may be the result of the fact that cool roofs reflect much of the solar heat, which reduces the work of the cooling system.

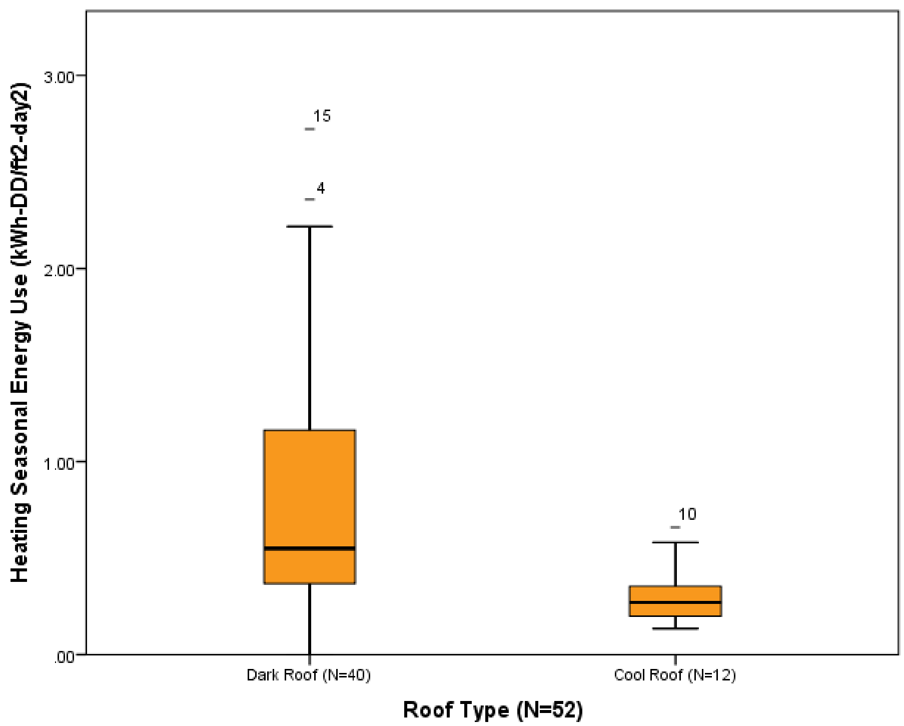


Figure 49: Buildings with cool roofs had lower heating seasonal energy use than buildings with dark roofs (p=0.024).

Figure 49 shows that **buildings with cool roofs had lower heating seasonal energy use compared to buildings with dark roofs (p=0.024)**. A probable reason of cool roofs resulting in decreasing heating loads may be that cool roofs could also have extra insulation installed in construction assembly – an attribute for which information could not be collected.

Both the figures also show a wider range of baseloads and heating loads for buildings with dark roofs, when compared to the narrower range of baseloads and heating load data for buildings with cool roofs. This points to these buildings with dark roofs having further problem areas, in terms of attributes and/ or systems not performing optimally. Hence, buildings with dark roof may be good targets for further analysis and energy audits.

4.1.11 Parabolic vs Non Parabolic Light Fixtures

Previous research had attempted to hypothesize that buildings using parabolic light fixtures or pendant lighting would have a lower baseload, since these kind of fixtures spread light over a larger piece of area than the surface mounted or recessed lights. The data was insufficient to obtain any relevant findings. The update to the dataset by adding another 20-25 buildings still does not reveal

any significant findings.

Figure 50: Lights Fixtures

4.1.12 Proximity Shading at 70 feet

Figure 51: Proximity Shading

Previous research had adopted 70 feet of proximity to other building structures as the cutoff threshold for proximal shading (CBEI, 2016), and the same threshold was followed for this research as well. Upon further examination of the dataset, it was found that there were just three buildings that had less than 70 feet of proximal shading from the surrounding structures. Even with the small sample size, certain significant results were seen with respect to inflection point.

4.2 Impact of Attributes on load breakdown

The buildings attributes were analyzed against the different parsed out loads, as obtained from previous research (CBEI, 2016) and the new data. For the previous analysis conducted, the data pool was just 25 buildings. With the addition of new buildings over the course of this year of research, the number has now doubled to 52. The methodology followed for the analysis involves three stages of statistics utilized for final deliverables. The first stage was the analysis of each single attribute against the LEAN analyses derived variables. A total of 520 statistics (one way ANOVAs) were run for this step, and the findings grouped according to the disaggregated energy loads. Only building attributes with trends having a p value of 0.35 and less have been listed below as probable combinations that would affect energy use.

4.2.1 Baseload: Sundays/ Holidays and Weekdays (n=52)

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Sunday Base	Rooftop Packaged AC Units	41 have ac units	Higher	0.192

Load (kWh/hr) (n=52)	**Cooling Towers**	**7 have towers**	**Higher**	**0.006**
	External Shading to North	**14 with**	**Lower**	**0.034**
	External Shading to South	15 with	Lower	0.164
	External Shading to East	***14 with***	***Lower***	***0.062***
	External Shading to West	12 with	Lower	0.107
	Clear vs Dark Glass	37 dark and 9 clear	Baseload increases for clear glass	0.219

Table 4: Sunday Electric Baseload one way ANOVA

This table supports the following conclusion: **Sunday baseloads of buildings are influenced by the presence of cooling towers and external shading. While external shading reduces baseload, presence of cooling towers increases Sunday baseload.**

Sunday baseload, as explained in the section before, is a function of the attributes of a building, with little to no impact of occupancy/ work hours seen, since the buildings would be unoccupied. When analyzed against presence of external shading, it was observed that baseload increased (Table 4). To examine this trend further, more ANOVAs were run, this time against the depth of external shading present. It was observed that while buildings with external shading of depth one to two feet had a higher Sunday baseload, it decreased when the depth of the shadings increased to four feet. This trend may be because the buildings with more than two feet of external shading were not being used for its intended purpose as a shading device, but aesthetically. Providing horizontal external shades on the East façade would not work since the sun's rays to the east are not at a steep angle, since its' the rising sun. Another point to keep in mind is the fact that shading is usually done to reduce cooling needs of a building, and not the baseload. To corroborate the statistics, ANOVAs were also run on Sunday baseload numbers normalized by square feet, and the trends observed were similar in nature.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Weekday Base Load (kWh/hr) (n=52)	**Rooftop Packaged AC Units**	**41 have ac units**	**Higher**	**0.042**
	Cooling Towers	7 have towers	Higher	0.256

Table 5: Weekday Baseload one way ANOVAs

This table supports the following conclusion: **Weekday baseloads of buildings are influenced by the presence of rooftop packaged AC units, which drive it higher.**

Table 5 lists some results that were observed for weekday baseloads. Since all systems would be fully functional and running during the weekday office hours, the baseload for the week would be higher. The high load would be because the electricity needed to run the chillers/ cooling towers/ AC units would be a part of baseload, and their operations would depend on how much shading a building has access to. The weekday baseload would also be affected by shading and operable windows. Shading would dictate how much lighting the interiors of the building would need. If the façade of the building has external shading to a greater depth, it may restrict the daylight entering through the windows. The restricted daylight would in turn increase lighting loads inside the building during daylit hours. Operable windows would logically decrease cooling loads, since operability would allow occupants to open windows when the outside temperature is cool and the environment is breezy. Cooling loads are also weather dependent, so even if the windows be operable, it would not help in reducing cooling energy if the weather or climate outside is not comfortable enough for people.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Sunday Base Load EUI (kWh/hr /sqft) (n=52)	Cooling Towers	7 have towers	Higher	0.134
	External Shading to North	**10 have extl shading**	**Higher**	**0.028**
	External Shading to North	14 with	Lower	0.166
	External Shading to South	15 with	Lower	0.119
	External Shading to East	14 with	Lower	0.327
	Dark vs Cool Roof	**12 cool**	**Lower with cool**	**0.004**
	Clear vs Dark Glass	***43 dark and 9 clear***	***Increases in buildings with clear glass***	***0.084***

Table 6: Sunday Baseload Normalized by Square Footage one way ANOVAs

<u>This table supports the following conclusion</u>: **Sunday baseloads normalized by gross floor area of buildings are influenced by external shading, presence of dark roofs and presence of clear glass. These three attributes increase baseload.**

Analyzing attributes against Sunday's baseload normalized by gross floor area or square footage gives an approximation of how many attributes are affecting baseload per square foot of the buildings. Table 6 lists the trends that building attributes show towards Sunday baseload normalized by gross floor area for a typical hour on any given Sunday or holiday. Since baseload includes the minimum energy required to run the HVAC equipment in the background for Sundays and/ or holidays, it would be affected by the presence of clear vs dark glass and also shading. This is because these attributes would help lower the internal temperature of the building, and may also delay, or shorten the runtime of the cooling equipment, if the internal temperature falls within the bands specified for those buildings. The second stage of analysis will explore these interactions in further detail.

Load	**Building Attribute**	**Number**	**Finding of Attribute Impact on Outcome**	**p Value**
Weekday Base Load EUI (kWh/hr/sqft) (n=51)	Rooftop Packaged AC Units	41 have ac units	Lower	0.135
	Proximity Shading	48 with less than 70 feet of shading	Less with less proximity	0.279
	Presence of External Shading to W/S	16 have extl shading	Lower	0.189

Table 7: Weekday Baseload Normalized by Square Footage one way ANOVAs

This table supports the following conclusion: **Weekday baseloads normalized by gross floor areas of buildings are influenced to a certain extent by the presence of rooftop packaged AC units.**

Buildings with external horizontal members for shading are consistently showing a decrease in baseload for a typical hour, in Table 7. This may be because of the angle of the sun where these buildings are located. A horizontal shade would block the sun's rays on the South, and to understand how horizontal shades fare against vertical or egg crate shades, further analyses were performed, but the results obtained were not significant.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
BaseLoad (kwh-DD /ft2day2) (n=50)	Rooftop Packaged AC Units	41 have ac units	Lower	0.199
	External Shading to North	**14 with**	**Lower**	**0.008**
	External Shading to South	**15 with**	**Lower**	**0.025**
	External Shading to East	**14 with**	**Lower**	**0.007**
	External Shading to West	**12 with**	**Lower**	**0.028**

Table 8: Weekday Baseload normalized by Square Footage for a typical day one way ANOVAs

This table supports the following conclusion: **Baseloads of buildings are influenced by the presence of external shading. The results for external shading on the East façade were the most statistically significant ones.**

Table 8 analyzes baseload per square foot for a typical weekday, and trends similar to the Sunday or holiday baseloads are observed. To validate these findings, the attributes were also analyzed against normalized baseload for a typical hour. Baseload for a typical hour decreases with increasing depth in external shading. Table 9 analyses the building attributes against baseloads normalized by square footage for a typical hour in any given weekday in a month. These trends are more statistically significant than the ones observed for the Sunday/ holiday baseloads, which may be attributed to the fact that all systems would be on and functional during working hours and this would result in a higher baseload.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
BaseLoad (kwh-DD/ft2day-hr) (n=51)	**External Shading to North**	**14 with**	**Lower**	**0.007**
	External Shading to South	**15 with**	**Lower**	**0.022**
	External Shading to East	**14 with**	**Lower**	**0.006**
	External Shading to West	**12 with**	**Lower**	**0.025**
	Presence of window AC units	**6 with**	**Higher**	**0.004**

Table 9: Weekday Baseload normalized by Square Footage for a typical hour one way ANOVAs

<u>This table supports the following conclusion</u>: **Bseloads of buildings are influenced by the presence of window AC units and external shading. While external shading results in decreasing baseload, window AC units increase baseloads.**

Table 9 analyses baseload energy normalized by gross floor area for a typical hour, and results were seen with respect to depth of external shading. Use of lights would be incumbent upon the number of daylit hours, as well as the offices inside the buildings having access to daylight. This may be possible if the offices are near the windows. Having an increasing baseload for buildings with upto four feet of external shading may be indicative of the buildings utilizing more energy during the winter months, as external shading would just prevent the building facades to gain solar heat.

Most relevant findings from the baseload statistical analyses are:

1. Buildings with upto 4 feet of shading to east, west and south show decrease in baseload energy use when compared to buildings that have no shading (p=0.06).

2. Buildings with clear glass show higher base energy use, when compared to buildings with dark glass (p=0.21).

3. Buildings with cooling towers have a higher baseload compared to buildings with no cooling towers (p=0.006).

4. Buildings with split or ac units have a higher baseload compared to buildings that do not have AC units or heat pumps (p=0.004).

5. Building's with cool roof had lower weekday baseload compared to buildings with dark roofs (p=0.035).

6. Building's with dark roof had a higher Sunday baseload EUI compared to buildings with cool roof (p=0.004).

4.2.2 Total Heating Electricity

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Total Heating Energy (kWh/hr) (n=49)	***External Shading to E/W/S***	***16 with***	***Higher***	***0.054***
	External Shading to W/S	**8 with**	**Higher**	**0.001**
	External Shading to South	**15 with**	**Increasing with inc depth**	**0.008**
	External Shading to East	14 with	Increasing with inc depth	0.206
	External Shading to West	**12 with**	**Increasing with inc depth**	**0.004**
	External Shade Type	6 are eggcrate, 10 are horizontal	Higher with eggcrate shading	0.136
	Clear vs Dark Glass	37 dark and 9 clear, 6 reflective	Increases for clear	0.127
	Shaded Cooling Equipment	22 with shade, 29 without	Higher	0.239
	Presence of Cooling Towers	7 have towers	Higher	0.001

Table 10: Total Heating Electricity one way ANOVAs

This table supports the following conclusion: **Total heating of buildings is influenced by the presence of external shading to South and West. These attributes result in higher heating loads in buildings.**

As can be seen in Table 10, heating energy use will increase if the buildings are shaded, since they won't be able to gain solar heat from the facades. Dark glass will generally have lower SHGC and limit solar heat being transmitted inside, but due to that same property, will also prevent the heat inside the building to transmit out to the exterior surroundings (TERI, n.d.). Total heating energy is dependent on the presence or absence of external shading. Having shading devices on the façade would in effect reduce the solar heat gain through the building envelop during winters, increasing heating energy needed to warm the building. No link between cooling towers and heating is apparent. The underlying factor linking these two variables together could be the kind of heating system being utilized by the buildings. Since information on heating was not collected, there is no way to pinpoint a cause or a reason for this finding. One way ANOVA were again run for heating energy normalized by square footage to validate the findings.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Heating Energy Normalized by gross floor area (kWh/hr/sqft) (n=49)	**Rooftop Packaged AC Units**	**41 have ac units**	**Higher**	**0.001**
	External Shading to E/W/S	**16 have extl shading**	**Higher**	**0.001**
	External Shading to North	**14 with**	**Increasing with inc depth**	**0.000**
	External Shading to South	**15 with**	**Increasing with inc depth**	**0.000**
	External Shading to East	**14 with**	**Increasing with inc depth**	**0.000**
	External Shading to West	**12 with**	**Increasing with inc depth**	**0.000**
	Proximity Shading with 70' threshold	3 with less than 70'	Low in buildings with less distance	0.234
	External Shade Type	6 are eggcate, 10 are horizontal	Lower with eggcrate shading	0.301
	Shaded Cooling Equipment	22 with shade, 29 without	Lower in buildings with shaded equipment	0.224

Table 11: Heating Energy Normalized by Square Footage one way ANOVAs

<u>This table supports the following conclusion</u>: **Heating energy normalized by gross floor area of buildings is influenced by the presence of external shading, resulting in higher heating energy loads.**

Upon comparing the results were corroborated. Shading would increase heating energy. Also, to understand the effect the kind of external shading will have on heating energy, statistical analyses were run, but no relevant or statistically significant results were observed.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value

Peak Heating Energy normalized by gross floor area (kWh/hr/sqft/F) (n=52)	**Rooftop Packaged AC Units**	**41 have ac units**	**Higher**	**0.000**
	Presence of Cooling Towers	7 have towers	Lower	0.119
	External Shading to North	14 with	Increasing with inc depth	0.091
	External Shading to South	**15 with**	**Increasing with inc depth**	**0.003**
	External Shading to East	14 with	Increasing with inc depth	0.092
	External Shading to West	12 with	Increasing with inc depth	0.231
	External Shade Type	6 are eggcrate, 10 are horizontal	Lower with eggcrate	0.278
	Clear vs Dark Glass	37 dark and 9 clear, 6 reflective	Decreases with clear glass	0.202
	Shaded Cooling Equipment	22 with shade, 29 without	Slightly lower	0.368

Table 12: Peak Heating Energy Normalized by Square Footage one way ANOVAs

This table supports the following conclusion: **Peak heating of buildings is influenced by the presence of rooftop packaged AC units and external shading. These attributes result in higher heating loads in buildings.**

Peak heating is for a typical hour on the cold days recorded in the dataset. It's the maximum heating energy use recorded for a building for the coldest days or temperatures of winter.

Table 10 validates the statistics for total heating energy variables, since trends observed are similar. External shading shades the building façade from solar heat, thereby reducing the need for mechanical cooling to a certain extent. The downside of having external shading is that the building façade is not able to gain heat (passive solar heating) during the winter months, and thus the buildings with external shading would need more heating than buildings without. The same reasoning may be applied to clear glass. Having no tint would allow solar heat to radiate inside, reducing heating needed in the building. The link between rooftop packaged AC units and heating is not apparent. The equipment used in rooftop packaged AC units may not be efficient. Another reason may be that buildings with rooftop packaged AC units may not have clearly defined or disorganized thermal zones.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value

Heating Curve Inflection Point (Dday/ F) (n=47)	**External Shading to W/S**	**8 have extl shading**	**Higher in buildings with shade**	**0.028**
	Presence of Cooling Towers	**7 have towers**	**Higher in buildings with cooling towers**	**0.02**
	External Shading to South		***Higher in buildings with shade***	***0.09***
	External Shading to East		**Increases to 2 feet,**	**0.001**
	External Shading to West		**Increases to 2 feet,**	**0.001**
	External Shade Type	6 are eggcrate, 10 horizontal	Higher with eggcrate shading	0.212

Table 13: Heating Curve Inflection Point one way ANOVAs

This table supports the following conclusion: **Heating curve inflection point of buildings is influenced by the presence of cooling towers and external shading.**

An inflection point for a line is when the slope changes. For LEAN charts, since the line is a curve and not straight, the inflection point would be when it is clearly visible that energy is being used to heat and/ or cool a building, apart from the baseload. A heating inflection point, in this case, would be the point from where the heating curve 'originates' or where energy for heating can be visibly differentiated from baseload. The inflection point (degree day or Fahrenheit) being lower, or closer to the comfort zone temperature, may be indicative of the building's setbacks not being managed properly, or the fact that the building does need thermal conditioning due to inefficient assets. Results depicted in Table 13 suggest that a high heating inflection point would be preferable for the building, especially when the buildings are externally shaded to a certain depth that would allow the incident rays of the sun to hit the wall façade. This would also increase daylighting inside the building, reducing the share of lights to the baseload. Presence of cooling towers usually mean that the building uses a central system for heating and cooling, and as such can be indicative of a heating system run on natural gas. Such a centralized system would also have heating setbacks that may be programmed to have a higher inflection point, or may indicate to very detailed thermal zoning which would lead to higher heating curve inflection points.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Heating Curve Highest Point (kwh/sqft/day)	Rooftop Packaged AC Units	41 have ac units	Higher	0.147
	External Shading to E/W/S	**16 have extl shading**	**Higher**	**0.003**

(n=51)	**External Shading to W/S**	**8 have extl shading**	**Higher**	**0.001**
	External Shading to North	14 with	Increasing with more depth	0.017
	External Shading to South	**15 with**	**Increasing with inc depth**	**0.009**
	External Shading to East	**14 with**	**Increases then plataeus**	**0.004**
	External Shading to West	**12 with**	**Increases with more depth**	**0.009**
	External Shade Type	6 are eggcrate, 10 are horizontal	Higher in buildings with eggcrate	0.169

Table 14: Heating Curve Highest Point one way ANOVAs

<u>This table supports the following conclusion</u>: **Heating curve highest point of buildings is influenced by the presence of external shading, increasing it as depth of shading increases.**

Table 14 records the highest energy consumption for a typical day in the winters. The findings validate the hypotheses that the presence of external shading would prevent the building to gain heat, putting extra load on the heating system.

Load	**Building Attribute**	**Number**	**Finding of Attribute Impact on Outcome**	**p Value**
Heating Seasonal Energy Use (kwh-DD/ft 2day2) (n=42)	**Rooftop Packaged AC Units**	**41 have ac units**	**Lower**	**0.001**
	External Shading to E/W/S	**16 have extl shading**	**Higher**	**0.015**
	External Shading to W/S	**8 have extl shading**	**Higher**	**0.001**
	External Shading to North		**Increasing with inc depth**	**0.001**
	External Shading to South		**Increasing with inc depth**	**0.002**
	External Shading to East		**Increasing with inc depth**	**0**
	External Shading to West		**Increasing with inc depth**	**0.004**

Table 15: Heating Seasonal Energy Use for a Typical Day one way ANOVAs

This table supports the following conclusion: **Seasonal heating energy use of buildings (using monthly data) is influenced by the presence of rooftop packaged AC units and external shading.**

For a given typical day in winters, the results of ANOVAs against building attributes and heating seasonal energy use were not statistically significant, apart from corroborating the fact that buildings with shading have high energy consumption, and buildings with rooftop packaged AC units had some underlying attribute that linked them to seasonal heating energy use. Other attributes like insulation can also explain why buildings which have rooftop packaged AC units had lower seasonal heating energy use compared to buildings that did not.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Heating Seasonal Energy Use (kwh-DD/ft2day-hr) (n=48)	Rooftop Packaged AC Units	41 have ac units	Lower	0.000
	External Shading to E/W/S	16 have extl shading	Higher	0.002
	External Shading to W/S	8 have extl shading	Higher	0.000
	External Shading to South	15 with	Increasing with inc depth	0.008
	External Shading to East	14 with	Increasing with inc depth	0.001
	External Shading to West	12 with	Increasing with inc depth	0.001
	Proximity Shading with 70' threshold	3 with less than 70'	Lower for buildings with less shading	0.272

Table 16: Heating Seasonal Energy Use for a Typical Hour one way ANOVAs

This table supports the following conclusion: **Seasonal heating energy use of buildings (using interval data) is influenced by the presence of cooling towers and external shading.**

When analyzing heating seasonal energy use for a typical hour, another attribute of proximal shading was also added to the mix. It was found that buildings with less than 70 feet of proximity shading had high heating seasonal energy use.

Most relevant findings for heating loads:

1. Heating energy is highly dependent on absence of shading. It is also affected by operability in windows, a central heating system and clear glass to an extent.

2. Buildings having more than 30% operable windows need more heating compared to buildings that have fixed glass windows (p=0.007).

3. Buildings having more than 30% operable windows show a higher inflection point compared to buildings that have fixed glass windows (p=0.004).

4. Buildings having presence of external shading to E/W/S utilize more heating (p=0.001), have a higher inflection point (p=0.028) and have a higher energy consumption (heating curve highest point (p=0.003) compared to buildings that do not

5. Buildings with cooling towers had higher heating curve inflection points, compared to buildings that did not (p=0.02).

6. Buildings with rooftop AC units show lower heating seasonal energy use with 0-11 rooftop package ac units and increases with more units (p=0.002)

7. Buildings with dark roofs show higher heating seasonal energy use compared to buildings with cool roofs (p=0.024).

4.2.3 Cooling Loads

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Total Cooling Energy (kWh/hr) (n=52)	Rooftop Packaged AC Units	41 have ac units	Higher	0.184
	External Shading to South	15 with	Decreases	0.269
	External Shading to E/W/S	16 with	Decreases	0.292
	Proximity Shading with 70' threshold	3 with less than 70'	Less	0.205

Table 17: Total Cooling Electricity one way ANOVAs

This table supports the following conclusion: **Total cooling energy does not have any attribute whose influence on it is statistically significant.**

Cooling energy would be affected by shading, and the trends observed validate that. Table 17 depicts results of analyses run against cooling energy for an average hour, and the only statistically significant as well as almost significant trends are observed with external shading. ANOVA or glass tint was not statistically significant, but numbers suggest that buildings with reflective glass utilize less cooling energy. Reflective glass would reflect the major chunk of incident solar radiation outwards, into the surroundings, and thus reduce transmittance of solar radiation to the interior.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Cooling Energy normalized by gross floor area (kWh/hr/sft) (n=52)	Operable Windows	5 have operable windows<30%	Increases	0.127
	External Shading to E/W/S	16 with	Lower	0.327
	External Shading to W/S	8 with	Lower	0.181
	External Shading to East	14 with	Lower	0.15
	External Shading to West	12 with	Lower	0.125

Table 18: Cooling Energy Normalized by Square Footage one way ANOVAs

This table supports the following conclusion: **Cooling energy normalized by gross floor area of buildings does not have any attribute whose influence on it is statistically significant.**

Table 18 closely resembles Table 17, since the former analyzes cooling energy normalized by gross floor area. The effect of other attributes on cooling is seen when other LEAN analyses derived dependent variables are analyzed, as seen in the subsequent tables.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Peak Cooling Energy normalized by gross floor area (kWh/hr/sqft/F) (n=52)	Rooftop Packaged AC Units	41 have ac units	Lower	0.232
	Presence of Cooling Towers	7 have towers	Lower	0.119
	External Shading to North	14 with	Lower	0.091
	External Shading to South	**15 with**	**Lower**	**0.003**
	External Shading to East	***14 with***	***Lower***	***0.092***
	External Shading to West	12 with	Lower	0.231
	External Shade Type	6 are eggcrate, 10 are horizontal	Lower in buildings with horizontal shading	0.278
	Clear vs Dark Glass	43 dark and 9 clear	Decreases for clear glass	0.202
	Shaded Cooling Equipment	22 with shade, 29 without	slightly lower with	0.368

Table 19: Peak Cooling Energy Normalized by Square Footage one way ANOVAs

This table supports the following conclusion: **Peak cooling energy is influenced by the presence of external shading to South and East, and decreases with depth.**

Peak Cooling for a typical day or hour would be the maximum energy used to cool a building during the summers. Table 19 analyzes peak cooling energy normalized by square footage or gross floor area against the building attributes, and strong co relations are observed between peak cooling and external shading, proximity shading and envelope material. Another trend observed was that peak cooling reduced for clear glass. A probable reason for this may be the presence of low e coating on these windows. Another reason for this finding may be that these clear windows would also be double paned, which results in lower cooling and heating energy, as is seen in the previous tables.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Cooling Curve Inflection Point (Dday/ F) (n=50)	Operable Windows	5 have operable windows<30%	Decreases	0.202
	External Shading to North	10 with	Higher	0.221
	External Shading to West	***12 have extl shading***	***Higher***	***0.081***
	External Shading to South	***15 with***	***Lower***	***0.08***
	External Shade Type	6 are eggcrate, 10 are horizontal	Lower with eggcrate shading	0.15

Table 20: Cooling Curve Inflection Point one way ANOVAs

<u>This table supports the following conclusion</u>: **Cooling curve inflection point of buildings is influenced by presence of external shading on the West and South to a certain extent, since the results of analyses are almost statistically significant.**

Table 20 analyzes inflection points of the cooling curves. These are the points where energy consumption for cooling can be visibly differentiated from the baseloads. This variable shows dependence to shading. Other variables depicted logical trends, but were not statistically significant or almost significant either.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Cooling Curve Highest Point	**Presence of Split Heat pumps/ window AC units**	**6 have**	**Higher**	**0.004**
	Depth of External Shading to North		**Lower**	**0.008**

(kwh/sqft/ day) (n=50)	**Depth of External Shading to South**		**Lower**	**0.018**
	Depth of External Shading to East		**Lower**	**0.007**
	Depth of External Shading to West		**lower**	**0.028**

Table 21: Cooling Curve Highest Point one way ANOVAs

This table supports the following conclusion: **Cooling curve highest point is influenced by external shading and presence of window AC units. While external shading decreases the highest point on the LEAN cooling curve, window AC units or heat pumps increase it.**

Table 21 depicts the co relations between attributes and cooling curve highest point. This point has been derived from LEAN monthly analyses, and indicate the energy use consumption at the highest degree day on the x axis. Apart from the effect of external shading on cooling, some weak co relations are also observed light fixture types and shaded cooling equipment. Another trend observed was that the cooling curve highest point was low only until a certain depth of external shading, and in fact started increasing when shading was between two to four feet. This would suggest that having more external shading does not have much impact on the cooling loads of a building.

Load	**Building Attribute**	**Number**	**Finding of Attribute Impact on Outcome**	**p Value**
Cooling Seasonal Energy Use (kwh-DD/ft 2day2) (n=51)	Presence of External Shading to E/W/S	16 with	Lower	0.107
	Presence of External Shading to W/S	**8 with**	**Lower**	**0.017**
	Depth of External Shading to North	**14 with**	**Decreases**	**0.008**
	Depth of External Shading to South	**15 with**	**Decreases**	**0.021**
	Depth of External Shading to East	**14 with**	**Decreases**	**0.008**
	Depth of External Shading to West	**12 with**	**Decreases**	**0.03**
	Presence of Split Heat pumps/ window AC units	**6 have**	**Higher**	**0.004**

Table 22: Cooling Seasonal Energy Use for a Typical Day one way ANOVAs

This table supports the following conclusion: **Seasonal cooling energy use (monthly data) is influenced by presence of external shading and presence of split heat pumps or window AC units. Shading decreases seasonal energy, while window AC units increases it.**

Table 22 depict results of ANOVA analyses of cooling seasonal energy use normalized by square footage or gross floor area against building attributes. Some contradicting trends are observed, in that clear vs dark glass and double paned windows did not see statistically significant results at all. Also, Buildings having more than 2 feet of shading saw more cooling seasonal energy use than buildings that did not. A probable reason for such a trend may be that most of these building are high rises, and as such those with up to two feet of shading are in fact low rises, so that the shading member can provide adequate protection against solar heat. Low rise buildings would not usually have more than 2 feet of horizontal overhangs, and these are tend to be found in high rises, where they would not be able to shade much. Another reason may be that the buildings with up to two feet of external shading may have it in the form of eggcrates. Coupling that with the assumption that these buildings are mid to low rises, they would have better shading than the other buildings in the dataset. This leads us to believe that collection of information for the attributes for shading need to be refined further, if they are to be analyzed against cooling loads.

Load	Building Attribute	Number	Finding of Attribute Impact on Outcome	p Value
Cooling Seasonal Energy Use (kwh-DD/ft2day-hr) (n=50)	External Shading to E/W/S	16 with	Decreases	0.114
	External Shading to W/S	8 with	Decreases	0.018
	External Shading to North	14 with	Decreases	0.01
	External Shading to South	15 with	Decreases	0.024
	External Shading to East	14 with	Decreases	0.009
	External Shading to West	12 with	Decreases	0.034
	External Shade Type	6 are eggcrate, 10 are H/V	higher with eggcrate	0.191
	Presence of Split Heat pumps	6 have	Higher in buildings with split heat pumps	0.004
	Shaded Cooling Equipment	22 with shade, 29 without	less with	0.384

Table 23: Cooling Seasonal Energy Use for a Typical Hour one way ANOVAs

This table supports the following conclusion: **Seasonal cooling energy use (interval data) is influenced by presence of external shading and presence of split heat pumps or window AC units. Shading decreases seasonal energy, while window AC units increases it.**

Table 23 also depict similar trends. One reason for this may be that cooling is affected by double paned and tinted glass in combination with other attributes, which need to be extracted from the datapool through further analysis in the next stage of statistical analyses. Further investigation of the effect of building attributes on cooling loads was then conducted. Relevant findings are as follows:

1. Buildings with 0-30% operable windows show a lower energy consumption for cooling compared to buildings that have fixed glass windows (p=0.015).

2. Buildings having more than 2 feet of external shading depth have high cooling energy consumptions compared to buildings with less depth of shading (p=0.009).

3. Buildings with two feet depth of external shading to south experience lower peak cooling (max energy used for a typical day or hour) per unit area compared to buildings that have no shading on the South (p=0.003).

4. Buildings with split heat pumps/ window ac units utilize more cooling seasonal energy use compares to buildings that do not have these heat pumps or window AC units (p=0.004).

5 Factor Analysis

Since the first step in analyzing building attributes against energy data was to run one way ANOVAs with individual attributes, the next step of running a multi variate analysis needed some more initial preparation. The database of buildings is still small, and there are around 15 variables that needed to be analyzed. Running multivariate analyses without knowing which building attributes to group together would result in in numerable permutations and combinations of attributes against energy loads. Fortunately, there is a technique in statistics that does not focus on testing hypotheses, but rather helps to understand which variables differ from each other at a significant level or order. Factor analysis comprises of reducing big data to manageable portions - in context of this synthesis, listing attributes in terms of “to what percentage do they explain that particular load variable”. This data reduction helped in formulation of the initial groups of attributes to conduct the next steps in the analyses. The primary reason for using factor analysis for this research is to understand the interrelations and connections between the different variables, and to group the attributes having similar tendencies (or shared variance) together. (Yong & Pearce, 2013). A lengthy procedure, it requires data screening beforehand. The results of this analysis are reflected in changes in the created test sets.

When conducting a factor analysis, a few things have to be taken into careful consideration. The method used here is called the ‘Principal Component Analysis’. It tries to combine the existing variables into groups that would explain the majority of the variance seen in the pattern of correlation. This techniques follows the following three steps to arrive at the results (Pallant, 2013):

1. Suitability of dataset for PCA/ FA:
   The size of the dataset is a big concern to identify if a particular dataset is suitable for factor analysis. It is general rule of thumb that larger a dataset, the better the results. Apart from the sample size, it is also the strength or weakness of the inter relationships between the variables that would also determine if a dataset is suitable to undergo factor analysis. This can be easily observed in the results generated by SPSS. The first way is to look at the Kaiser – Meyer – Olkin (KMO) measure of sampling adequacy. This number is an index, with the minimum value being 0 and maximum 1. Different sources suggest different KMO values for quantifying the suitability of the dataset, but a KMO value of 0.4-0.6 is generally taken as a good indication of a suitable dataset. The second measure to assess data suitability is the significance of Bartlett’s test of Sphericity ($p<0.05$)

2. Factor Extraction:

This is the step that provides results as to which variables co relate with each other, and to what extent. For example, the dataset has the thirteen building attributes listed above, and factor extraction will allow to create groups listing attributes that are interacting with each other closely. There are two contradictions that need to be balanced when doing factor extraction though: the first is to extract or rather identify as few factors or attributes as possible, so that the results are as statistically significant as possible, and the second is to explain as much variance as possible displayed by the factors or attributes.

3. Interpretation:
   Once the factors have been extracted, they need to be interpreted by the researcher. In an ideal situation, there should be three or more items are to be loaded on each component in the result of the factor analysis. Any loadings above .35 is considered to be strong, and the results provide probable groupings of the factors or attributes.

The first factor analysis conducted was using the following building attributes:

1. Presence of Rooftop Packed AC units
2. Shaded Cooling Equipment
3. Central vs AC unit cooling (decentralized cooling)
4. Proximity Shading
5. High mass vs low mass envelope
6. Presence of dark glass vs clear glass
7. Presence of external shading to the East, West and South
8. Internal Shading Device type – roller sashes vs venetian blinds
9. Type of Light Fixtures used – parabolic vs non parabolic
10. Single vs Double Glazed Windows
11. Lights ON at Night

12. Window Frame Material

13. Dark vs Cool Roofs

The KMO index for this analysis was 0.506, which indicates that multiple regression analysis would yield significant results with groupings, with a significant Bartlett's Test of Sphericity ($p=0.02$). The first six listed attributes explain about 60% of the variance in the dataset, and show strong correlations with other attributes. The Pattern Matrix show strong positive correlations between rooftop packaged AC units with proximity shading and buildings with dark roofs, presence of dark glass with high mass envelope, venetian blinds and proximity shading, while showing negative correlations between lights ON at night with high vs low mass envelope and shaded cooling equipment with presence of dark glass and proximity shading.

1. Rooftop Packaged AC units with Proximity Shading

2. Central vs AC cooling with Rooftop packaged AC units

3. Proximity Shading with Central vs AC cooling

4. High mass Envelope with presence of dark glass

5. Presence of dark glass with proximity shading

6. Presence of EWS shading with shaded cooling equipment

7. Presence of venetian blinds with dark glass

8. Light fixture type with shaded cooling equipment

9. Buildings with dark roof with buildings having ac units.

Multivariate analyses of the test sets obtained from the one way ANOVAs and the factor analyses were then conducted, to identify potential rebate bundles that would be successful in savings energy and costs.

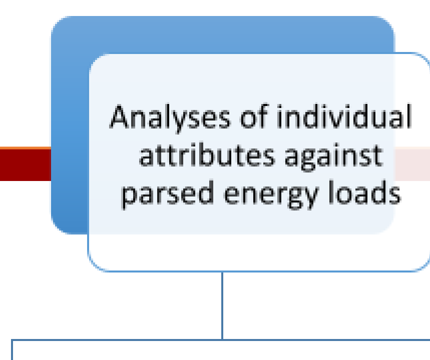


Figure 52: Stages of Statistical Analysis

The next factor analysis performed was by considering attributes that affect cooling loads only. One point to remember is that majority of the statistically significant results were observed for heating loads, and not cooling loads. This is due to the fact that the buildings are situated in Philadelphia, which is in a heating dominated climate. Winter months usually begin from September – October and last uptil March – April. So, we see a repetition of certain attributes that affect energy consumption in buildings. For cooling loads, the following attributes were used:

1. Depth of External Shading to East, West and South
2. Presence of Cooling Towers
3. Presence of Rooftop Packaged AC Units

4. Presence of Split or Window AC Units

The KMO index was 0.691, again indicating the suitability of conducting multiple regression analysis using the selected attributes. Bartlett's test of Sphericity also obtained statistical significance (p=0.00). Principal Component Analysis yielded two components that had an eigenvalue of more than 1. These components explained 48% and 20% of the variance observed respectively. Following the scree test as well, these two components were retained. For further analysis, Oblimin Rotation was conducted, and strong loadings for external shading and split/ window air conditioner units were observed for component 1. Cooling Towers loaded strongly on component 2, while rooftop packaged AC units was the only variable that loaded negatively, on component 2. These two components are very weakly correlated as well (r=-0.08). This analysis justifies a multiple regression between these attributes. The one way ANOVAs provide an indication that these attributes would be affecting cooling loads.

The next factor analysis was conducted using attributes for heating loads only. The following attributes were used:

1. Depth of External Shading to East, West and South

2. Presence of Rooftop Packaged AC Units

3. Presence of Dark Roof

The KMO index was 0.747, again indicating the suitability of conducting multiple regression analysis using the selected attributes. Bartlett's test of Sphericity obtained statistical significance (p=0.00). Principal Component Analysis yielded two components that had an eigenvalue of more than 1. These components explained 55% and 20% of the variance observed respectively. Following the scree test as well, two components were retained. For further analysis, Oblimin Rotation was conducted, and strong loadings for external shading and rooftop packaged AC units were observed for component 1. Presence of dark roofs as an attribute loaded strongly on component 2. All components had positive correlations. These two components are very weakly correlated as well (r=-0.143). The problem was that only one variable loaded on component 2. So, another factor analysis was conducted, with more attributes. The following attributes were then used:

1. Depth of External Shading to East, West and South

2. Presence of Rooftop Packaged AC Units

3. Presence of Dark Roof

4. Presence of Cooling Towers

With the addition of cooling towers, the KMO index went down to 0.7, which is still above 0.5. Bartlett's test of Sphericity was significant too (p=0.00). 2 components again had eigenvalues more than 1, and explained 46% and 19% of the variance respectively, and the second component had strong loadings on 3 attributes. This analysis justifies the use of the four attributes listed above for multiple regression analysis with heating loads. The two components correlated weakly as well (r=-0.195)

The last part of factor analysis was done with attributes that affect baseloads. The attributes are similar to those for heating loads, along with the addition of clear glass. The following attributes were analyzed for data reduction:

1. Depth of External Shading to East, West and South
2. Presence of Rooftop Packaged AC Units
3. Presence of Dark Roof
4. Presence of Clear Glass

The KMO index was 0.723, indicating the suitability of conducting multiple regression analysis using the selected attributes. Bartlett's test of Sphericity obtained statistical significance (p=0.00) too. Principal Component Analysis yielded two components again, that had an eigenvalue of more than 1. These components explained 46% and 20% of the variance observed respectively. Following the scree test as well, two components were retained. For further analysis, Oblimin Rotation was conducted, and strong loadings for external shading and rooftop packaged AC units were observed for component 1. Presence of clear glass as an attribute loaded strongly on component 2, while dark roof as an attribute loaded negatively. Rooftop packaged AC units loaded negatively on component 2 as well. These two components are very weakly correlated (r=-0.162).

The factor analyses performed in the previous section helped identify potential grouping of attributes that would be good candidates for multiple regression or multi variate analyses. This was a very important step that could not be skipped, for reason that will be explained in this section. Multivariate analysis is a combination of techniques that help researchers explore and identify interactions between a certain set of independent variables, which are hypothesized to have an effect on one dependent variable. Since multivariate analysis is based off on correlations between the independent variables, it is extremely helpful in exploring the inter relationships between the building attributes, for this synthesis. This reason makes multi variate analysis very apt for real life data analytics (Pallant, 2013). These analyses need to have a sound justification for the selection of attributes though, which is provided by the one way ANOVAs and factor analyses done in the previous sections of this research. Multi variate analysis has been used to understand to what extent the combinations of attributes would predict the disaggregated energy loads, and for the context of this research, has been used to answer the following three questions:

1. How well are the combinations or bundles of attributes predicting energy loads?

2. Which attribute from said combinations is the most influential in predicting energy loads?

Multivariate analysis has the following three major categories:

1. Standard/ Simultaneous multiple regression:
   The independent variables are entered into the software at the same time, with no sequence. This is the most common kind of analysis done, and is used when researchers need to explore how much variance in a dependent variable do the selected independent variables explain.

2. Hierarchical/ Sequential multiple regression:
   The independent variables are entered into the software for analysis in an order or particular sequence that is decided beforehand and has sound theoretical or statistical justification. The hierarchical multiple regression analysis is used when researchers need to control for certain variables, to see which variable has the most effect or influence on the dependent variable, by assessing the relative contribution of each variable.

3. Stepwise multiple regression:
   The variables to be entered (along with the sequence to be entered) for multi variate analysis are not decided by the researchers, but by the program itself. This is done by using three different techniques: forward selection, backward deletion and stepwise regression.

For the purpose of this research, the first method of multiple regression or multi variate analysis has been followed. Attributes selected for analysis have been selected from the results of the one way ANOVAs, represented in the previous chapter. Beta values of each attribute analyzed has been presented, along with the p value. Attributes with beta values of 0.3 or above are said to have strong correlations with energy load being analyzed. The most significant results have been explained below.

Multiple Regression: Cooling Loads

Dependent Variable	Independent Variables	R Square	Sig – p value	Beta	p Value
Cooling Curve Highest Point N=50	**Presence of Split Heat Pumps/ Window AC units**	35.5%	0.003	**0.3**	**0.03**
	Presence of Rooftop Packaged AC Units			**-0.27**	**0.05**
	Depth of External Shading to East			***0.4***	***0.11***
	Depth of External Shading to South			0.17	0.44
	Presence of Cooling Towers			-0.09	0.5
	Depth of External Shading to West			-0.1	0.74

Table 24: Multiple Regression Cooling Loads 1

This table supports the following conclusion: **Six building attributes influenced cooling curve highest point of buildings, of which window AC units, rooftop packaged AC units and external shading to East had the maximum influence (R^2=36%, p=0.003)**

Table 24 displays results obtained from a multiple regression analysis performed using depth to external shading to three cardinal directions and the kind of system a building utilizes for its cooling purposes. This analysis was carried out to understand the inter relationship between the cooling system and if external shading has some influence on its working and energy consumption. The analysis pointed out that buildings which had window/ split heat pumps and rooftop packaged AC units were influenced to a certain extent by external shading to the East experienced higher cooling curve highest points. The attributes of cooling towers and external shading to West and South did not influence the highest point.

Dependent Variable	**Independent Variables**	**R Square**	**Sig - p Value**	**Beta**	**p Value**
Cooling Curve Highest Point N=50	**Depth of External Shading to East**	35%	0.001	0.43	0.002
	Presence of Split Heat Pumps/ Window AC units			0.3	0.02
	Presence of Rooftop Packaged AC Units			-0.28	0.04
	Presence of Cooling Towers			-0.1	0.4

Table 25: Multiple Regression Cooling Loads 2

This table supports the following conclusion: **Out of four building attributes, external shading to East and window AC units had the maximum influence on cooling curve highest point of buildings, (R^2=35%, p=0.001)**

To understand how much does external shade contribute to cooling curve highest point, a hierarchical multiple regression was run, and it was observed that only 1% of the variance observed was explained by external shading to West and South. Table 25 shows that window/ split heat pumps affect cooling more than rooftop packaged AC units. As mentioned earlier, buildings with window or split units are the older ones in the dataset, with clear glass and single paned windows.

Dependent Variable	Independent Variables	R Square	Sig - p Value	Beta	p Value
Cooling Seasonal Electric Use N=50	**Presence of Split Heat Pumps/ Window AC units**	35.8%	0.002	**0.3**	**0.03**
	Presence of Rooftop Packaged AC Units			**-0.28**	**0.04**
	Depth of External Shading to East			***0.4***	***0.1***
	Presence of Cooling Towers			-0.1	0.4
	Depth of External Shading to South			0.15	0.48
	Depth of External Shading to West			-0.1	0.73

Table 26: Multiple Regression Cooling Loads 3

This table supports the following conclusion: **Out of six building attributes, external shading to East, rooftop packaged AC units and window AC units had the maximum influence on seasonal cooling electric use. (R^2=35%, p=0.001)**

Table 26 analyses these particular attributes in Table 24 against seasonal cooling energy use as well. These variables explain about 36% of the variability in the seasonal cooling energy data (R squared value), which is equal to the value of R square observed for cooling curve highest point. Table 26 depicts that the presence of split heat pumps increases seasonal cooling energy, as observed with one way ANOVAs. The table also depicts that the presence of rooftop packaged AC units would also increase seasonal cooling energy, since the beta associated with that attribute is negative. Another reason for the beta to be negative is that buildings will not have both rooftop packaged AC units and split heat pumps or window AC units together. This finding validates the use of multiple regression analysis as it is able to delineate inter relations that were not visible at first. In this example, ANOVA results showed that buildings with rooftop packaged AC units would have lower cooling loads, but the multiple regression analyses depicted that the presence of these units would act adversely on cooling loads.

A hierarchical multiple regression analysis was conducted to see how much variance is explained by the other variables not included in the subsequent multi variate analyses, and it was observed that depth of shading to South and West and presence of cooling towers explained only 2% of the variance. So, another multivariate analysis was conducted, but without these surplus attributes.

Dependent Variable	Independent Variables	R Square	Sig - p Value	Beta	p Value
Cooling Seasonal Electric Use N=50	Depth of External Shading to East	34%	0.00	0.43	0.02
	Presence of Split/ Window Heat Pumps			0.3	0.02
	Presence of Rooftop Packaged AC Units			-0.26	0.05

Table 27: Multiple Regression Cooling Loads 4

This table supports the following conclusion: **Out of the three building attributes, none had any influence on seasonal cooling electric use. (R^2=34%, p=0.00)**

Table 27 shows that the removal of all the other attributes does not affect the R squared value, and that it is only external shading to the East that decreases cooling loads, while the presence of heat pumps is resulting in high seasonal cooling energy use.

Multiple Regression: Heating Loads

Dependent Variable	Independent Variables	R Square	Sig - p Value	Beta	p Value
Total Heating N=49	**Depth of External Shading to East**	51%	0.00	**-0.854**	**0.00**
	Depth of External Shading to West			**1.54**	**0.00**
	Depth of External Shading to South			***-0.36***	***0.06***
	Presence of Rooftop Packaged AC Units			-0.83	0.4
	Presence of Dark Roof			0.002	0.987

Table 28: Multiple Regression Heating Loads 1

This table supports the following conclusion: **Out of five building attributes, external shading to East, West and South had the maximum influence on total heating. (R^2=51%, p=0.00)**

Shading is important / imo of dynamic shading Mention strong beta West – hottest time in afternoon, south negligible, east – morning sun – something else happening, other variable not collected. Table 28 represents results observed in a multiple regression analysis involving total heating energy with depth of external shading to East, West and South, presence of rooftop packaged AC units and dark roofs. It was found that it was external shading itself that had maximum influence on heating. According to the multiple regression, external shading to East and South would result in lower heating energy. Presence of dark roof did not have any significant impact on heating, probably due to confounding factors like height and number of floors in a building. Also, even though beta value for rooftop packaged AC units was high, that attribute was not considered for further analysis since its effect on heating was not statistically significant.

Dependent Variable	Independent Variables	R Square	Sig - p Value	Beta	p Value
Total Heating N=49	**Depth of External Shading to East**	50%	0.00	**-0.86**	**0.00**
	Depth of External Shading to West			**1.5**	**0.00**

Table 29: Multiple Regression Heating Loads 2

This table supports the following conclusion: **External shading to East and West have the maximum influence on total heating. (R^2=50%, p=0.00)**

A hierarchical multiple regression was performed again, where it was observed that dark roof, rooftop packaged AC units and external shading to South together explained just about 1% of the variance in Total Heating, so these variables were removed and another multi variate analysis was done. Table 29 depicts results from that analysis, and depth of external shading in different directions explain 50% of the variance observed in the data all by themselves.

Dependent Variable	**Independent Variables**	**R Square**	**Sig - p Value**	**Beta**	**p Value**
Heating EUI N=49	**Depth of External Shading to East**	**66%**	**0.00**	**0.3**	**0.09**
	Depth of External Shading to South			0.26	0.1
	Depth of External Shading to West			0.27	0.179
	Presence of Dark Roof			0.1	0.3
	Presence of Rooftop Packaged AC Units			0.07	0.43

Table 30: Multiple Regression Heating Loads 3

This table supports the following conclusion: **Out of five building attributes, only external shading to East had the maximum influence on heating energy normalized by gross floor area. (R^2=66%, p=0.00)**

Table 30 shows results from multiple regression analysis between heating energy normalized by gross floor area (heating EUI) for a typical hour with depth of external shading, presence of dark roofs and presence of rooftop packaged AC units. All the attributes taken together fitted/ explained 66% of the data, but one of the attributes had statistically significant results. Even though depth of external shading correlated strongly in this analysis, the results were not statistically significant.

Dependent Variable	Independent Variables	R Square	Sig - p Value	Beta	p Value
Peak Heating N=52	**Depth of External Shading to East**	65%	0.00	**0.37**	**0.03**
	Depth of External Shading to South			***0.27***	***0.08***
	Presence of Rooftop Packaged AC Units			0.1	0.25
	Depth of External Shading to West			0.17	0.4
	Presence of Dark Roof			0.04	0.7

Table 31: Multiple Regression Heating Loads 4

This table supports the following conclusion: **Out of five building attributes, external shading to East and South had the maximum influence on peak heating. (R^2=65%, p=0.00)**

Table 31 depicts analysis between peak heating and external shade, rooftop packaged AC units and dark roofs. The results validate the findings observed in the previous tables, that it is external shading that has the maximum influence on heating. The difference observed is that for peak heating, it is not the external shading on West that predicts energy consumption, unlike for total heating energy.

Hierarchical analysis of the above variables revealed that external shading to East and South explained 63% of the variance in peak heating. Multivariate analysis with just these two attributes was then performed.

Dependent Variable	**Independent Variables**	**R Square**	**Sig - p Value**	**Beta**	**p Value**
Peak Heating N=52	**Depth of External Shading to East**	**65%**	0.00	**0.37**	**0.03**
	Depth of External Shading to South			***0.27***	***0.08***

Table 32: Multiple Regression Heating Loads 5

This table supports the following conclusion: **Out of two building attributes, external shading to East and South had the maximum influence on peak heating. (R^2=65%, p=0.00)**

Table 32 depicts that the measure of how strongly depth of external shading to East and South remain unchanged from Table 31, and just these two attributes influence 65% of the peak heating data observed.

Dependent Variable	**Independent Variables**	**R Square**	**Sig - p Value**	**Beta**	**p Value**

Heating Curve Highest Point N=51	Presence of Rooftop Packaged AC Units	31%	0.004	0.2	0.1
	Depth of External Shading to South			0.3	0.16
	Depth of External Shading to East			0.3	0.2
	Presence of Dark Roof			0.1	0.43
	Depth of External Shading to West			-0.16	0.57

Table 33: Multiple Regression Heating Loads 6

<u>This table supports the following conclusion</u>: **Out of five building attributes, none of them had any statistically significant influence on heating curve highest point. (R^2=31%, p=0.00)**

Table 33 analyses attributes against heating curve highest point, and all of the attributes taken together yielded a statistically significant result. Even then, none of the individual attributes had any statistically significant results.

Dependent Variable	**Independent Variables**	**R Square**	**Sig - p Value**	**Beta**	**p Value**

Heating Seasonal Energy Use N=48	**Presence of Rooftop Packaged AC Units**	56%	0.00	**0.3**	**0.01**
	Depth of External Shading to East			**0.5**	**0.02**
	Presence of Dark Roof			**0.23**	**0.03**
	Depth of External Shading to South			0.21	0.23
	Depth of External Shading to West			-0.16	0.5

Table 34: Multiple Regression Heating Loads 7

This table supports the following conclusion: **Out of five building attributes, external shading to East, rooftop packaged AC units and dark roofs had the maximum influence on seasonal heating energy use. (R^2=56%, p=0.00)**

Analyzing seasonal heating energy use against the attributes decided by the one way ANOVAs revealed an R squared value of 56%. It was observed that depth of external shading to East correlated strongly with seasonal heating energy use as a predictor, followed by rooftop packaged AC units and dark roofs. Table 34 lists the attributes in order of statistical significance. So, even if East external shade had the highest beta value and correlated the most, it was rooftop packaged AC units that provided the most statistically significant results, followed by East external shading and then presence of dark roofs.

Dependent Variable	Independent Variables	R Square	Sig - p Value	Beta	p Value

Heating Seasonal Energy Use (interval data) N=48	**Depth of External Shading to East**	50%	0.00	**0.55**	**0.00**
	Presence of Rooftop Packaged AC Units			**0.3**	**0.00**

Table 35: Multiple Regression Heating Loads 8

<u>This table supports the following conclusion</u>: **Out of two building attributes, both had the maximum influence on peak heating. (R^2=50%, p=0.00)**

Hierarchical analysis revealed that rooftop packaged AC units and depth of external shading to east explained 50% of the variance observed in seasonal heating energy use. Another multivariate analysis was run with just these two attributes next, with the results displayed in Table 35. It was found that depth of external shading to East correlated more strongly to seasonal heating energy use.

Multiple Regression: Baseloads

<u>**Dependent Variable**</u>	<u>**Independent Variables**</u>	<u>**R Square**</u>	<u>**Sig - p Value**</u>	<u>**Beta**</u>	<u>**p Value**</u>
Sunday/ Holiday	**Presence of Dark Roof**	25%	0.035	**0.423**	**0.002**

Baseload EUI N=52	***Depth of External Shading to South***			***0.42***	***0.07***
	Presence of Rooftop Packaged AC Units			-0.16	0.26
	Depth of External Shading to West			-0.25	0.4
	Depth of External Shading to East			0.06	0.8
	Presence of Clear Glass			0.013	0.92

Table 36: Multiple Regression Base Loads 1

This table supports the following conclusion: **Out of six building attributes, external shading to South and presence of dark roof had the maximum influence on Sunday/ holiday baseload normalized by gross floor area. (R^2=25%, p=0.04)**

Table 36 shows results from the analyses of attributes influencing baseloads, as identified by one way ANOVAs in the previous chapter. It was observed that dark roofs would influence Sunday or holiday baseloads the most, closely followed by South External shading.

Dependent Variable	**Independent Variables**	**R Square**	**Sig - p Value**	**Beta**	**p Value**

Baseload N=50	**Presence of Rooftop Packaged AC Units**	29%	0.02	**-0.33**	**0.02**
	Presence of Clear Glass			-0.17	0.23
	Depth of External Shading to East			0.3	0.24
	Depth of External Shading to South			0.141	0.53
	Depth of External Shading to West			0.12	0.68
	Presence of Dark Roof			0.048	0.71

Table 37: Multiple Regression Base Loads 1

This table supports the following conclusion: **Out of six building attributes, only rooftop packaged AC units had the maximum influence on Sunday/ holiday baseload normalized by gross floor area. (R^2=25%, p=0.04)**

Table 37 displays results of multiple regression between baseload and attributes selected in Chapter 4.2. Where dark roof had a significant influence on Sunday/ holiday baseloads, it doesn't affect weekday baseloads. It was also expected that presence of clear glass would also correlate strongly with weekday baseload, since clear glass would allow maximum daylight to enter the building. Natural day light would in turn play a role in reducing lighting loads, which would be visible in reduced baseloads. Clear glass had moderate correlations, but the results were not statistically significant.

6 Results and Recommendations

This research was carried out to see if there is a quantitative way to help PECO reduce the thousands of buildings it has as its customers in Philadelphia to a more manageable number, to recommend them for further analysis and energy audits. On the basis of these analyses and audits, PECO would recommend comprehensive packages of rebates and energy efficiency measures to reduce energy loads in buildings. To achieve that result, energy data from fifty two buildings were statistically analyzed against a delimited set of building attributes. The energy data was obtained in the form of utility bills from PECO. Disaggregated energy loads of baseloads, heating loads and cooling loads were parsed from the bills using LEAN analysis methodology. These LEAN derived energy metrics were then analyzed against twelve attributes that were relevant for retrofits, using SPSS – a statistical software. The entire statistical analysis was done in three stages. The first stage involved analyzing each single individual attribute against the LEAN derived energy metrics, using one way ANOVAs. About 520 ANOVAs were conducted. This stage provided us with a listing of all the statistically significant attributes ($p<0.05$), as well as other relevant trends ($0.05<p<0.3$). Trends not significant but with a p value from 0.05 to 0.3 were also considered for further analysis since the main focus of this research was to explore the interplay between different attributes. These selected attributes were then used for the second stage analysis. This second stage was the factor analysis – a data reduction technique that helped in reducing the numerous significant results to a more smaller number – by specifying which particular bundles of attributes would be more suitable for further analysis. A factor analysis is a statistical technique that allows you to put in multiple attributes that may be correlated with each other and determine which ones are having the biggest impact on a particular outcome. For example, with one way ANOVAs it was observed that heating loads were being influenced by presence of clear glass, external shading to the cardinal directions, presence of rooftop packaged AC units, dark roofs and window AC units or split heat pumps. To find out if which attributes would have the maximum influence on heating loads by analyzing their inter relationships with each other, factor analyses is conducted. Of the eight attributes, the factor analyses helps in narrowing down the selection to, say two or three attributes that would have strong beta values (a predictor of the measure of variance of energy loads) and influence heating loads.

Factor analysis is especially important with datasets such as the one in this thesis because many of the building attributes are correlated with each other and simply including all of them into one multivariate analysis formula could bring a statistical error called multicollinearity where the p value is significant but the results are invalid. The factor analysis reduces the chances of a multi-collinearity error. The third stage of the statistical analysis involved utilized multiple regression analysis. This regression was done to analyze the LEAN derived energy data metrics with the bundles or groupings of attributes as decided by the factor analysis. The end result was to understand how much variance in the energy data metrics is explained by the attributes taken together, and the results of these analyses are explained below.

6.1 Patterns affecting load breakdown

External shading affects baseloads, heating loads and cooling loads. It reduced baseloads when compared to buildings that did not have external shading (p=0.06), reduced cooling loads (p=0.01) but increased heating loads (p=0.02) and these buildings had a higher heating curve (p=0.00) as well. External shading is preferable when cooling loads reduce in buildings, but not at the cost of heating bills. To explore this finding more, another analysis was scrutinized. These analyses depicted that when external shading was beyond two feet in depth energy loads increased steeply. A closer inspection of the dataset also revealed that the majority of the external shading found on buildings were horizontal projections, placed on the East and West facades. Horizontal facades don't block the sun's rays when the sun rises and sets, and the West façade would be where the maximum solar gain occurs. Also, the statistics support the use of dynamic facades as shading devices, since heating loads are increasing while cooling loads decrease. At present, the numbers suggest that external shading is not being done correctly, and more research needs to be conducted in this field.

Clear glass as a variable should affect all the disaggregated energy loads – baseloads, heating loads and cooling loads. A clear or no tint to glass would allow daylight to enter the building, reducing the need to use artificial lighting during the daylit hours. The less use of lights should be visible as a clear reduction visible in the proportion of baseloads obtained from the LEAN methodology. Also, clear glass should theoretically allow solar heat gain from the windows, if the solar heat gain coefficient (SHGC) is high enough. Since SHGC was another attribute not collected for this research, the reason for certain findings observed cannot be stated with conviction.

The effect dark roof has on the disaggregated energy loads was clearly visible from the one way ANOVAs. The dataset had twelve buildings that had cool roofs. Buildings with dark roofs experienced higher Sunday and holiday baseloads (p=0.00) and higher weekday baseloads (p=0.03) compared to buildings with cool roofs. Cool roofs reflect back much of the solar heat which keeps the interior building spaces cool, thereby reducing cooling loads. Cool roofs help in downsizing air conditioning systems (Energy Star, 2007).

Cooling systems present in the dataset of buildings was also analyzed to see which system resulted in lower energy loads. Buildings which had window AC units were older construction, with single glazed clear glass windows. Such a cooling system is also too dependent on occupant control to function optimally. Statistics revealed that buildings with window AC units had higher baseloads (p=0.00), higher heating loads (p=0.02) and higher seasonal cooling loads (p=0.00). As mentioned in the previous chapters, information on the age and specifications of the AC units could not be collected, which may be probable reasons for such the buildings to experience high energy loads.

Most of the statistically significant results were observed for heating loads, which was expected because the dataset is limited to buildings located in and around Philadelphia – a heating dominated climate.

6.2 Trends and Findings

1. Buildings with rooftop packaged AC units had lower baseloads (p=0.02) – indicative of influence of attributes that were not collected, and increased heating loads (p=0.00)

2. Buildings with shaded cooling equipment had tighter range of, and higher Energy Star score than buildings which did not (p=0.02)

3. Buildings with cool roofs had less heating seasonal energy use (p=0.02) and lower Sunday baseload (p=0.00)

4. External shading to East, West and South increased heating loads with increasing depth (p=0.00), and decreases seasonal cooling energy use (p=0.00)

5. Buildings with window AC units/ split heat pumps had higher cooling seasonal energy use when compared with buildings that did not (p=0.004).

6. Depth of external shading and presence of window heat pumps increases seasonal cooling electric use, while rooftop packaged AC units decreases it.

7. Seasonal heating energy use increases with East external shade, but decreases with cool roofs and clear glass.

8. Heating EUI decreases with rooftop packaged AC units, increases with shade

9. The following attributes need further research:

    a. External shading – depth

b. External shading – type

c. Operable Windows

d. Light Fixtures

e. Clear vs Dark Glass

f. Operable Windows

g. Single vs Double Glazed Windows

h. Internal Shading Device

i. Proximity Shading

6.3 Recommendations for Utilities and Building Owners

Rebate managers need to conduct an in depth energy audit and analysis of buildings that apply for any rebate program. They pitch energy efficiency measures and rebate programs by targeting particular buildings and customers, whom they believe would benefit the most from these programs.

On the basis of the results obtained from one way ANOVAs and the multiple regressions, the following attributes may be used as a criteria to select potential buildings from PECOs dataset for further analysis to target rebates:

1. Buildings which have rooftop packaged AC units
2. Buildings with dark roofs
3. Buildings with windows AC units

4. Buildings with rooftop packaged AC units
5. Buildings with more than external shading

The following attributes may be bundled to provide rebates for relevant buildings:

1. Cool Roofs
2. Upgrading rooftop packaged AC units to a central cooling system
3. Upgrade clear glass to have low e coating

7 Conclusions

Discussions with PECO and the utility manager conducted over the course of a year revealed that there is a need to create a methodology that would help the utilities to target a particular set of buildings for further analysis by conducting energy audits. This targeting needs to be done because to create new rebates or energy efficiency programs, PECO needs to know how to target buildings. They need an algorithm that would help them narrow down potential candidates for retrofits from the thousands of customers that they have, to a few select hundreds that have some underlying problems with their energy loads (PECO & DNV GL, Discussion on Rebates, 2015). This research was conducted to understand which attributes interacted together to influence disaggregated energy loads, in an effort to help narrow down the pool of buildings for targeting further analysis and subsequently rebates. The dataset of around twenty five buildings with energy data, taken from a previous study (CBEI, 2016) was utilized, and more buildings were added to it. The number of buildings in the dataset which have energy data now stands at fifty two. LEAN analysis, developed in the previous study was utilized to parse out disaggregated energy loads of the new buildings in the dataset. One way analysis of variance (ANOVAs) were conducted to identify the impact of individual attributes on energy data.

The new methodology developed for this research utilizes results obtained from the one way ANOVAs, and uses them in a multiple variate regression analysis. The one way ANOVAs provide a listing of selected attributes that affect disaggregated loads. To obtain a more manageable groups or bundles of attributes from the listing, factor analyses were first conducted on the selected attributes. The factor analyses informs which particular bundle or group would have statistical significance for multiple regression analyses. Around seven hundred statistical analyses were conducted to explore which attributes bundled together would have the maximum influence on the 30 LEAN derived disaggregated energy metrics. Of these seven hundred, five hundred were the one way ANOVAs to obtain updated findings on how attributes influence the LEAN derived energy data.

Factor analysis is a statistical technique that allows you to put in multiple attributes that may be correlated with each other and determine which ones are having the biggest impact on a particular outcome. Factor analysis is especially important with datasets such as the one in this thesis because many of the building attributes are correlated with each other and simply including all of them into one multivariate analysis formula could bring a statistical error called multicollinearity where the p value is significant but the results are invalid. Factor analysis reduces the chances of a multi-collinearity error. Fifty factor analyses were performed to arrive at an exhaustive list of bundles of attributes.

The third stage of analyses involved multiple regression. Multiple regression is a statistical procedure that focuses on the relationship between a dependent variable (energy load) and two or more than two independent variables (building attributes). Another one hundred fifty multiple regression analyses were performed based on the results of the factor analysis. There were two kinds of multiple regressions conducted. The first was the standard regression with multiple variables and the other was the hierarchical regression. With standard regression, the variables are entered into the software in no specific order, while in hierarchical regression, attributes are divided into blocks or groups, and entered one group at a time, to explore which group has more influence on LEAN derived disaggregated energy loads. It was observed that a few attributes would always not contribute enough to make a difference. This difference in influence was visible through the hierarchical regression analyses.

The third stage of analysis yielded results that showed which attributes were influencing particular LEAN derived disaggregated energy loads the most. Based on this analysis, a prioritized list of attributes influencing the LEAN derived disaggregated energy loads could be inferred.

This new methodology of using factor analysis and multiple regression analysis was tested and has proven to be successful in identifying potential pools of buildings that would be relevant candidates for further analysis for targeting rebates and other energy efficiency measures. Factor Analyses and Multiple Regression Analyses are also really useful tools in identifying collections of attributes that influence energy loads.

This research may not yield a long list of specific rebates, however the methodology utilized does provide a process that can be adopted by utility companies like PECO and utility managers like DNV GL to select potential buildings for energy audits. Additionally, results have indicated that certain attributes can definitely be considered for rebates as they are the most statistically significant. Among these statistically significant attributes, cool roofs were the most promising. Also, results suggest that providing dynamic shading seems to be a good rebate to offer, but further research is needed to suggest it as a rebate with conviction. Also, for a heating dominated climate like Philadelphia, switching to low e coated clear glass from tinted glass would offer year round benefits. Clear glass would allow natural daylight to enter the building, reducing weekday baseloads. This trend is not quite statistically significant, and is assumed that a larger dataset would help in achieving a statistically significant result. The low e coating helps in reducing emissivity of glass reducing radiation of heat from the windows. This reduction in heat radiation would help in lowering heating energy loads, by reducing heat inside the building from being radiated to the outside surroundings.

The premise of this research was that the inter relationships of building attributes with each other would impact energy loads, instead of a single attribute influencing energy use. This was tested and confirmed with statistical analyses.

7.1 Limitations

A lot of limitations were faced when conducting this research. The first limitation faced was with the data collection. Not all data could be gathered accurately, and a visual inspection of the exterior of the building yield a limited dataset of building attribute information. The second limitation faced was in the collection of utility bills. There were a total of one hundred and sixteen buildings in the dataset for which energy star scores were tabulated. Of these one hundred sixteen, annual energy data was available for one hundred and sixteen while monthly and interval level data was available for just fifty two buildings. The problem with access to energy data was that from 116 buildings, the dataset was reduced to half its size. Sample sizes of both buildings for which energy data was available and the variety of attributes collected were what limited this research.

<u>Limitation in Attribute Collection:</u>

This research focused on attributes that would be relevant for retrofitting. As such, the variety of attributes needed for the statistical analysis reduce due to the scope. It was not possible to collect information on certain building attributes for which we had no permission to access, like:

1. Insulation used in construction assembly
2. Thermal resistance of construction materials
3. Thermal Breaks
4. SHGC of windows
5. Heating system specifications – efficiencies/ COP of boiler or furnace,
6. Fan motor efficiency, COP and output capacity of AHUs
7. Window AC unit specifications

Apart from the building attributes, no information was collected on scheduling of the buildings. A lot of results obtained probably could have been explained via building management attributes like:

1. Occupancy Scheduling
2. Thermal Zoning

Limitation in Sample Size:

Sample size limitations occurred in attribute collection as well as statistical analyses. Data collection for external shading needs to be re worked, to reflect the way it is being done and treated presently. Limiting the sample size due to not being able to access utility bills of other seventy four buildings also constrained the statistical analysis to a great degree. No valid and significant findings could be obtained for at least nine separate attributes. For example, trends observed for dark vs clear glass and also for single vs double paned windows followed concepts laid out by building science, but could not be presented since they were not statistically significant at all. A bigger sample hopefully would have yielded better significant and relevant results. Another limitation was that due to the small sample size, the analysis could not be controlled for variables that would show multicollinearity like:

1. Age of the buildings,
2. Layout of buildings,
3. Depth of buildings,
4. Window to wall area ratio
5. Number of floors

7.2 Future Work

This research was a continuation of previous work (CBEI, 2016) (Spencer & Kaufman, 2015) which analyzed attributes against parsed energy data in isolation. Future work to understand how attributes interact with one another to influence energy loads can be divided into three main parts:

1. Increase sample size
   This step would help in in obtaining statistically significant results for attributes that have as yet not been observed in this research
2. Increase attribute information by including attributes not collected previously
   This would help in analyzing findings obtained from the statistical analysis. A lot of underlying reason for certain findings would then be clear.
3. Automate methodology
   A step forward would be to create an algorithm based on this method, so that people who are not experts in statistics can easily conduct the analysis as well. It would help in creating awareness about energy efficiency measures that a building owner may take to reduce energy loads.

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9 Appendices

9.1 Appendix A: Federal Rebates - DSIRE

Program	Implementing Sector:	Category:	Incentive Type:	Administrator	Eligible Efficiency Technologies:
Energy-Efficient Commercial Buildings Tax Deduction	Federal	Financial Incentive	Corporate Tax Deduction	U.S. Internal Revenue Service	Equipment Insulation, Water Heaters, Lighting, Lighting Controls/Sensors, Chillers, Furnaces, Boilers, Heat pumps, Air conditioners, Caulking/Weather-stripping, Duct/Air sealing, Building Insulation, Windows, Siding, Roofs, Comprehensive Measures/Whole Building, Other EE, Tankless Water Heater
USDA - Rural Energy for America Program (REAP)	Federal	Financial Incentive	Loan Program	U.S. Department of Agriculture	Solar Water Heat, Solar Space Heat, Geothermal Electric, Solar Thermal Electric, Solar Photovoltaics, Wind (All), Biomass, Hydroelectric, Hydrogen,

Loan Guarantees					Geothermal Heat Pumps, Combined Heat & Power, Tidal, Wave, Ocean Thermal, Wind (Small), Hydroelectric (Small), Geothermal Direct-Use, Anaerobic Digestion, Fuel Cells using Renewable Fuels, Microturbines
U.S. Department of Energy - Loan Guarantee Program	Federal	Financial Incentive	Loan Program	U.S. Department of Energy	Geothermal Electric, Solar Thermal Electric, Solar Thermal Process Heat, Solar Photovoltaics, Wind (All), Biomass, Hydroelectric, Fuel Cells using Non-Renewable Fuels, Landfill Gas, Tidal, Wave, Ocean Thermal, Daylighting, Fuel Cells using Renewable Fuels
USDA - Rural Energy for America Program (REAP) Grants	Federal	Financial Incentive	Grant Program	U.S. Department of Agriculture	Solar Water Heat, Solar Space Heat, Geothermal Electric, Solar Thermal Electric, Solar Photovoltaics, Wind (All), Biomass, Hydroelectric, Hydrogen, Geothermal Heat

					Pumps, Combined Heat & Power, Tidal, Wave, Ocean Thermal, Wind (Small), Hydroelectric (Small), Geothermal Direct-Use, Anaerobic Digestion, Fuel Cells using Renewable Fuels, Microturbines
USDA - High Energy Cost Grant Program	Federal	Financial Incentive	Grant Program	USDA Rural Utilities Service	Solar Water Heat, Solar Space Heat, Solar Thermal Electric, Solar Thermal Process Heat, Solar Photovoltaics, Wind (All), Biomass, Hydroelectric, Wind (Small), Hydroelectric (Small)

9.2 Appendix B: State Rebates - DSIRE

Program	Implementing Sector:	Category:	Incentive Type:	Administrator	Eligible Efficiency Technologies:
Small Business Pollution Prevention Assistance Account Loan Program	State	Financial Incentive	Loan Program	Pennsylvania Department of Environmental Protection	
High Performance Buildings Incentive Program	State	Financial Incentive	Loan Program	Department of Community and Economic Development	Solar - Passive, Solar Water Heat, Solar Space Heat, Solar Photovoltaics, Wind (All), Biomass, Geothermal Heat Pumps, Daylighting
Alternative and Clean Energy Program	State	Financial Incentive	Loan Program	Department of Community and Economic Development	Geothermal Electric, Wind (All), Biomass, Hydroelectric, Geothermal Heat Pumps, Municipal Solid Waste, Combined Heat & Power, Fuel Cells using Non-Renewable Fuels, Landfill Gas, Daylighting, Wind (Small),

					Hydroelectric (Small), Geothermal Direct-Use, Anaerobic Digestion, Fuel Cells using Renewable Fuels
Small Business Advantage Grant Program	State	Financial Incentive	Grant Program	Department of Environmental Protection	Wind (All), Geothermal Heat Pumps, Wind (Small)
High Performance Building Incentives Program	State	Financial Incentive	Grant Program	Department of Community and Economic Development	Solar - Passive, Solar Water Heat, Solar Space Heat, Solar Photovoltaics, Wind (All), Biomass, Geothermal Heat Pumps, Daylighting, Wind (Small), Hydroelectric (Small)
Alternative and Clean Energy Program	State	Financial Incentive	Grant Program	Department of Community and Economic Development	Geothermal Electric, Wind (All), Biomass, Hydroelectric, Geothermal Heat Pumps, Municipal Solid Waste, Combined Heat & Power, Fuel Cells using Non-Renewable Fuels, Landfill Gas, Daylighting, Wind (Small),

					Hydroelectric (Small), Geothermal Direct-Use, Anaerobic Digestion, Fuel Cells using Renewable Fuels

9.3 Appendix C: Utility Rebates - DSIRE

Program	Implementing Sector:	Category:	Incentive Type:	Administrator	Eligible Efficiency Technologies:
PPL Electric Utilities - Commercial, Industrial and Agricultural Energy Efficiency Rebate Program	Utility	Financial Incentive	Rebate Program	PPL Electric Utilities	Refrigerators/Freezers, Lighting, Lighting Controls/Sensors, Heat pumps, Combined Heat & Power, Custom/Others pending approval, Other EE, Commercial Refrigeration Equipment
Duquesne Light Company - Commercial and Industrial Energy Efficiency Program	Utility	Financial Incentive	Rebate Program	Duquesne Light Company	Refrigerators/Freezers, Equipment Insulation, Lighting, Lighting Controls/Sensors, Air conditioners, Motors, Motor VFDs, Custom/Others pending approval, Other EE, Food Service Equipment, Commercial Refrigeration Equipment
PECO Energy (Electric) -	Utility	Financial Incentive	Rebate Program		Refrigerators/Freezers, Lighting, Lighting Controls/Sensors,

Non-Residential Energy Efficiency Rebate Program					Boilers, Heat pumps, Air conditioners, Combined Heat & Power, Motor VFDs, LED Lighting, Commercial Refrigeration Equipment
FirstEnergy (MetEdison, Penelec, Penn Power) - Commercial and Industrial Energy Efficiency Program	Utility	Financial Incentive	Rebate Program	SAIC	Water Heaters, Lighting, Lighting Controls/Sensors, Chillers, Heat pumps, Air conditioners, Motors, Motor VFDs, Custom/Others pending approval, Other EE, Food Service Equipment, Vending Machine Controls
Philadelphia Gas Works - Residential and Small Business Equipment Rebate Program	Utility	Financial Incentive	Rebate Program	Philadelphia Gas Works	Lighting, Furnaces, Boilers, Programmable Thermostats

Philadelphia Gas Works - Commercial and Industrial Equipment Rebate Program	Utility	Financial Incentive	Rebate Program	Philadelphia Gas Works	Water Heaters, Furnaces, Boilers, Heat recovery, Steam-system upgrades, Energy Mgmt. Systems/Building Controls, Motors, Comprehensive Measures/Whole Building, Commercial Cooking Equipment
Philadelphia Gas Works - Residential and Commercial Construction Incentives Program	Utility	Financial Incentive	Rebate Program		Comprehensive Measures/Whole Building
PECO Energy (Gas)- Commercial Heating Efficiency Rebate Program	Utility	Financial Incentive	Rebate Program		Furnaces, Boilers

9.4 Appendix D: Statistical Analyses

```
ONEWAY UnoccupiedSundayElectricBaseLoadkWhhBY ExtSWD
  /STATISTICS DESCRIPTIVES HOMOGENEITY BROWNFORSYTHE WELCH
  /PLOT MEANS
  /MISSING ANALYSIS
  /POSTHOC=TUKEY ALPHA(0.05).
```

Oneway

Notes

Output Created		30-JUL-2016 23:48:56
Comments		
Input	Data	C:\Users\Prachi\Documents\CMU\RA\thesis\SPSS\MR\trial run_MR.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	116
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each analysis are based on cases with no missing data for any variable in the analysis.
Syntax		ONEWAY UnoccupiedSundayElectricBaseLoadkWhhr BY ExtSWD /STATISTICS DESCRIPTIVES HOMOGENEITY BROWNFORSYTHE WELCH /PLOT MEANS /MISSING ANALYSIS /POSTHOC=TUKEY ALPHA(0.05).
Resources	Processor Time	00:00:00.61
	Elapsed Time	00:00:00.66

Warnings

Post hoc tests are not performed for Unoccupied Sunday Electric Base Load (kWh/hr) because there are fewer than three groups.

Page 1

MR: Heating EUI (kWh/hr-ft2) against Cooling Towers/ Presence of North Ext Shade**/ Depth of Ext Shading East**/ Depth of Ext Shading South/ External Shade Type/ **Internal Shading Device**/ Dark vs Clear Glass/ Light Fixture Type **(sig values below 0.05 in coefficients table)**

Sig: 0.033, N=49, r sq= 84%

MR: cooling EUI (kWh/hr-ft2) against Cooling Towers/ Presence of North Ext Shade/ Depth of Ext Shading East/ Depth of Ext Shading South/ External Shade Type/ Internal Shading Device/ Dark vs Clear Glass/ Light Fixture Type

NA due to correlations

MR: Peak Heating (kWh/hr-ft2-F) against Cooling Towers/ Presence of North Ext Shade**/ Depth of Ext Shading East**/ Depth of Ext Shading South/ External Shade Type/ **Internal Shading Device**/ Dark vs Clear Glass/ Light Fixture Type **(sig values below 0.05 in coefficients table)**

Sig: 0.027, N=52, r sq= 85%

MR: Total Cooling Electricity (kWh/hr)/ Cooling Towers/ Depth of Ext Shading East/ Depth of Ext Shading South**/ External Shade Type**/ Internal Shading Device/ Dark vs Clear Glass**/ Shaded Cooling Equipment**/ Proximity Shading **(sig values below 0.05 in coefficients table)**

Sig: 0.07, N=52, r sq= 79%

MR: Heating EUI in Occupied Hours_(kWh/hr-ft2)/ Cooling Towers/ Depth of Ext Shading East/ Depth of Ext Shading South/ External Shade Type/ Dark vs Clear Glass/ Shaded Cooling Equipment/ Proximity Shading **(sig values below 0.05 in coefficients table)**

Sig: 0.036, N=49, r sq= 83%

MR: Heating EUI in Occupied Hours_(kWh/hr-ft2)/ **Dark vs Clear Glass**/ Central vs AC cooling / Shaded Cooling Equipment/ Number of Glazing Layers/ **Presence of EWS Ext Shade (sig values below 0.05 in coefficients table)**

Sig: 0.000, N= 49, r sq= 47%

MR: peak heating)/ **Dark vs Clear Glass**/ Central vs AC cooling/ Shaded Cooling Equipment/ Number of Glazing Layers/ **Presence of EWS Ext Shade (sig values below 0.05 in coefficients table)**

NA due to low correlations/ sig: 0.000, N= 52, r sq= 42%

MR: Total Heating Electricity (kWh/hr)/ Number of Glazing Layers / **cooling towers (sig values below 0.05 in coefficients table)**

Sig: 0.007, N= 49, r sq= 24%

MR: Total Heating Electricity (kWh/hr)/ **Cooling Towers**/ Shaded Cooling Equipment/ **Air Conditioners**/ Proximity Shading/ Envelope Material/ Dark vs Clear Glass/ *Presence of EWS Ext Shade*/ Internal Shading Device/ **Operable Windows**/ *Light Fixture Type*/ Lights ON at Night/ Number of Glazing Layers/ Roof Color and Reflectivity **(sig values below 0.05 in coefficients table)**

Sig: 0.003/ N= 49, r sq= 54%

MR: Total cooling Electricity (kWh/hr)/ Cooling Towers/ Shaded Cooling Equipment/ Air Conditioners/ Proximity Shading/ Envelope Material/ Dark vs Clear Glass/ Presence of EWS Ext Shade/ Internal Shading Device/ **Operable Windows**/ Light Fixture Type/ Lights ON at Night/ Number of Glazing Layers/ **Roof Color and Reflectivity (sig values below 0.05 in coefficients table)**

Sig: 0.065/ N= 52, r sq= 39%

MR: weekday baseload (kWh/hr)/ Cooling Towers/ Shaded Cooling Equipment/ Air Conditioners/ **Proximity Shading**/ Envelope Material/ Dark vs Clear Glass/ Presence of EWS Ext Shade/ Internal Shading Device/ Operable Windows/ Light Fixture Type/ Lights ON at Night/ Number of Glazing Layers/ **Roof Color and Reflectivity (sig values below 0.05 in coefficients table)**

Sig: 0.02/ N= 52. R sq= 45%

Bivariate correlation: Dark vs clear glass and internal shading device – small correlation with p=0.002

Bivariate correlation: cooling towers and internal shading device – very very small correlation, p value too high