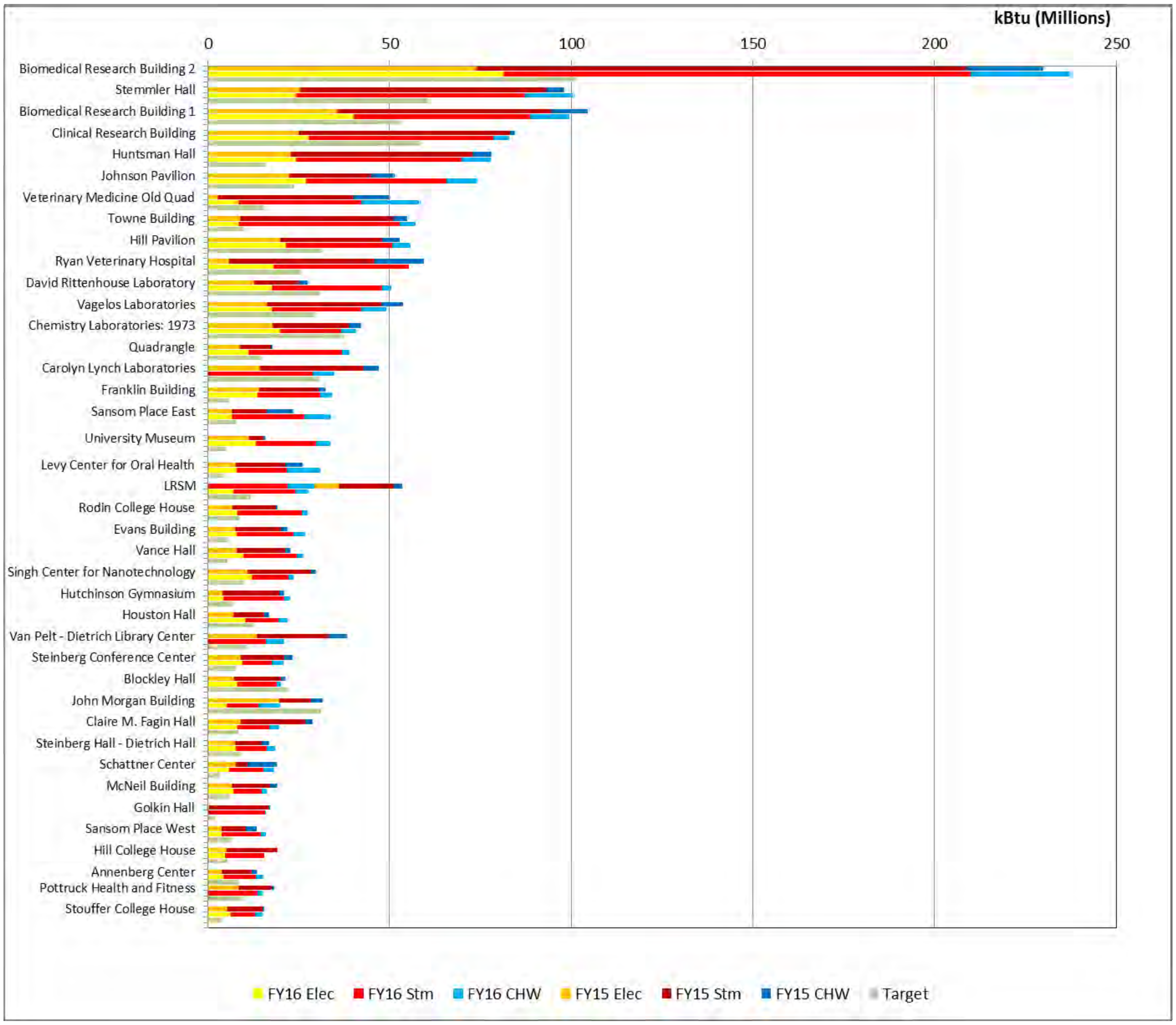
University of Pennsylvania
Facilities and Real Estate Services (FRES)

Building Energy Reporting and Performance Analysis



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CENTER FOR ENVIRONMENTAL BUILDING DESIGN

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1.0- Introduction

The capacity of technology to capture and store data from utility meters has increased dramatically in recent years. However, while virtual mountains of information are being collected, in many cases the question of what to do with that data in order to make it useful has yet to be answered. The Center for Environmental Building & Design (formerly the T.C. Chan Center) has assisted the University of Pennsylvania's Facilities and Real Estate Services (FRES) in the analysis of energy consumption and greenhouse gas production for nearly a decade. As energy meters in individual building around campus have come online in recent years, this work has sought to answer that core question: now that the data has been collected, what can we do with it to increase its utility and value?

The Center for Environmental Building & Design (CEBD) has been centrally involved in the environmental initiatives of University of Pennsylvania since 2005-06, when the first Sustainability Plan was prepared. That initial research report concluded that building energy consumption was one of the key elements of campus operations to be regulated, and proposed both that buildings be individually metered and that a provisional program of building auditing begin immediately. For the following two years, performance assessments were conducted using a Building Performance Assessment Tool (BPAT) that combined “walk-around” audits of buildings with simplified performance simulations, allowing the University of identify buildings for renovation and upgrade. That program continued over the following years with more detailed systems evaluations and helped initiate a program of continuous re-commissioning.

Beginning in 2007, when the University President signed the carbon reduction pledge, the CEBD provided most of the data analysis and research that was used as the basis for the Climate Action Plan 1.0. While this analysis has followed many different paths, the ongoing service provided by the CEBD has been the calculation of the current carbon footprint for the campus and the projection of that footprint into the future under a variety of envisioned scenarios. In the initial action plan the campus was examined as an aggregated whole and the reductions possible from each category were estimated over the course of a 30-year scenario. This method was used to set initial targets for reductions in the 5-year timeframe once the plan had been enacted and to estimate the scale of reductions that would be possible before 2042. The built environment of the University of Pennsylvania accounts for approximately 85% of the carbon produced by the main campus through the use of electricity, steam, and chilled water.

After the launch of Climate Action Plan 1.0 in 2009, the CEBD began to explore the question in greater depth by breaking down the aggregated campus into individual buildings with different degrees of improvements. It created the framework for more accurate projections of carbon reductions once meter data becomes available. In 2012 a financial calculator was added to the individual carbon projections to evaluate the net present value (NPV) of renovation scenarios. Estimates of the cost and effectiveness of each renovation planned within a scenario can be calculated; the NPV of the costs and the growing energy savings from each project can be estimated as well. The combination of these individual building worksheets and financial calculators allows for a more detailed examination of the potential for carbon reductions in the built environment.

All three tools were used together in 2013-14 to develop a more nuanced and realistic Carbon Action Plan 2.0, though this was still based mostly on estimates of individual building energy consumption. The 2.0 scenarios considered a range of options for the renovation of campus buildings focused around the Century Bond projects and the potential improvements that could be achieved by bringing the worst performing facilities up to a contemporary standard. The final scenario was developed by assuming that the top 20% of poorly performing buildings would be renovated and that they would be brought to current or next generation code.

The 2015 fiscal year (FY15) was the first for which most of the meters were operational for the entire year, making it the first year that this type of research was possible. The meter data was aggregated, normalized, and compared against regional benchmarks by building type in order to identify those that had the greatest potential for energy reductions. The 40 buildings with the most potential for reductions were put forward for further investigation. In order to better communicate energy information regarding these buildings an annual report was developed to present this data on a building's performance with as much clarity and information on one page.

However, there were a number of limitations that hindered the utilization and presentation of the gathered energy information. This year's work has been to overcome those limitations and to expand the utility of the meter data that has been collected. The first issue has been largely self-correcting and is regarding the quality of the raw data being recorded. As FY15 was the first year of operation for most of the meters, many experienced calibration issues, recorded in the wrong units, or simply had large gaps in the data. By FY16, however, most of these issues had been corrected and so the errors encountered were of a smaller scope.

A second limitation in the previous year's work regards the means of handling and storing the data. This was largely due to the use of Excel to store the aggregated data used to generate the annual energy reports. The size limitations and limited data import capabilities of Excel required the raw data to be aggregated as a separate process to generate an output of monthly energy consumption for each building, losing the original temporal resolution recorded in the raw data. Additionally, the manual importing of data required by this process made it prone to transcription errors that complicated the efforts. Further, the data was only available as a backup file of the FRES database for the entire year, which made it more difficult to obtain and extract the data.

To overcome these limitations, by switching from Excel to a Filemaker database this year the process of obtaining the energy data was streamlined and standardized. Because Filemaker is as a true database, it provides better importing and handling of large data sets. This allows more information to be captured and the process of collecting and entering it into the database to be more automated, reducing the potential for human error. Filemaker was also chosen for its ability to generate custom reports, allowing the energy information collected to be presented in a variety of different ways depending on the intended audience.

In addition to overcoming setbacks encountered in the previous year, this year's work sought to improve the utility of the information that has been collected. One method of accomplishing this has been through the identification and development of energy metrics most pertinent to specific audiences and the generation of reports that are tailored to those metrics. A second tactic has been the use of mathematical techniques to correlate energy consumption to external and internal variables such as weather data, occupancy schedules, and data from SCADA (supervisory control and data acquisition) systems. These techniques provide the potential for fault detection, load management, and the overall analysis of a building's performance.

2.0- A Streamlined Procedure for Obtaining and Cleaning Data

The first step in obtaining useful information from the building energy meter data gathered by FRES is to simply transpose it into a format from which the data can be easily obtained, stored, and manipulated reliably. While this may seem to be a trivial step it provides the groundwork for all of the analysis and data visualization that could later take place using this data. In order to accomplish this, the energy meter data obtained from FRES must be 'cleaned'—or post-processed— to remove outliers and to interpolate missing sections of data. Finally, the clean data must be transferred to a database where it can be easily stored, analyzed, and formatted for reporting. This year's work establishes the protocol for standardizing and streamlining this effort, and addresses some of the complications encountered in the previous year.

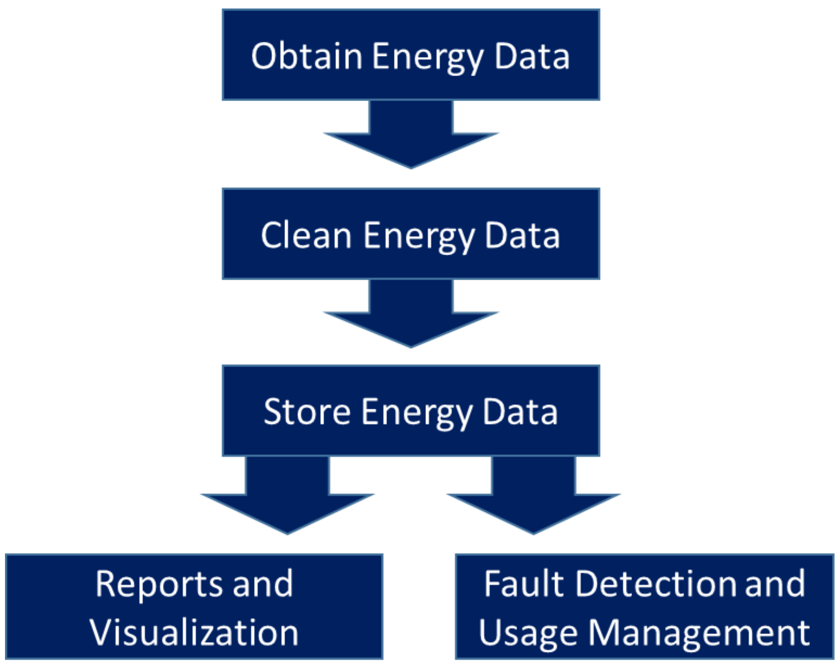


Figure 1- Data flow and utilization

2.1- *Obtaining the Energy Meter Data*

One of the primary roadblocks encountered in FY15 had to do with the initial handling and processing of the raw data that was obtained from FRES. To obtain the meter data for FY15, the only means of transferring the information was as a backup of the FRES energy database that then needed to be physically transferred on an external hard drive due to its size. The data was then extracted from this backup file using Python, and machine learning techniques were applied to remove outliers and interpolate missing data. This cleaned data was then aggregated into monthly consumption of electricity, chilled water, and steam for each building and exported to a spreadsheet format. From here it was entered into Excel for the generation of the annual energy report and comparison of the energy performance of each building. However, this process was inefficient and introduced several opportunities to introduce error into the data.

In order to improve this process, the CEBD worked with Andrew Zarynow, FRES Energy Planning Engineer, to develop a method to regularly provide updated energy meter data from the FRES database in a standardized format, and that would require minimal processing before being imported into the CEBD database. The data is now provided in the form of a monthly comma-separated values (.csv) file, which can be easily transferred electronically without undergoing significant reformatting or calculation. Optimally, in the future this process would be automated such that new data would transfered every month to the CEBD for analysis, where it would be added to the database and reports updated to provide real-time feedback.

Aug 01, 2015	Demand (kW) : Aug 01, 2015			
	Time	Total Avg. Demand (kW)	By Data Series	
8/1/2015			Annenberg Center (kW)	Anatomy-Chemistry (kW)
8/1/2015	12:00:00 AM	20172.77	251.48	106.72
8/1/2015	12:15:00 AM	20305.58	254.26	106.77
8/1/2015	12:30:00 AM	20702.07	246.34	102.32
8/1/2015	12:45:00 AM	21154.75	253.95	110.31
8/1/2015	1:00:00 AM	20201.11	244.65	119.14
8/1/2015	1:15:00 AM	20808.05	253.84	112.82
8/1/2015	1:30:00 AM	20771.6	253.11	111.31
8/1/2015	1:45:00 AM	21049.56	254.18	104.64
8/1/2015	2:00:00 AM	20990.99	252.65	103.78
8/1/2015	2:15:00 AM	20854.54	244.9	113.53
8/1/2015	2:30:00 AM	21068.68	257.14	117.26
8/1/2015	2:45:00 AM	21374.74	246.29	116.24
8/1/2015	3:00:00 AM	20985.79	255.02	112.73

Figure 2- An example of raw steam use data

As shown in the above figure, the raw data (in this case, steam usage) is displayed at 15-minute intervals. The database size is significant, in excess of a million records, even when only a single year is considered, and is beyond the capability of Excel to process. Therefore the data was concatenated using programming techniques (Python). Standardized date and time calendar were used as the main tag to query the energy use data out of the database and export them into separate files by building. During the concatenation, missing meter readings and zero (null) readings were found in the raw data.

Building	SqFt	Old Quality(Ele	Old Quality(CHW)	Old Quality(STM	New Quality(Elec	New Quality(CHW)	New Quality(STM)	Change in Data		
3401 Walnut	######	35.9%			99.4%			63.5%		
3537 Locust Walk	5,647	10.6%		18.9%	0.0%		6.8%	#####		-12.1%
3615 Locust GSC	13,489						50.2%			50.2%
3637 Locust Delta Psi										
3643 Locust Womens Center										
3808-10 Walnut Street	15,205				95.8%			95.8%		
Anatomy-Chemistry	######		28.5%	81.8%	6.0%	96.9%	98.9%	6.0%	68.4%	17.1%
Annenberg Center	######	74.7%	78.9%	94.8%	99.5%	90.3%	95.4%	24.8%	11.4%	0.6%
Annenberg School	92,900	84.0%	65.4%	55.9%	99.6%	79.1%	74.2%	15.6%	13.7%	18.3%
APPC	54,896	35.9%	34.3%	57.3%	99.5%	29.4%	69.3%	63.6%	-4.9%	12.0%
ARCH	32,567		22.1%	7.0%	99.5%	70.8%	78.9%	99.5%	48.7%	71.9%
Blockley Hall	######	37.0%	98.4%	98.2%	99.3%	99.4%	99.1%	62.3%	1.0%	0.9%
BRB I Stellar Chance	######	40.7%	97.9%	98.5%	99.6%	98.9%	100.0%	58.9%	1.0%	1.5%
BRB II	######	74.0%	99.1%	91.7%	97.0%	99.3%	99.9%	23.0%	0.2%	8.2%
Carriage House	8,050	74.5%	78.9%	87.3%	99.6%	0.0%	86.8%	25.1%	-78.9%	-0.5%
Caster Bldg (Social Work)	24,636	73.5%	97.1%		99.6%	99.2%		26.1%	2.1%	
Charles Addam	44,335	72.6%	68.8%	98.7%	99.6%	78.6%	99.9%	27.0%	9.8%	1.2%
Chem 58	42,250		55.3%	94.9%	99.6%	78.7%	98.9%	99.6%	23.4%	4.0%
Chem 73	######		52.4%	65.9%	99.6%	75.4%	93.8%	99.6%	23.0%	27.9%
Chemistry CRET	22,645				99.6%		30.6%	99.6%		30.6%
Civic House	5,852	67.0%			99.6%			32.6%		
Class of 1920 Dining Common	45,668	79.8%	55.6%	31.5%	99.6%	99.5%	52.9%	19.8%	43.9%	21.4%
Class of 1925 (LowRise West)	39,766	72.3%		33.3%	99.6%	0.0%	99.9%	27.3%	0.0%	66.6%
Cohen (Logan) Hall	88,434	62.2%	47.1%	77.1%	94.1%	99.3%	96.1%	31.9%	52.2%	19.0%
College Hall	######	72.6%	98.8%	96.8%	99.6%	95.4%	91.6%	27.0%	-3.4%	-5.2%
Colonial Penn Center	17,256									
CRB	######	74.3%	40.9%	43.4%	99.6%	97.6%	99.9%	25.3%	56.7%	56.5%
Cyclotron	11,907	68.1%	92.3%	31.3%	99.6%	99.4%	19.5%	31.5%	7.1%	-11.8%
Dietrich Grad Library	######		69.1%	41.5%		88.0%	80.7%		18.9%	39.2%
Dietrich Hall (Steinberg_Dietric	######	97.8%	98.7%	97.7%	99.6%	97.8%	99.7%	1.8%	-0.9%	2.0%

Figure 3- A comparative chart illustrating the increase in quality of data from FY15 to FY16

Compared to data received from 2015, this year's data quality is significantly improved, particularly in terms of the percentage of null meter readings (See Figure 3). However, several buildings reported no electrical consumption, which may meant they are being fed through another building and the consumption is misattributed. The percentage in the figure above corresponds to the non-null and non-zero data compared to the entire whole dataset. This issue of data quality, specifically regarding the buildings with problematic and significantly absent data, was discussed at length with FRES. After the concatenation and analysis of data quality, the data was aggregated into hourly time steps, which matches the hourly weather data from the local weather data vendor. The introduction of the local weather data is given in section 2.3.

2.2- Removing Outliers from the Raw Data

The data received from FY15 was quite 'messy'. Most of the meters had only recently been installed, either just before or early in the fiscal year, and as a result much of the earlier data collected contains a variety of errors. Many of the meters needed to be calibrated and data collected prior to that was unreliable. Many were missing significant durations of data either from before they were turned on or as they were switched off to correct issues with the incoming data. It was therefore very important to develop methods for identifying areas of faulty or missing data and to be able to replace them with an accurate estimate of how much energy the building would have been using at that time. This allowed accurate monthly and annual estimates of consumption to be determined for each building while relying on as much real data as possible.

By FY16, most of the meters were in their second year of operation, so there were far fewer periods of questionable or missing data. However, there will always be error in recorded data and it was still necessary to identify outliers and fill in missing data points. This was accomplished by using machine learning and mathematical regression to correlate energy consumption to external and internal variables that can serve as predictors of building behaviors including: weather, solar irradiance, time and date, and occupancy schedules. This section will describe the procedure and computational techniques used to identify the bad data points and how they were replaced.

A double MAD (median absolute deviation) method was used to recognize and remove outliers in the building energy use data. One of the common methods to identify and remove outliers in one-dimensional data is to mark as a potential outlier any point that is more than two standard deviations from the mean. However, the presence of outliers is also likely to have a strong effect on the mean and the standard deviation, making this technique unreliable. So it is recommended to use a measure of distance that is robust against outliers. MAD is good in dealing with this kind of problem because it uses the mean absolute deviation from the median. However, MAD outlier recognition requires that the data distribution not be skewed or asymmetric. It works well with, for example, a symmetric statistical distribution like normal distribution, or uniform distribution. For asymmetric distributions, double MAD should be used. This is a synergy of two MAD methods: (1) the mean absolute deviation from the median of all points less than or equal to the median, and (2) the mean absolute deviation from the median of all points greater than or equal to the median. The former is used to calculate the distance from the median of all points less than or equal to the median; the latter is necessary to calculate the distance for points that are greater than the median. By using this double MAD-based outlier removal method, it is possible to recognize and remove the outliers that exist in the building energy use data. The percentage-based outlier removal method, which screens outliers by the top percentage of biased points, was compared with the double MAD-based method. Percentage-based removal, most of the time, removes too many incorrectly identified outliers that are actually valid data points.

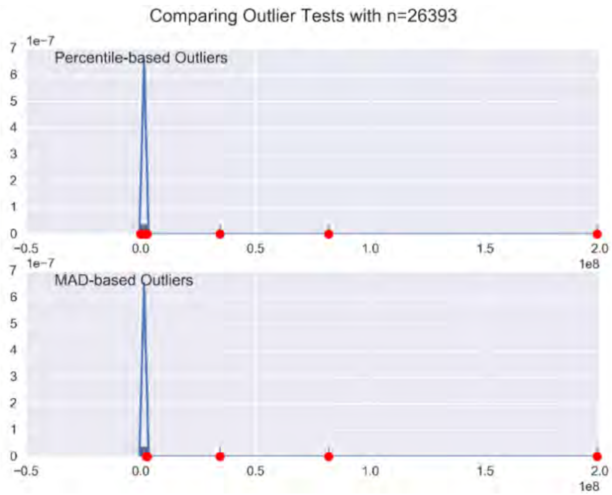


Figure 4- Comparison of percentile-based and MAD-based outlier removal methods, Annenberg Center Chilled Water

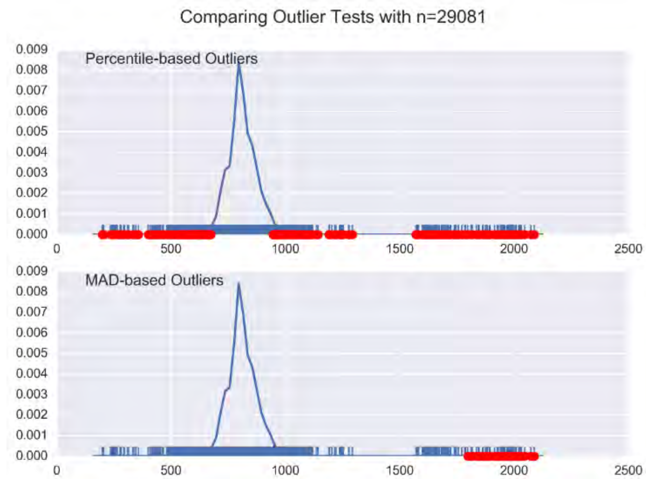


Figure 5- Comparison of percentile-based and MAD-based outlier removal methods, Stemmler (Med Ed Bldg) Electricity

The red points shown in the figure above are the outliers detected by the two different methods. Here the comparison between the two building's energy use data before and after outlier removing are also plotted below. It can be seen that the double MAD based method is successful at handling the outliers in the building energy use data.

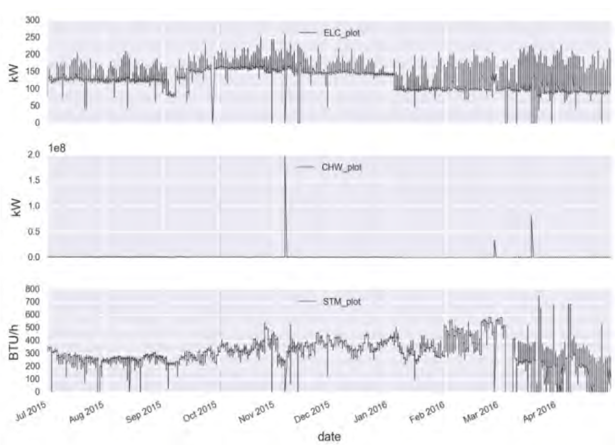


Figure 6- Annenberg Center before outlier removal using double MAD method

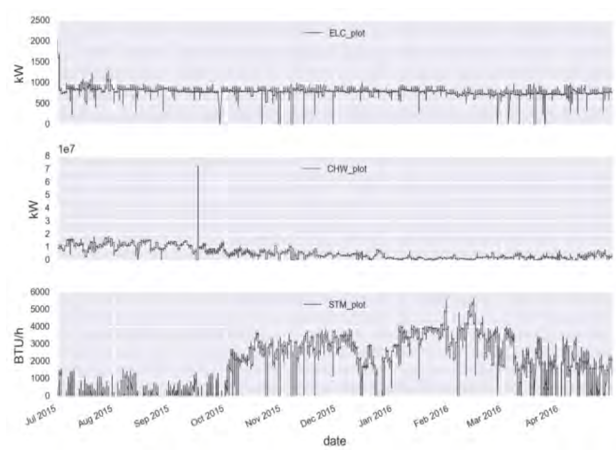


Figure 7- Stemmler (Med Ed Bldg) before outlier removal using double MAD method

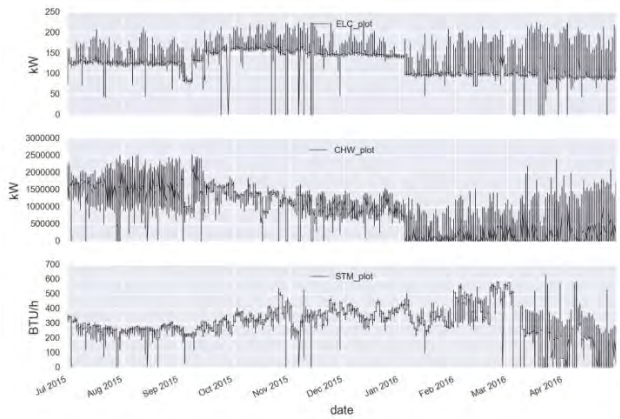


Figure 8- Annenberg Center after outlier removal using double MAD method

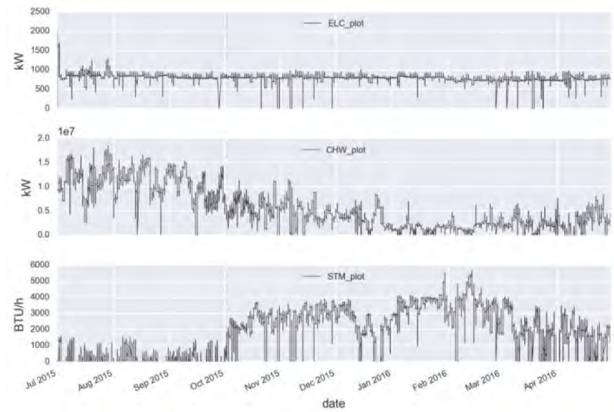


Figure 9- Stemmler (Med Ed Bldg) after outlier removal using double MAD method

2.3- Hourly Energy Use Interpolation

The process of outlier-removal creates, in some cases, a significant number of missing data points in addition to those that were already missing from the meter readings. In order to better reflect the "reality" of the building energy use, the missing data points were filled in by using regression models constructed by machine learning algorithms. In this study, a random forest regression model was adopted and trained from "good" data points. Then we used the trained model to predict how the energy use should behave for the missing data time steps. The variables chosen for the regression model mainly include climatic variables like outdoor temperature, relative humidity, etc., as well as a scheduling proxy used to emulate the building occupancy such as month, hour of day. In this section, the weather data (purchased from a local weather data vendor) will be reviewed first and compared with weather data recorded onsite in the past. The interpolation results will then be discussed and evaluated.

2.3.1- Weather Data: Overview

High resolution and high quality weather data is important for the Penn campus building energy data analysis and research since it provides vital, synchronized information of how buildings perform in reaction to the exterior environment. A local weather station is installed and located on the top floor of Meyerson Hall at Penn Campus serving as the source of local weather data. This is the source of the weather data that is used to analyze Penn campus energy use in the last years. Here in this report, the weather data from Meyerson Hall is referred as Meyerson Weather. However, because of technical reasons, the station was down for almost half a year, from the middle of 2015 to the beginning of 2016. Hence, alternative high quality local weather data sources are considered indispensable for the research.

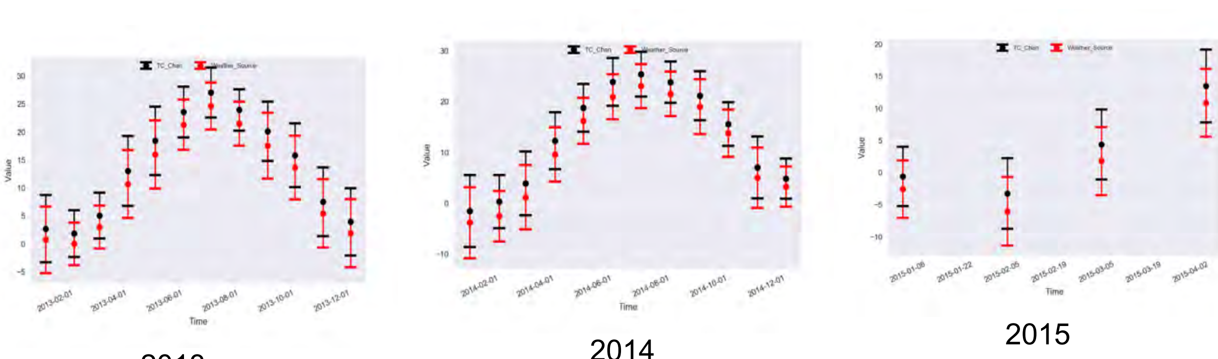
We obtained local hourly weather data from a weather data vendor called WeatherSource, who provides high quality weather data at the required temporal and spatial resolution according to their zip code. This database is called OnPoint Weather, and is near real-time, quality-controlled, error-checked, and gap-filled. More detailed information regarding OnPoint can be found on their website: http://weathersource.com/onpoint-weather and a product overview can be found at: https://app.hubspot.com/presentations/505859/view/1199611?accessId=bcc9c9. More importantly, the climatic variables recorded in the database are nearly comprehensive, and include solar related data. The following climatic variables are contained in the database (in ".csv" format):

time_valid_lcl	temperature_air_2m_f	temperature_wetbulb_2m_f
temperature_heatindex_2m_f	humidity_relative_2m_pct	humidity_specific_2m_gpkg
wind_speed_10m_kts	wind_direction_10m_deg	wind_speed_80m_kts
precipitation_in	snowfall_estimated_in	cloud_cover_pct
temperature_dewpoint_2m_f	temperature_feelslike_2m_f	temperature_windchill_2m_f
pressure_2m_mb	pressure_tendency_2m_mb	pressure_mean_sea_level_mb
wind_direction_80m_deg	wind_speed_100m_kts	wind_direction_100m_deg
radiation_solar_total_wpm2	rain_ind	freezing_rain_ind
ice_pellets_ind	snow_ind	

The weather data used is from the weather station located at Lat: 39.9659 and Lon: -75.2731, which is in West Philadelphia. Because of the difference in geological location between Meyerson Weather data and OnPoint Weather, difference in weather data values is anticipated. After acquiring the required weather data, consisting of hourly weather data from the beginning of year 2013 to May of 2016, the CEBD conducted comparisons with the Meyerson Weather data with respect to three important shared variables: temperature in Celsius, relative humidity, wind speed, and solar irradiation. In 2015, only the weather data of January to April is compared with OnPoint's since there is only data logs lasting from January to April in 2015 for Meyerson Weather.

2.3.2- Weather Data: Temperature

Outdoor dry-bulb air temperature is a very important indicator for building energy performance. It was thus important to compare the temperature data from Meyerson Weather with that from OnPoint Weather, see figures below. The error bar figures illustrates that the temperature data sourced from OnPoint Weather conforms to the pattern of Meyerson Weather airport data, but that the temperature from OnPoint is generally lower than Meyerson Weather by approximately 1 to 2 degree Celsius, which may be due to the influence of urban heat island.



2013 2014 2015

Figure 10- Error bar chart of monthly mean temperature from Meyerson Weather (black) and OnPoint Weather (red) from 2013- 2015

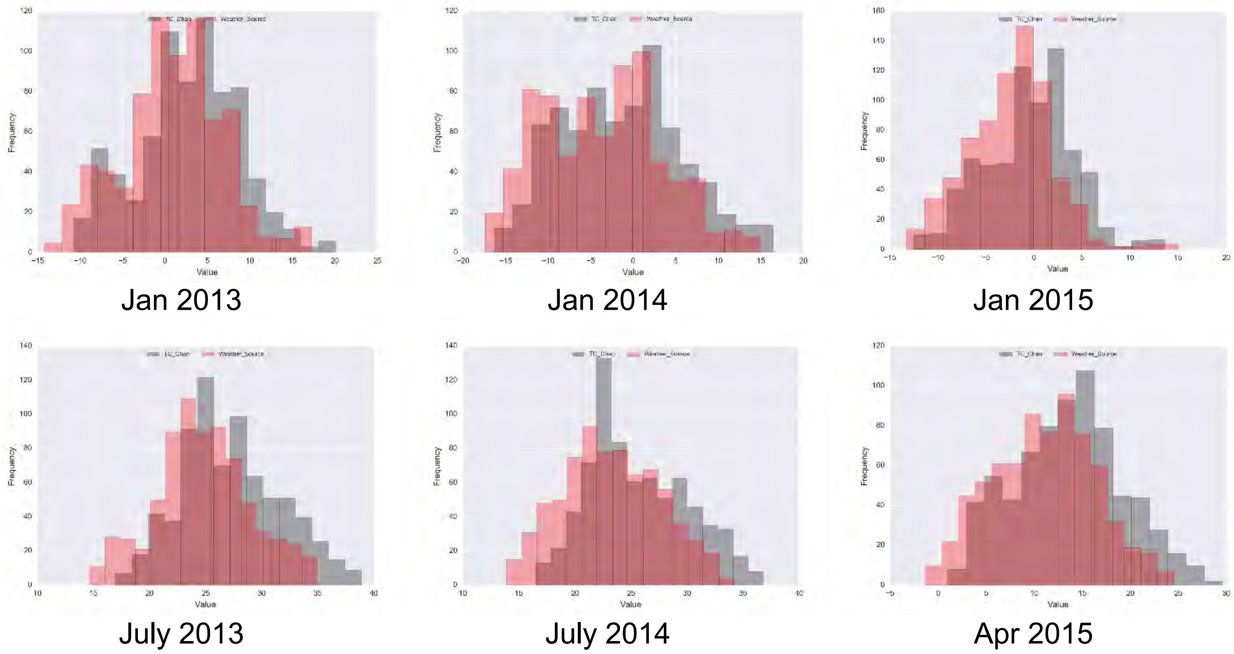


Figure 11- Histogram of hourly temperature data in January from Meyerson Weather (grey) and OnPoint Weather (red)

The histogram indicates that the OnPoint temperature data of each month has a lower bound than that of the Meyerson weather station. The Meyerson weather data has higher peak in temperature. Generally, the two distributions correspond with each other from year to year except that the OnPoint distribution shifts slightly more to the left in the histogram compared to the Meyerson Weather data.

2.3.3- Weather Data: Relative Humidity

Also compared between the two weather data sources was relative humidity data:

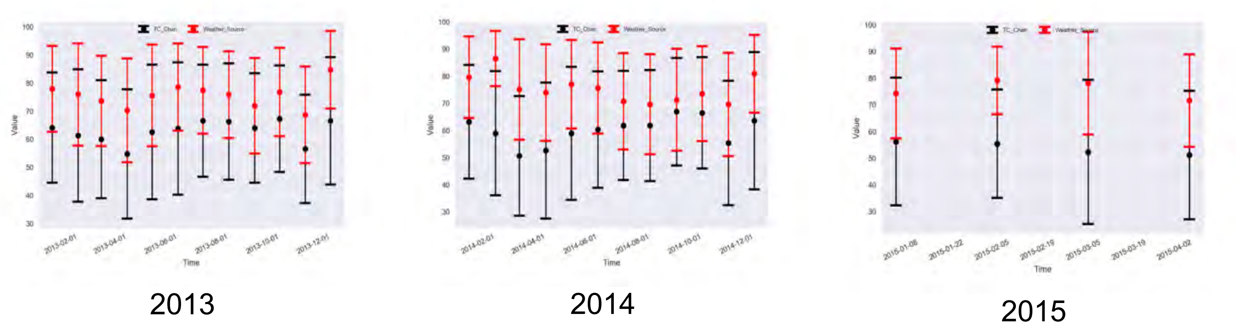


Figure 12- Error bar chart of monthly mean relative humidity from Meyerson Weather (black) and OnPoint Weather (red)

The relative humidity data values from OnPoint are higher compared to the Meyerson Weather data because the weather stations are located in different geological locations, thus the surrounding urban environments of the weather stations vary as well.

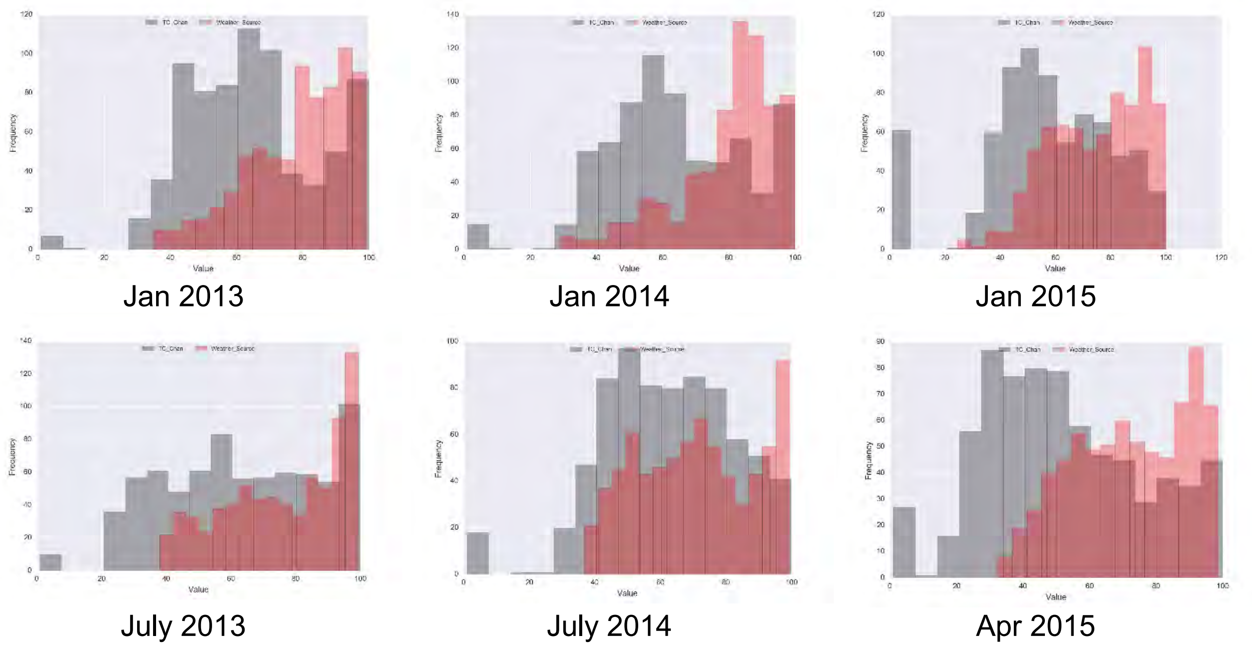


Figure 13- Histogram of hourly relative humidity data in January from Meyerson Weather (black) and OnPoint Weather (red)

The histogram indicates that the majority of relative humidity values recorded by OnPoint during the winter are around 80%. Meyerson Weather's relative humidity values are averaged around 55%. However, according to the histogram of hourly relative humidity for each month, there are some error readings of relative humidity from Meyerson Weather because hardly can relative humidity value be zero in outdoor environment. This may be attributed to the unstableness of the communication system of Meyerson Weather as well as the onsite meter error. Generally, the relative humidity data from OnPoint is more reliable than Meyerson Weather's.

2.3.4- Weather Data: Wind Speed

We also compared the difference in onsite wind speed data from Meyerson Weather and OnPoint Weather. The mean monthly wind speed recorded by OnPoint Weather is much higher than that collected by the Meyerson Weather, which is also true for the standard deviation of the wind speed. The difference of wind speed from OnPoint Weather and Meyerson Weather is approximately between 4m/s to 5m/s.

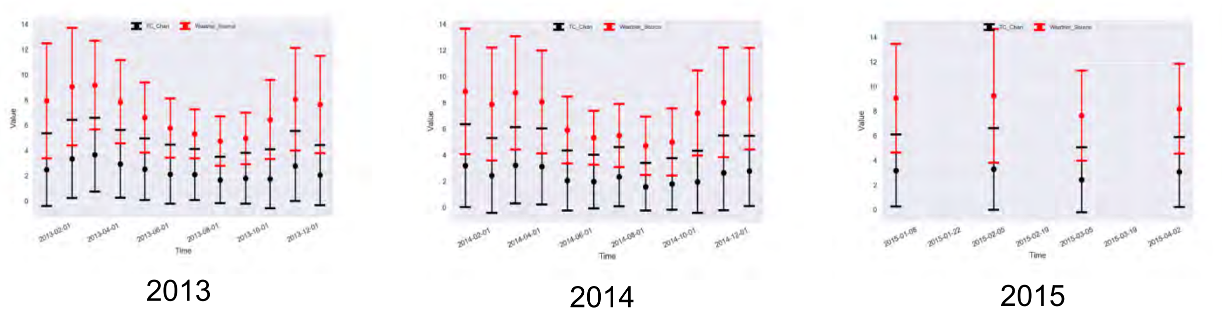


Figure 14- Error bar chart of monthly mean wind speed from Meyerson Weather (black) and OnPoint Weather (red)

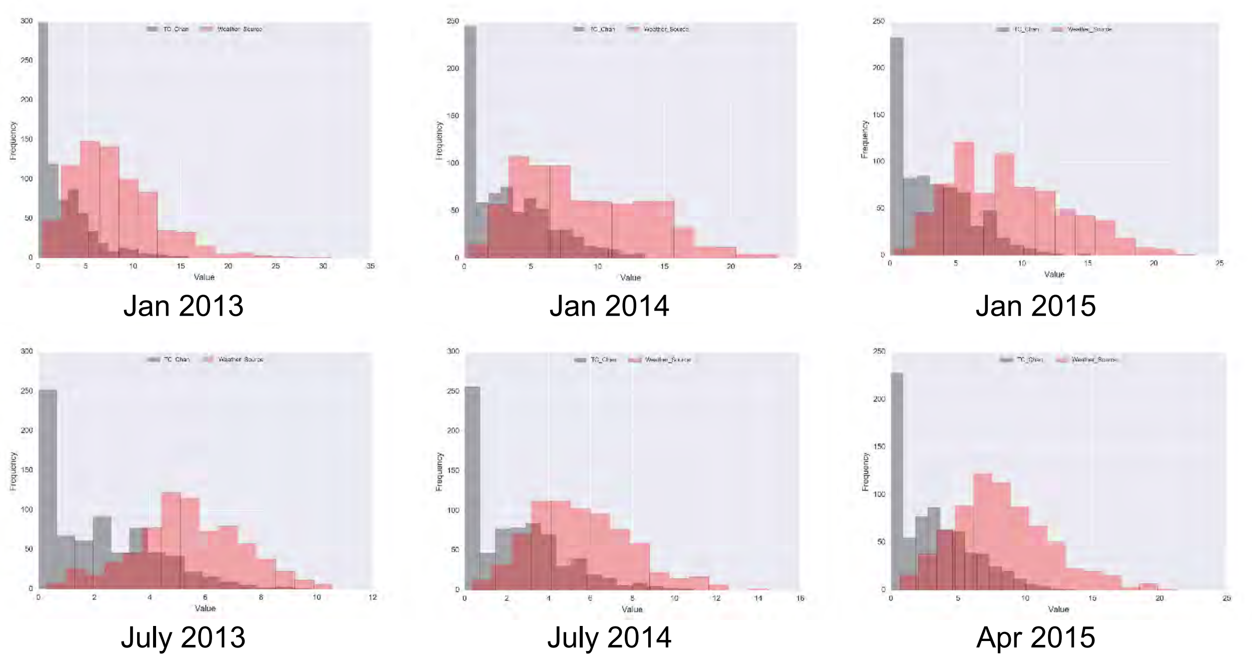
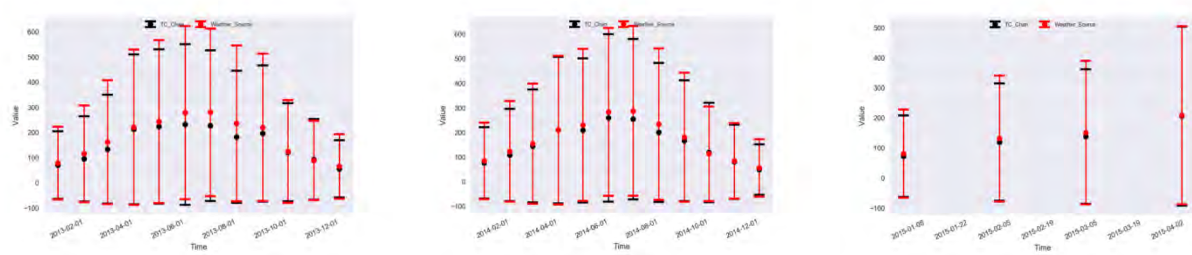


Figure 15- Histogram of hourly wind speed data in January from Meyerson Weather (black) and OnPoint Weather (red)

After plotting the histogram of hourly wind speed in January and July from 2013 to 2015, we can find that there is big difference between the pattern of the wind speed from OnPoint and Meyerson Weather. Meyerson Weather has lots of zero wind speed readings, which may be due to the uncalibrated meter or malfunction of the meter. The difference in the wind speed peak from two parties makes sense due to the notably different boundary conditions: one is located in suburban area, and the other is in airport where higher wind speed is more often witnessed, and the readings are typically taken at a higher altitude. As for the wind data, the OnPoint records show more potential for this research as they are more reliable on the accuracy of the readings.

2.3.5- Weather Data: Solar Irradiation

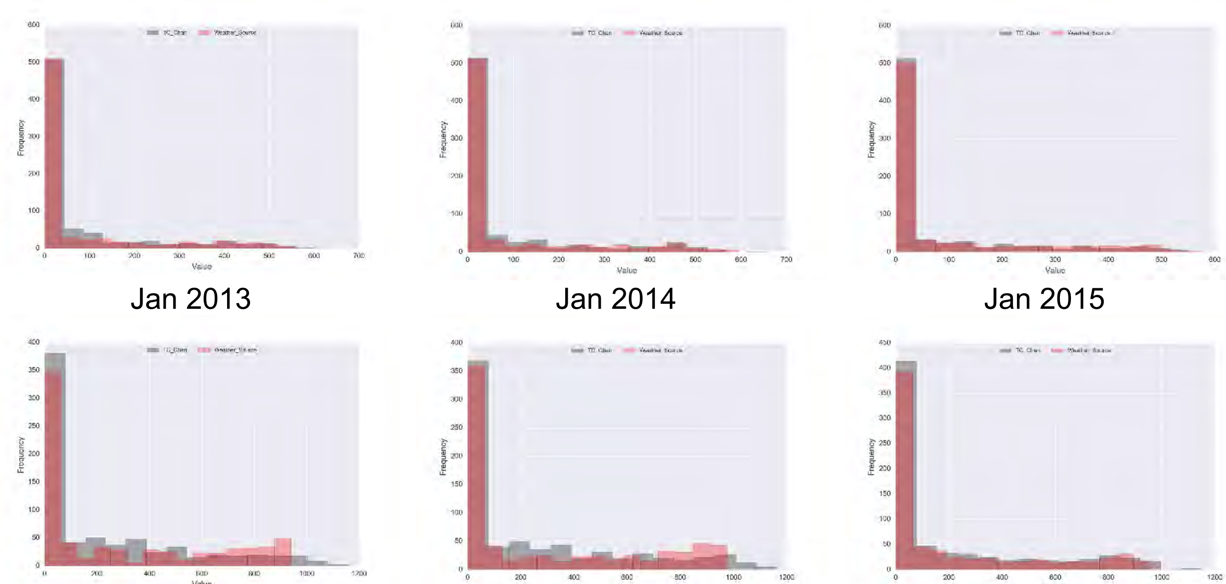
The difference in onsite solar irradiation data from Meyerson Weather and OnPoint Weather is also compared:



2013 2014 2015

Figure 166- Error bar chart of monthly mean solar irradiation from Meyerson Weather (black) and OnPoint Weather (red)

According to Figure 16, the pattern of the solar irradiation from OnPoint and Meyerson Weather is very similar except that the monthly mean of OnPoint is a little higher than Meyerson Weather's. It makes sense since OnPoint's weather station is located in an area with less density in buildings and populations, which potentially gives more exposure to sunlight.



Jan 2013 Jan 2014 Jan 2015

July 2013 July 2014 Apr 2015

Figure 177- Histogram of hourly solar irradiation data in January from Meyerson Weather (black) and OnPoint Weather (red)

The histrogram shown in figure 17 indicates that the solar irradiation data pattern is similar between OnPoint and Meyerson Weather. The Meyerson Weather has higher frequency of low irradiation data points, which may be due to that the urban environment where Penn locates tends to have more chances to be covered by cloud or by surrounding high rises.

2.3.6- Weather Data: Conclusion of Weather Data Quality

The weather data from Meyerson Weather and OnPoint Weather are compared in terms of four important shared climatic variables: outdoor dry bulb temperature, relative humidity, wind speed, and solar irradiation. The OnPoint data has the following advantages:

- It has more useful variables compared with the Meyerson Weather data, such as snow indicator, detailed cloud cover percentage.
- The OnPoint weather data can be a good reflection of Penn campus microclimate. It has similar pattern in temperature and solar irradiation with Meyerson Weather. Moreover, in regard with relative humidity and wind speed, the readings from OnPoint are more reliable considering its error-freeness.

Thus, it is decided that because the OnPoint Weather data can be served as a proxy for local weather data for Penn campus, it is sensible to use this data for building energy use study. The hourly weather data points from OnPoint Weather database will be used for campus building energy analysis including regression modeling, data mining, mal-data and missing data interpolation, etc.

2.3.7- Data Interpolation Results and Implications

Once reliable, local weather data has been acquired, the data training and interpolation process can begin. The interpolation results of two example buildings, Annenberg Center and Stemmler Building, are shown in the following figures:

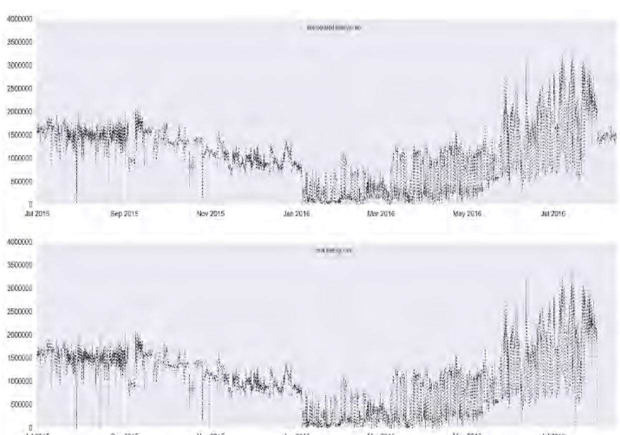


Figure 18- Annenberg Center Chilled Water Interpolated Data

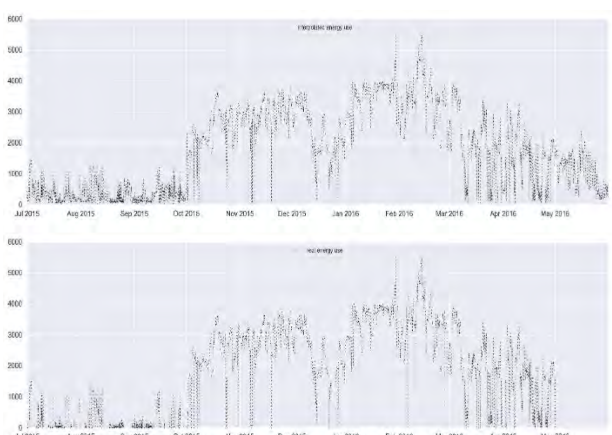
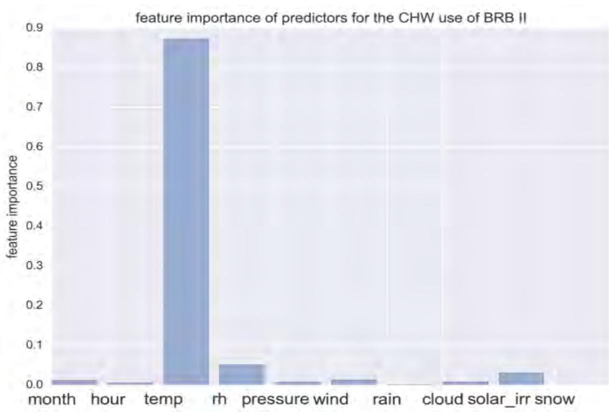


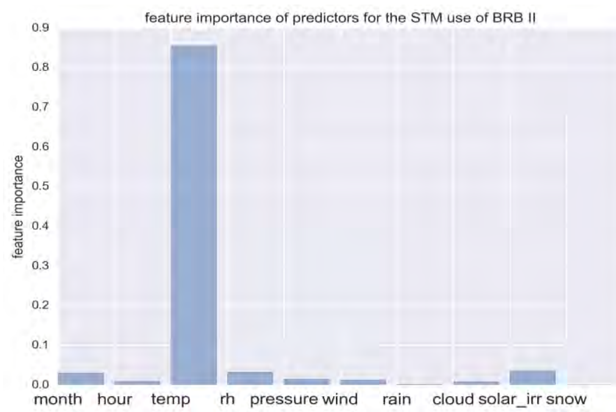
Figure 19- Stemmler (Med Ed Building) Steam Interpolated Data

The interpolation results shown above indicate that this procedure works well to fill in missing data points and reflect the reality of the building's energy use level at each hourly time step. This process was carried out for all end-use types of buildings that had previously missing data points, specifically in cases with 40% or more missing data points. This cutoff was established because interpolating the data of the buildings with too much missing data will make the prediction biased, as not enough training data would be available to build a reliable regression model.

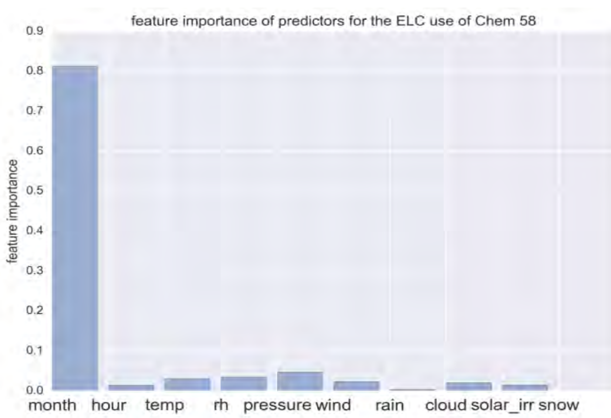
The regression model that was trained for each building can also be evaluated for the importance of the different driving forces for energy use of each building. As shown in the following figure, for most of the buildings, the driving force for chilled water and steam use is unambiguously outdoor temperature. However, for electricity use, it is rather hard to pinpoint which schedule proxy is dominant. In some instances, one particular schedule proxy may work very well, for example regarding electricity use of Chem-58; but for the electricity use of BRB-II, the regression model does not identify a dominant factor driving electricity use.



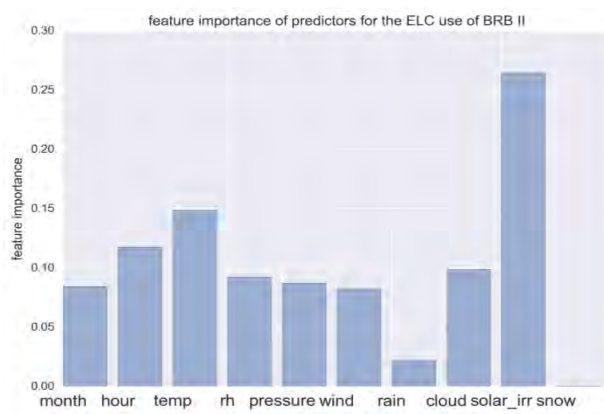
BRB II_CHW



BRB II_STM



Chem-58_ELEC



BRB_ELEC

Figure 20- Feature Importance of Predictors for Energy Use

The question of finding a good proxy for building occupancy schedule is important for regression model construction in the future because it will improve prediction power of the regression model and serve as an indicator of strategies for energy reduction. Preliminarily, the CEBD has identified that network/WiFi activity shows a strong correlation with electricity use data, which indicates great potential for using it as an accurate proxy for building occupancy. The following figure shows the WiFi client connection data for a single day in September for

BRB-II. Though the CEBD has been provided only with network activity reports (shown below), and not yet obtained a usable dataset from the ISC (Information Systems and Computing) department at Penn, it is believed that this data could significantly facilitate building energy use prediction, fault detection, and diagnosis in our future work.

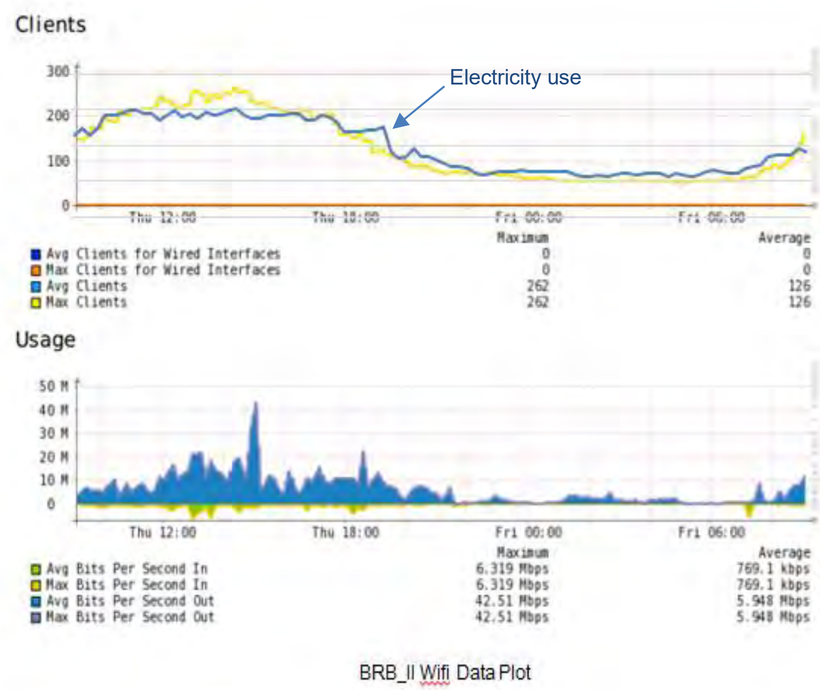


Figure 21- Network Activity Graph from BRB II with Overlaid Electricity Use (yellow)

2.5- The Energy Consumption of the Penn Buildings

Although a large amount of metered data from individual buildings has now been gathered, for many years only their monthly consumption of electricity was determined, while a a few buildings were individually metered for the consumption of steam and chilled water. The recent initiative to introduce steam and chilled water metering to the majority of the buildings served by these loops has dramatically changed that situation and for the first time has begun to make it practical to consider scenarios that track individual buildings and renovations rather than campus totals and broad assumptions for growth and change.

Once all the data has been cleaned and processed, it is possible to paint a complete picture of the energy consumption for each building on the University of Pennsylvania campus. This is an important first step in determining where to focus energy reduction efforts as it identifies the largest consumers with the greatest potential for energy reductions. However, this information is insufficient in truly identifying the worst performing buildings as it does not account for the physical size of the building, the purpose of the facility, or the scale of the activities occurring within its walls. Larger facilities will naturally use more energy than smaller ones, as will buildings with higher occupancy spaces, but that does not necessarily imply that they are using that energy less efficiently. While the magnitude of energy consumption does provide an initial starting point for the identification of the greatest potential energy reductions, it is insufficient on its own.

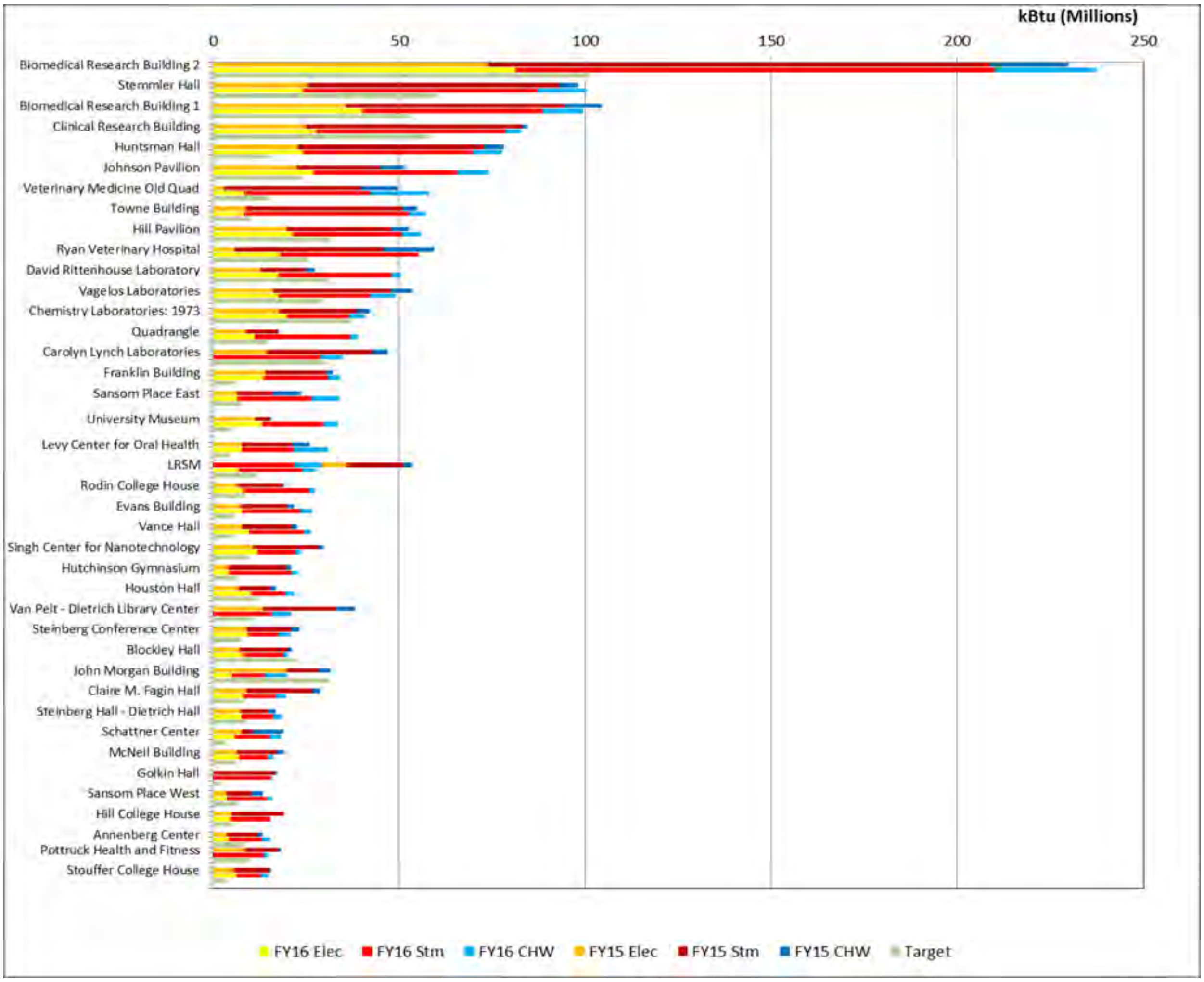


Figure 22- Total energy consumed per building for Top 40 Consumers, FY15 and FY16

Figure 20, above, shows the energy consumption for the highest energy consuming buildings on campus for which meter data was available and ranks them from largest to smallest consumer. Data for FY15 and FY16 was included, along with a benchmark target for consumption. This chart shows the 40 largest consumers of energy on campus which between them account for 80.3% of the campus’s total energy consumption, even though they only represent approximately 20% of the buildings. These buildings represent a large majority of energy consumed on campus. In addition to the current ranking by magnitude of consumption, this chart also displays how the consumption of these buildings has changed from FY15. For the most part this change was a modest increase or decrease, however a few buildings show a dramatic change, which for the most part can be explained by irregularities in the data, usually the FY15 data, rather than an actual dramatic change in consumption. This is most obvious in Harrison House, which shows a huge increase that defies logic given the nature of the structure. Indeed this increase can be traced to a meter problem in a single month in FY16 which could not be corrected and so this building was removed from consideration for this year.

Additionally, as mentioned previously, several buildings did not have any reported electrical consumption and it is not yet clear if this use is not being metered or if it is coming through another building and being attributed to the other building. This may also be occurring in a slightly different way with buildings that are physically connected, in which caseone building may be fed entirely from the steam or chilled water meters in another building or they may simply share conditioned spaces, making it impossible to determine how much heating or cooling was used by each space. Further investigation and discussion with FRES will be required to determine if each meter is being correctly assigned to a space and what consumption is not being metered. If shared consumption cannot be disaggregated then the spaces may need to be analyzed as one combined unit.

3.0- Benchmarking and Comparison of Building Performance

The work described until this point has largely centered on understanding how much energy is used by individual buildings on campus, and a great deal of work is involved in setting up the process by which data is obtained from the meters and cleaned to remove outliers and gaps. This section describes one method commonly used to help understand what that energy usage actually means in terms of the performance of the building. Benchmarking is a practice where the consumption of a building is compared against the average performance of similar buildings or where the current energy consumption of a building is compared against its own historical usage. This provides a much better gauge for how well a building is performing compared to simply looking at the magnitude of consumption.

This section describes how to approach two of the basic questions we face when evaluating energy performance: how much are we using and how much should we be using given the weather and occupancy conditions? While we can determine how much energy each building is using, how that compares to their previous performance, and how the buildings rank in terms of absolute consumption, these factors do not answer questions such as how much energy each building c*ould or should* be using. This is important because the energy used by a building will vary greatly depending on the size and purpose of the building. Inherent differences in the uses and equipment found in different categories of buildings will lead to significantly different ranges of energy consumption. The difference between the target level and the actual consumption of the building forms the basis for generating an ordered list of buildings with the greatest potential for savings via renovation or other changes. This section will describe how these benchmarks for each building can be generated.

3.1- External vs. Internal Benchmarking

Benchmarking typically focuses on either a comparison to other similar buildings or a comparison to its own historical performance. Both methods are useful in different situations. Creating external benchmarks based on the performance of other similar buildings allows the data consumer to compare the performance of a building to the typical performance seen in similar structures. To create a valid comparison, the consumption of all the buildings is typically normalized to account for variables that will intrinsically affect the consumption of a facility due to its scale. For example, if comparing two buildings that serve the same purpose but are of different sizes it would be natural to assume that the larger building will use more energy.

One common factor for normalization is the area of the buildings being considered, which is typically useful if the density of the activities taking place within the structures are similar. But a variety of situations can arise that makes the use of area for normalization less appropriate. For example, if comparing office buildings, it would be important to consider whether they are located in urban or suburban locations. As space becomes more expensive in urban areas, offices may increase their density. While some energy uses will scale, to some degree, relative to the physical size of the facility, others will be tied to other factors such as number of employees or customers served. Figure 21 shows how the choice of factor for benchmarking of carbon emissions affects the evaluation of different segments of the Penn facilities by considering both area and employee normalization. It is always important to consider how energy consumption should be normalized when developing benchmarks.

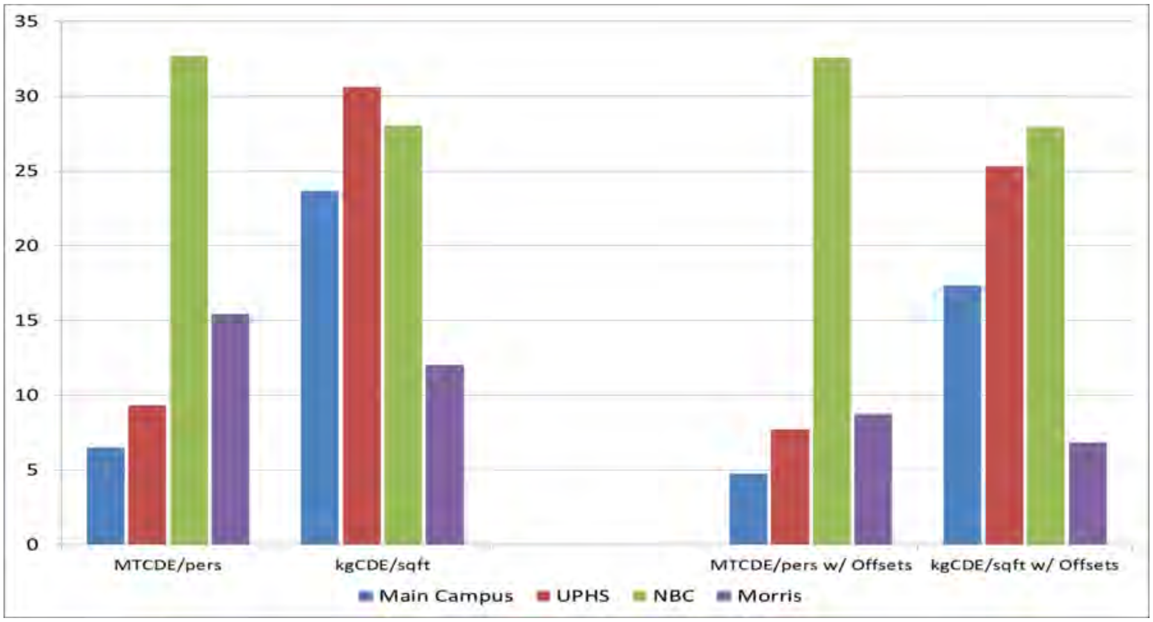


Figure 23- Comparison of energy consumption normalizing factors for UPenn campuses

Creating performance benchmarks based on the normalized energy consumption of similar structures provides a relatively quick but reliable method for determining the level of performance of a building compared against its peers. Depending on the data available, benchmarks are often a single target value representing the average of similar real buildings or it is increasingly represented as a statistical distribution. The latter allows a building operator to determine whether their building falls within an acceptable range of performance. This can be useful when a category of building has a wide range of energy consumption that could be considered normal.

Ultimately this technique is limited by the inherent differences that exist in the construction, systems, and usage of buildings, even when they are utilized for the same broad purpose. While large databases of building energy use exist that can be filtered and queried to provide information about ever-more specific subgroups of buildings, as the criteria for what can be included narrows the number of buildings falling within that defined category drops rapidly. As a result, these benchmarks are a compromise between matching the building construction, location, systems, and usage as closely as possible while maintaining a large enough pool of buildings within that grouping to be able to perform statistically valid analyses. As the collection and storage of building utility consumption is increasingly made more available in some form to the public, this benchmarking method should continue to improve.

An alternative approach to external benchmarking is internal benchmarking, where the building's energy consumption for a given period is compared against its own historical performance rather than the performance of other buildings. This type of benchmarking is very useful for tracking the changing performance of a building although it cannot indicate whether the building is performing well overall, only if it has improved or gotten worse. This type of benchmarking is therefore especially useful when trying to gauge the effectiveness of energy conservation programs, interventions, and renovations.

There are several different methodologies for developing internal benchmarks that are largely dependent on the level of data that is available for analysis. At the broadest level, internal benchmarking can be accomplished by comparing the energy consumption during one period against the energy consumption of a comparable period. Simply comparing the energy consumption for one year against the previous year would be the simplest version, but other temporal resolutions are equally valid for comparison.

However, the simple comparison effectively combines changes due to a wide variety of factors: weather, singular events, renovations, and depreciation. As a result, internal benchmarking often seeks to account for these other variables so that the expected performance during a given time period can be adjusted to account for its historical correlation between energy consumption and variations in those variables. Regression analysis can be used to identify the mathematical correlation between a wide set of variables and energy consumption from past behavior. By applying that correlation to the value of those variables during a current or future period, an estimate of expected energy consumption can be generated. Thus, any deviation from that expected usage can be attributed to an actual change in the energy performance of the building rather than a difference in weather or other external variables.

Internal benchmarking is a powerful tool for understanding how building energy consumption and performance change over time, but this method faces some limitations. While comparisons between periods of time can be made using data that is only available in large temporal increments, this tends to result in data with a limited number of individual data points. This makes regression analysis impossible and therefore removes the ability to account for the influence of other variables on the energy consumption of a building in one time period compared against another. Preferably, reliable data for both energy consumption and the correlating variables should be available at a frequency such that thousands of data points could be collected for analysis, requiring hourly readings or daily readings over an extended period. This often is not feasible in some applications.

3.2- FY16 Benchmarks

One of the primary goals of this work is to gauge the potential for energy use reduction of the University of Pennsylvania central campus. While prior attempts to forecast this potential over the course of 30 years were limited to generalized assumptions about the changing nature of the campus built environment or effectiveness of potential interventions on a broad scale, the recent access to meter data provides a wealth of new detail. This extends the focus on individual buildings established in the Carbon Action Plan 2.0, and facilitates more precise strategies, targeted to achieve the anticipated reductions.

In forming the Climate Action Plan 2.0 one of the primary tasks was to revisit the original carbon reduction goals that were set in 2009 and to determine if those goals were still appropriate and accurate. To accomplish this task different scenarios were tested of specific renovations that would upgrade a select percentage of the worst-performing buildings to a contemporary code standard. Four separate scenarios were developed using benchmarks based on the renovation of buildings to current or next-generation ASHRAE 90.1 building code between the years 2016 and 2042.

This technique had several limitations that reduced the ability to gauge the potential energy reduction that could be exacted from specific buildings. In addition to a paucity of metered information of the actual energy used by buildings, the targets were limited in two ways. Firstly, the targets were very specific, indicating potential without providing additional information regarding the range and distribution of normal energy consumption by buildings of that type. So, while the single point target value provided by ASHRAE offered a general guide to the potential savings, it did not provide sufficient information to truly indicate how well the building is performing, just that it could do better. Additionally, EnergyPro, the tool that was utilized to generate the ASHRAE targets, is based on many levels of generic assumptions that do not necessarily fit campus buildings, and occasionally produced unreasonable results.

This year's research focused on a more dynamic benchmarking method that placed building consumption in a larger context than the single number provided by the ASHRAE code target. In previous years, some individual metered data was available, but the rest was estimated. This provided figures for the actual consumption of energy by each building that could be compared to different kinds of benchmarks. Energy simulation models, EnergyStar targets, and the ASHRAE 90.1 model code have all been used, but they each have their limitations.

Detailed simulations are very time consuming, while streamlined simulations like the EnergyPro package used to establish ASHRAE 90.1 values are inherently generic. The approach used by EnergyStar is statistically based, but is only available for a few building types and includes several internal corrections to emphasize the performance of the building envelope. The new benchmarking process we developed uses the longstanding Commercial Building Energy Consumption Survey (CBECS) database, the more recent DOE Building Performance Database (BPD), and the growing LABS21 database of laboratories. These databases all maintain normalized building energy consumption data categorized per an array of features and provide built-in statistical information regarding selected data.

Figure 24- Example of building energy consumption distribution from Building Performance Database

The Building Performance Database (BPD) was used to identify hundreds or thousands of buildings in our region for each building type, excluding laboratories for which there are too few for statistical analysis. These were then statistically analyzed to establish the range of normal levels of energy consumption for each building type. As a basic benchmark, we chose to use the range of consumption from the 25th (better performers) to the 75th (worse performers) percentiles. Figure 23. The 25th percentile in kBtu/sqft for each category was established as the working target of potential energy consumption for each building type. Data for laboratories was gathered from the Labs21 database and was used to generate similar ranges of normal building behavior. The target was further subdivided into heating (steam), cooling (chilled water), and other power consumption (electric) based on the average breakdown of energy usage for each category of building found in the CBECs database. These results are displayed in Figures 25 & 26.

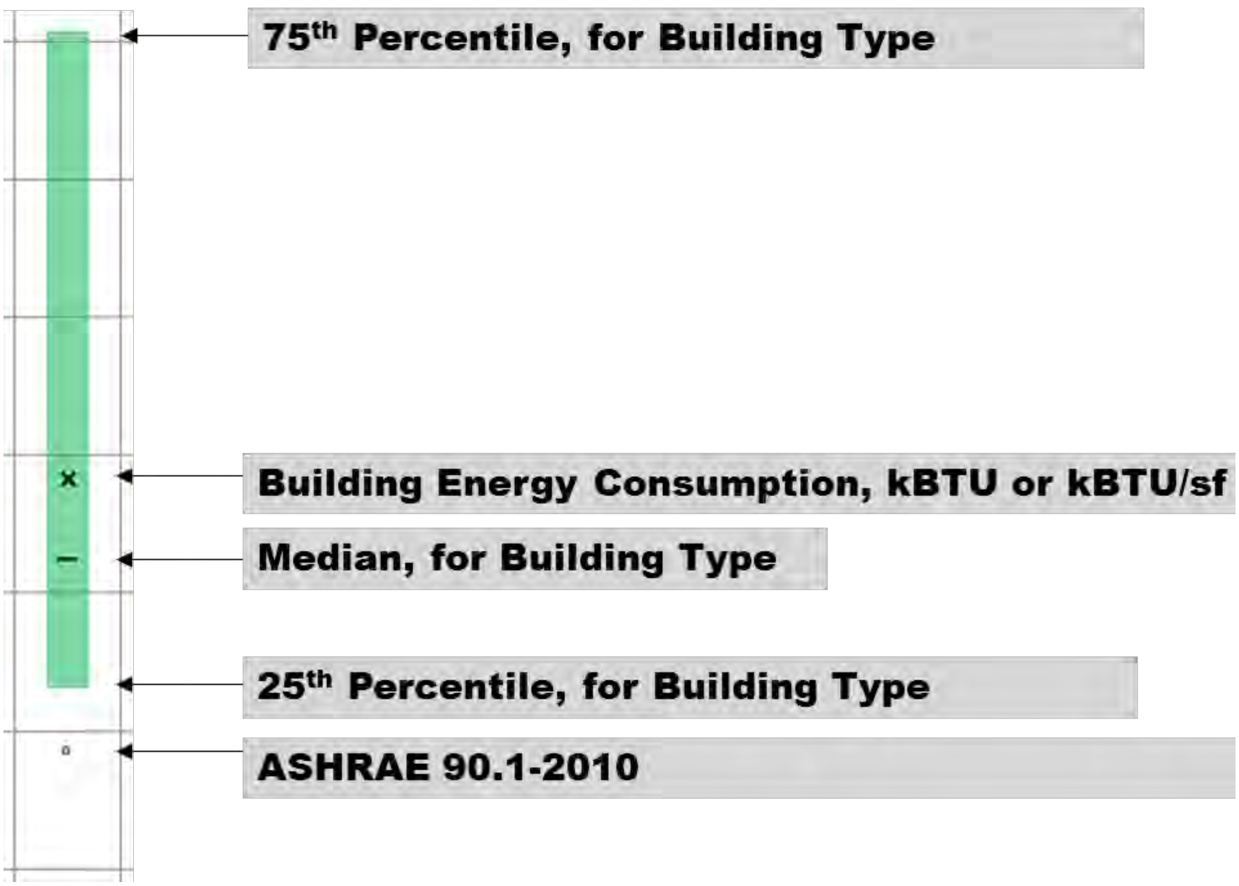


Figure 25- Format for displaying normalized building energy consumption against benchmark based on distribution of similar buildings

These category-based energy consumption targets were multiplied by the square footage of each building to establish the total target consumption for each building. These targets are compared to the actual utility consumption for each building in order to calculate their individual potential savings. This provides the basis for an ordered list that can be utilized to identify and prioritize buildings with the greatest potential for energy reduction for renovation.

Basing the benchmarking targets on statistical data removes a great deal of the uncertainty found in previous iterations of this research. Rather than defining a single value as the desired level of energy consumption, the range of normal behaviors defined around the median creates a more informative perspective of how each building relates to other buildings of its type. While the 25th percentile data point is used as a numerical goal for each building, considering the actual consumption in relation to the normal range provides a more complete picture of the potential for energy savings. The numerical target is useful for the purposes of ranking, but it is very helpful in understanding how far a campus building departs from the norm, and highlights the difficulties for improvement. A building that is well outside the normal range can likely be improved in many ways, while a building that is within the range will need a more detailed investigation to evaluate potential improvements. Both kinds of buildings may be identified as having great potential for reductions, because although some very large consumers fall within the normal range, even a small improvement can yield large savings.

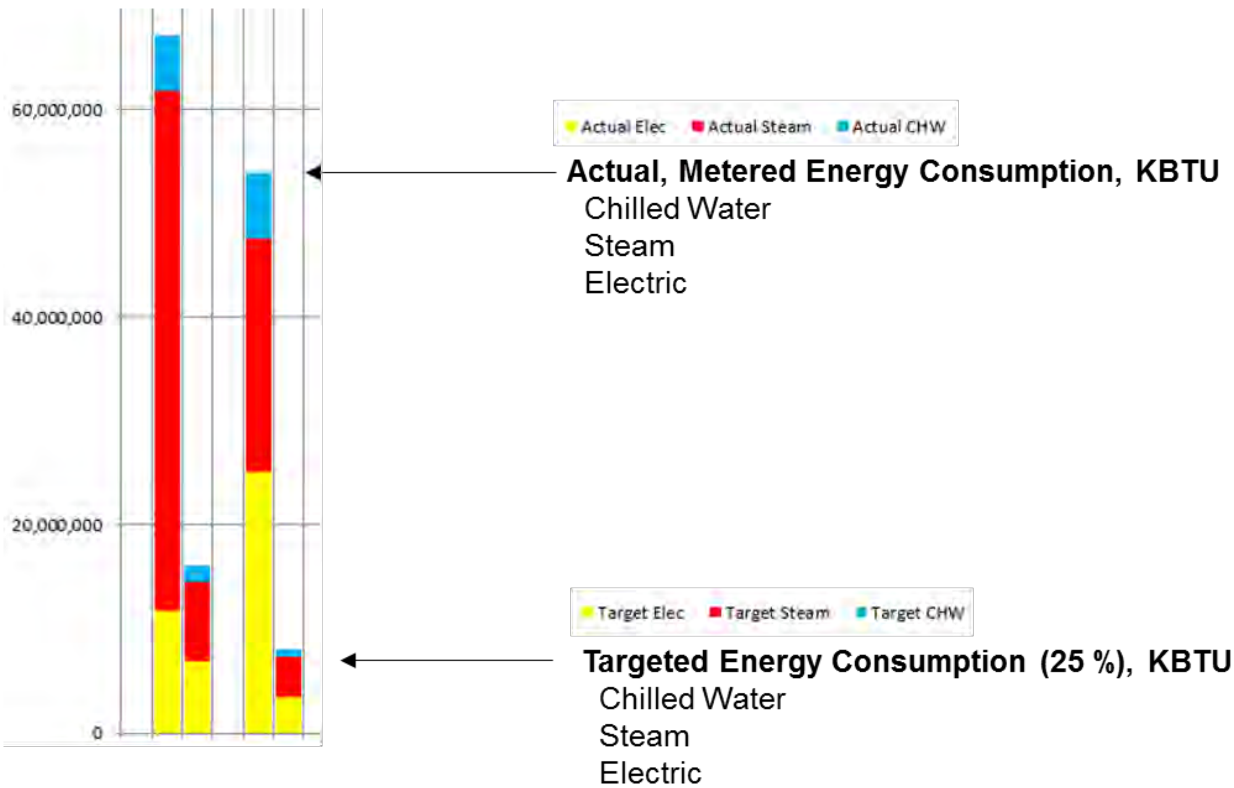


Figure 26- Format for displaying actual consumption of building against target based on 25th percentile of benchmark distribution

	Mean	25%	Median	75%	Notes
Education: University	85.5	50.1	79.8	104.2	
Education: Uncategorized	51	21.2	47.7	71.8	
Food Service: Rest./Caf.	258.3	147	294.2	659.9	Region expanded to entire US
Food Service: Uncategorized	258.3	147	294.2	659.9	Region expanded to entire US
Laboratory: Physical 0-25	241.1	126.6	194.5	279.1	Region expanded to entire US
Laboratory: Physical 25-50	248.9	166.1	213.9	296.8	Region expanded to entire US
Laboratory: Physical 50-100	285	128.1	253	407.7	Region expanded to entire US
Laboratory: Chem/Bio 0-25	266	147.3	247.5	336.7	Region expanded to entire US
Laboratory: Chem/Bio 25-50	362.8	241.2	333.8	476.5	Region expanded to entire US
Laboratory: Chem/Bio 50-75	361.7	247.1	335.8	484.5	Region expanded to entire US
Laboratory: Chem/Bio 75-100	445.8	285.8	424.3	595.9	Region expanded to entire US
Lodging: Dorm/Frat	66.8	28.3	55	74.6	
Lodging: Uncategorized	76.6	47.8	71.4	98.4	
Medical: Inpatient	226.3	172	219.6	267.7	
Medical: Outpatient	114	46.1	105.1	156.9	Region expanded to entire US
Offices: Admin/Prof.	98	57.9	71.5	101.6	
Offices: Uncategorized	98	57.9	71.5	101.6	
Public Assembly: Theatre	92.5	78.2	92.5	135.6	Region expanded to entire US
Public Assembly: Library	79.8	53.4	75.7	98.2	Region expanded to entire US
Public Assembly: Recreation	113	62.7	96.5	168.6	Region expanded to entire US
Public Assembly: Social / Meeting	81.9	48.7	69.9	97.1	Region expanded to entire US
Public Assembly: Uncategorized	89.3	28.3	63.1	104.1	Region expanded to entire US
Service: Uncategorized	103.8	60.5	91	126	Region expanded to entire US

Figure 27- Statistical data from BPD and Labs21 on building energy usage by category

	Total	Heat	Cool	%Elec	%Heating	%Cooling
Education: University	83.1	39.4	8	43%	47%	10%
Education: Uncategorized	83.1	39.4	8	43%	47%	10%
Food Service: Rest./Caf	258.3	43.1	17.4	77%	17%	7%
Food Service: Uncategorized	258.3	43.1	17.4	77%	17%	7%
Laboratory: Physical	249.2	91.8	18.6	56%	37%	7%
Laboratory: Chem/Bio	249.2	91.8	18.6	56%	37%	7%
Lodging: Dorm/Frat	100	22.2	5.9	72%	22%	6%
Lodging: Uncategorized	100	22.2	5.9	72%	22%	6%
Medical: Inpatient	249.2	91.8	18.6	56%	37%	7%
Medical: Outpatient	94.6	38.1	7.2	52%	40%	8%
Offices: Admin/Prof.	92.9	32.8	8.9	55%	35%	10%
Offices: Uncategorized	92.9	32.8	8.9	55%	35%	10%
Public Assembly: Theatre	93.9	49.7	9.6	37%	53%	10%
Public Assembly: Library	93.9	49.7	9.6	37%	53%	10%
Public Assembly: Recreation	93.9	49.7	9.6	37%	53%	10%
Public Assembly: Social / Meeting	93.9	49.7	9.6	37%	53%	10%
Public Assembly: Uncategorized	93.9	49.7	9.6	37%	53%	10%
Service: Uncategorized	77	35.9	3.8	48%	47%	5%

Figure 28- Statistical data from CBECs on breakdown of building energy usage by category

Figure 27, below, shows the same data as Figure 20 in Section 2, however it has been sorted differently. Rather than ordering the top 40 buildings by magnitude of energy consumption, it compares the FY16 total consumption to the energy that would be used by the building if it operated at the energy efficiency achieved by the best 25th percentile of similar buildings within the region. This difference can be considered as an estimate for the potential improvements that could be made to the building via renovation and recommissioning.

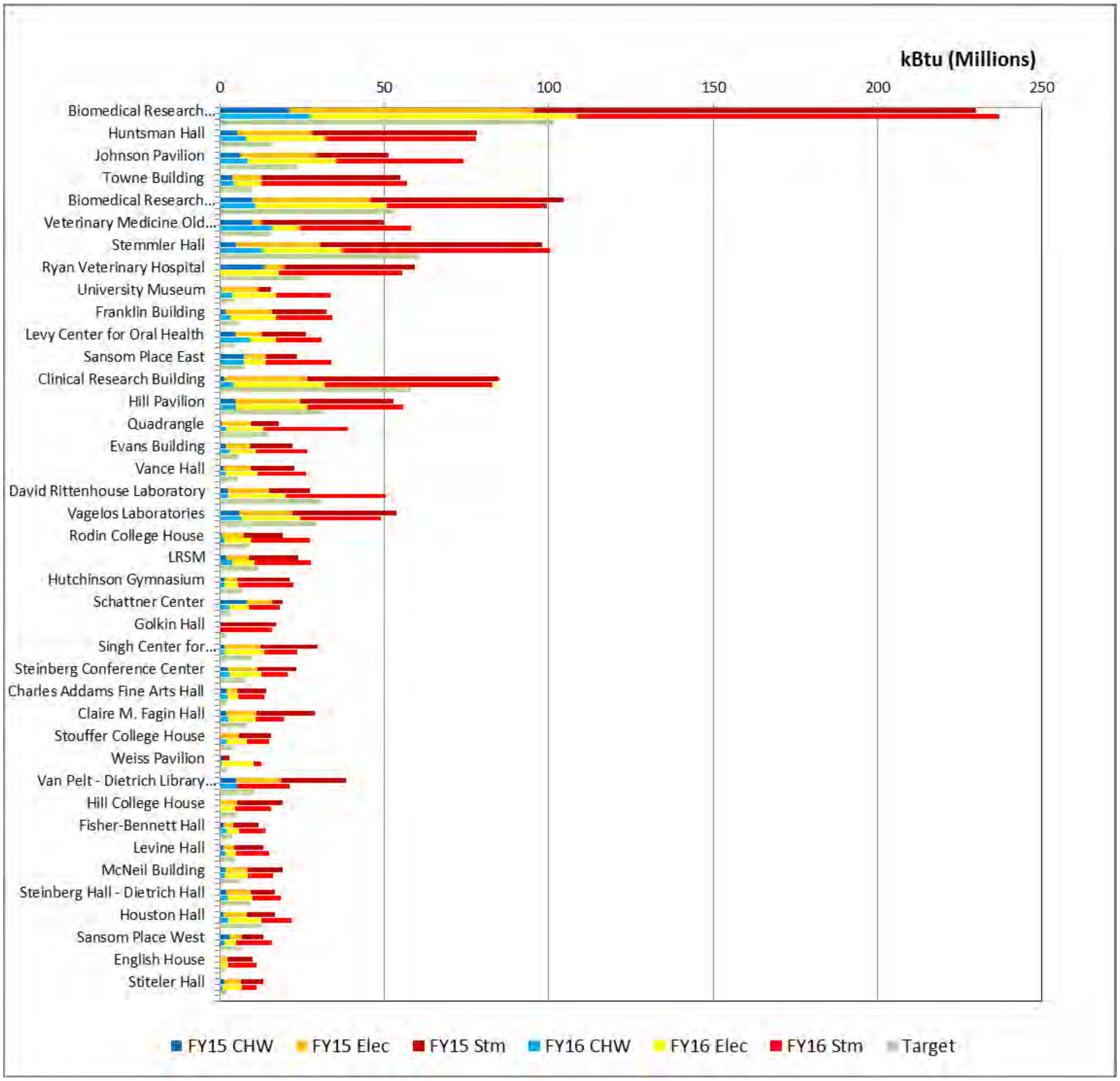


Figure 27- Top 40 campus buildings ranked by potential energy savings, kBTU/yr

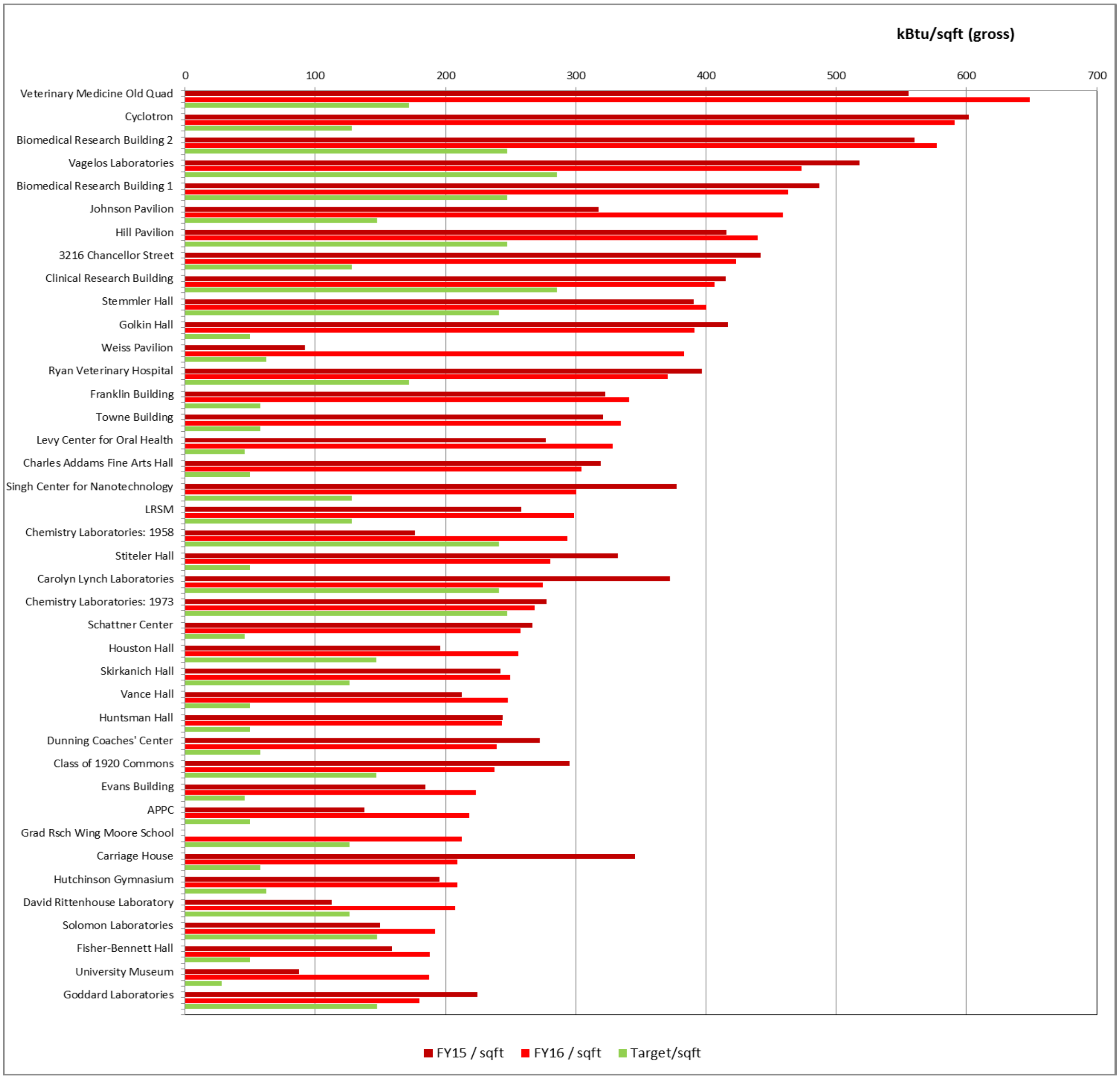


Figure 28- Top 40 campus buildings ranked by energy intensity, kBTU/sf

Figure 28, above, shows similar data, except it has been normalized to display the energy intensity of each building and sorted to show the 40 buildings with the greatest energy intensity. This is often more useful than simply considering magnitude, as buildings with large differences in energy intensity compared to their potential targets may have more cost effective options for renovation compared to buildings with a higher overall consumption or magnitude of potential savings. Figure 29, below, shows the same data only ordered to show the 40 buildings with the greatest difference between the current energy intensity and the 25th percentile target of best performing building a within that category of facility. This shows where the some of the most cost effective changes may be possible.

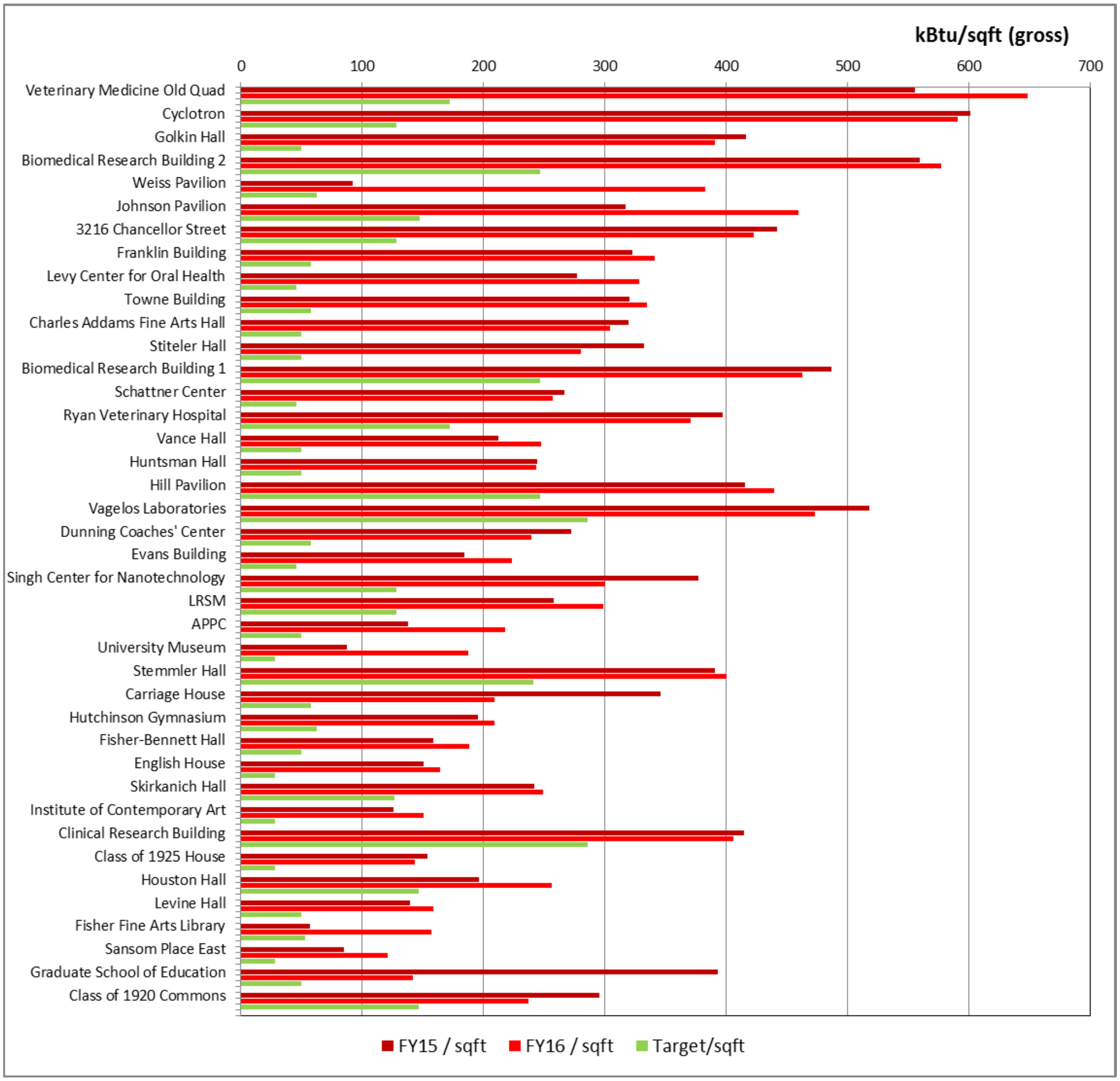


Figure 29- Top 40 campus buildings ranked by difference in energy intensity between actual and 25 percentile target, kBTU/sf

4.0- Energy Reporting

4.1- Data Visualization

A critical step in energy reporting is to visualize the energy and performance data in forms useful to audience using them. Beginning with the central question, “How can we obtain the most information from the wealth of new building energy consumption data?” it is just as important to deliver and visualize it in a useful format as it is to collect and process it. Before considering methods of data presentation and utilization, it was necessary to simultaneously catalog the possible end-users and what their needs might be, particularly with respect to the rate at which the data would be needed (See Figure 30). Depending on the needs of the reporting audience, data delivery and visualization can range from annual reporting to real-time delivery. The visualization methods considered are data dashboards, spatial representation of data, and data visualization for decision making.

Figure 30 - Identification of Possible Reporting Audiences

The most common method for displaying large quantities of data reported from multiple entities, such as in a campus-wide or city-wide setting, is the data dashboard (See Figure 31). Typically, due to the technical, as well as data security requirements, the data displayed in this manner is *static.* Generally, this data is visualized in charts, tables, graphs, and in 2D on a web-based mapping platform, which allows users from varying skill-levels to interact with the dashboard by making filter queries and selecting individual items to display detailed information. In terms of the complexity of displayed information and user interaction, the dashboard is the simplest platform for visualizing data such as energy consumption. This example provides a path of least resistance toward connecting a wide variety of users to at-a-glance summary visualizations, which are particularly helpful to quickly spotting outliers and anomalies, as well as more detailed information about specific buildings.

Spatial representation of building consumption data is also particularly significant in understanding a building, its type, use, and other distinctive characteristics within its immediate and broader contexts. While reports of static data are capable of underlining a particular building’s performance, within the larger bracket of similar building types as well as within the context of voluntary standards such as ASHRAE 90.1, they typically fail to identify trends spatially. And due to their static nature, such reports are incapable of any manner of forward-looking trend prediction—a feature that, if implemented, can mean the difference between a visualization tool and decision-making tool. Data visualization for decision-making is not a novel concept, but with the era of big data and high-resolution spatial data models the notion of data visualization for decision-making has taken on a greater intensity.

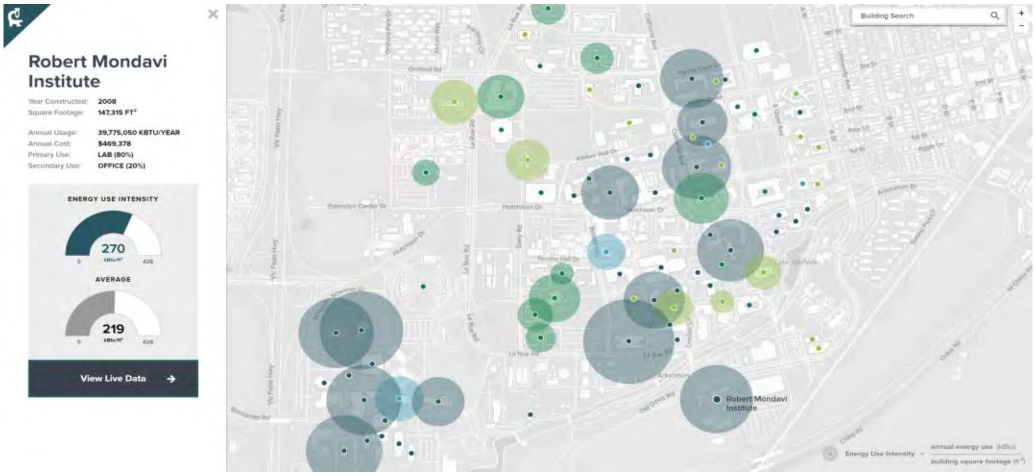


Figure 31- Example of a data dashboard from UC Davis

The ability for a data visualization technique to be both spatial and dynamic is therefore paramount in transforming a simple visualization platform into a tool for decision making. These two attributes permit flexibility in potential user interaction while exploiting the same database of information. One example of such a platform is currently being developed at the University of Florida under the supervision of Ravi Srinivasan, PhD. The d-SIM—or dynamic SIM—platform was provisionally supplied with data from the Penn Campus (See Figure 32) is an attempt to bridge the gap between raw, live data feeds, such as those that are output from BMS (building management system), BAS (building automation system), and SCADA systems and their practical delivery to the end user to aid in making real-time decisions. This integrated approach aims not only to visualize building performance and act as an auditing method but to, more importantly, model, simulate, and visualize “what-if” scenarios to virtually implement possible strategies for energy reduction. Furthermore, the tool is capable of operating at the building, campus, and city scale, which paves the way for truly integrative environmentalism across the board. The ultimate goal of such a platform is the early integration of these various forms of data analysis into the decision-making process regarding the operation and maintenance of buildings and their environment.

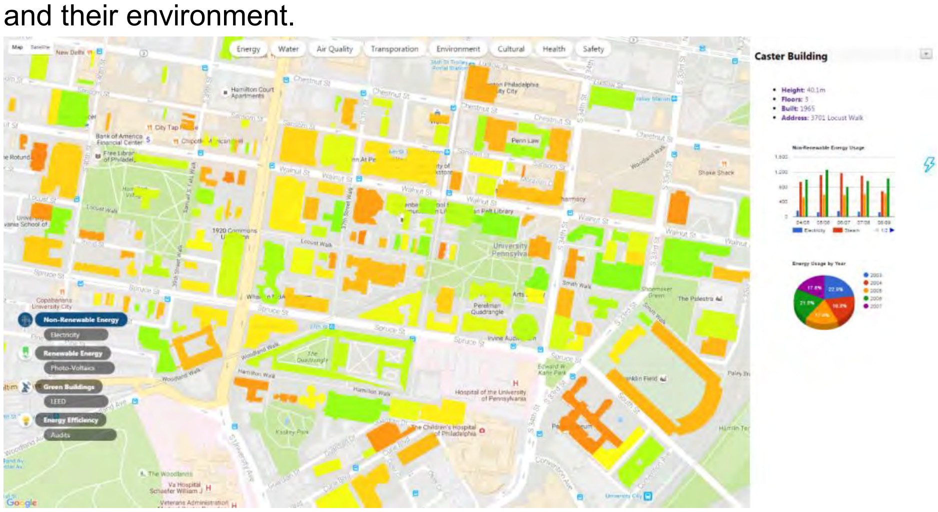


Figure 32 University of Pennsylvania Main Campus in the Dynamic-SIM platform, University of Florida School of Construction Management

In the field of building diagnostics the use of infrared cameras for documenting and visualizing actual, physical energy loss in the form of heat is a widely used auditing technique. Even at low resolution, having the ability to combine this data with metered building performance data allows for a comprehensive snap-shot of a building's environmental behavior. It is not implausible to imagine the integration of thermal data, BIM (building information modeling) data, energy consumption, performance data, and machine-learning protocols for real-time building diagnostics and fault detection. At the very minimum, supplemental IR data is critical for catching a glimpse of otherwise unseen or misunderstood data present in a SCADA database. For instance, even with building performance data, utility consumption data, construction information, and occupancy schedules it is often possible to miss critical factors such as envelope heat loss. This can result in a building hemorrhaging heat through single pane windows, or at slab-wall junctions (See Figure 30).

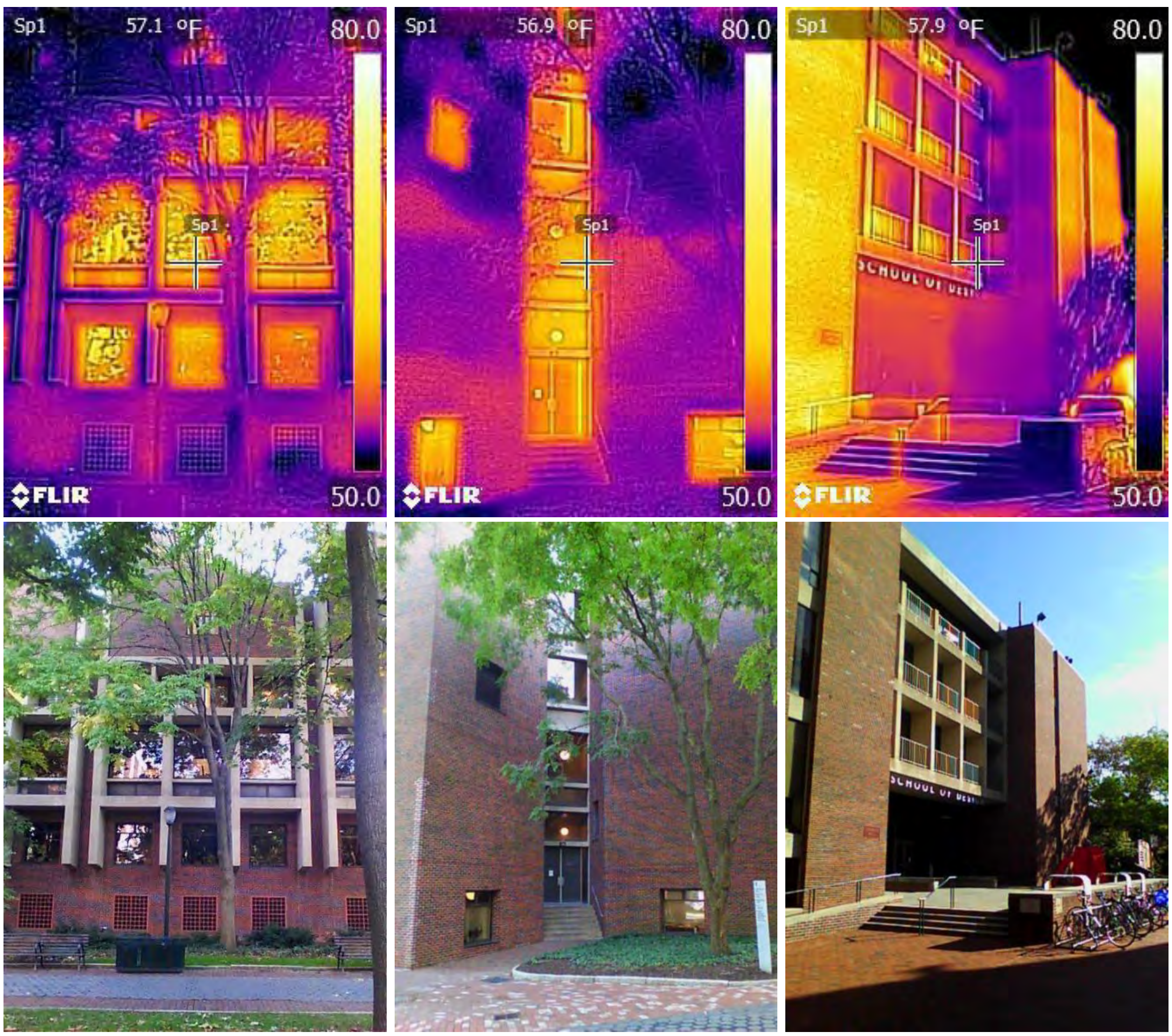


Figure 29- IR Images of Meyerson Hall taken at 930am, showing sections of uninsulated wall leaking heat

4.2- The Database Energy Reports

One of the most significant tasks of this year's work was to develop a database structure that could both house the energy meter data as well as produce informative reports that could assist in the performance evaluation of individual buildings and in the decision-making process. Databases are inherently better at storing and analyzing very large data sets and, with more than 3.5 million data points from meter readings each year, Excel was no longer capable of efficiently examining the full data set, instead requiring significant aggregation and manual importation. In addition to better analytical and data storage capabilities, databases are also highly flexible in terms of reporting energy data, allowing for custom reports to be quickly and simply generated to accommodate a wide variety of needs.

The structure of the database used considers two types of data for campus buildings: single data point information and data series. The single data point information consists of information on the building, such as the building's name, area manager, area, envelope type, etc. The data series information consists of building information that may have multiple values. This is primarily the energy meter information, which consists of thousands of data points every year per building for each utility type. Also included is information like notes on the buildings' history, each of which would be stored as a separate record.

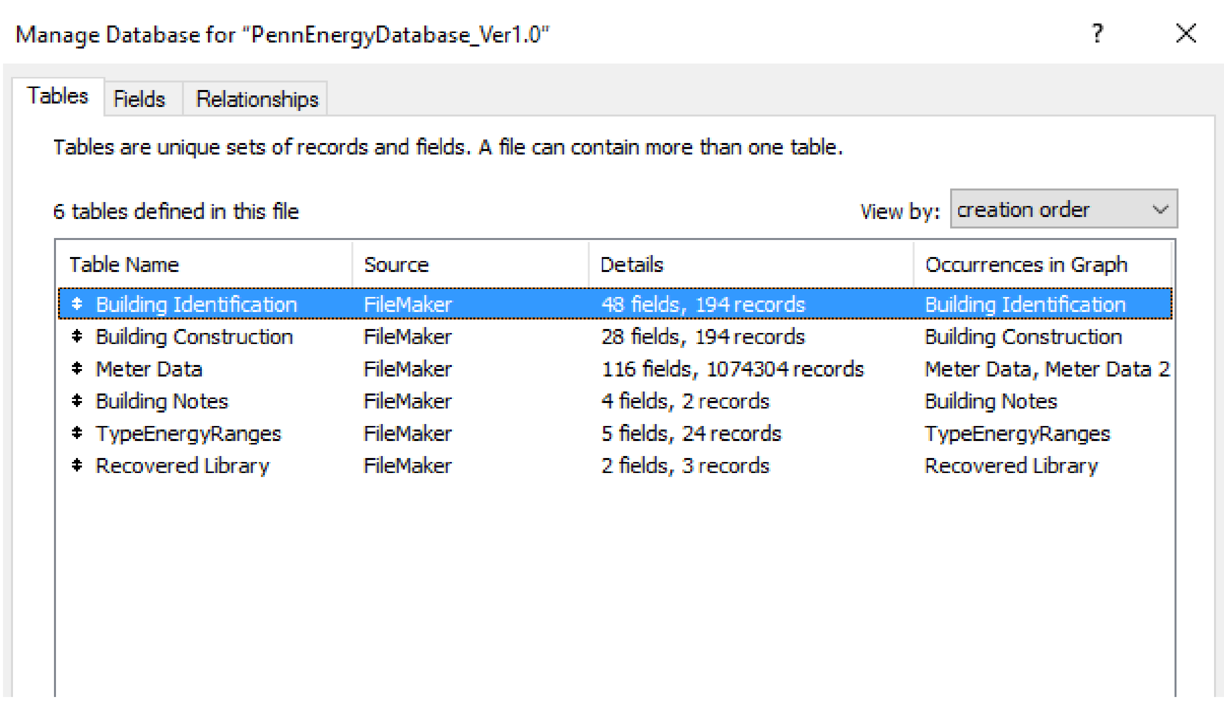


Figure 30- Tables defined in Filemaker database

The single data point information serves as the basic organizer of the database, with a single record for each building containing most of the information collected about it. Calculation fields in those individual building records search through the data series information to aggregate energy information into single data points calculating energy consumption for specific periods or time or for normalization and benchmarking purposes. This aggregation can occur based on a schedule or it can be on demand as new energy data is made available. The results of the aggregation are stored such that they do not need to be recalculated each time they are viewed if no new information was made available.

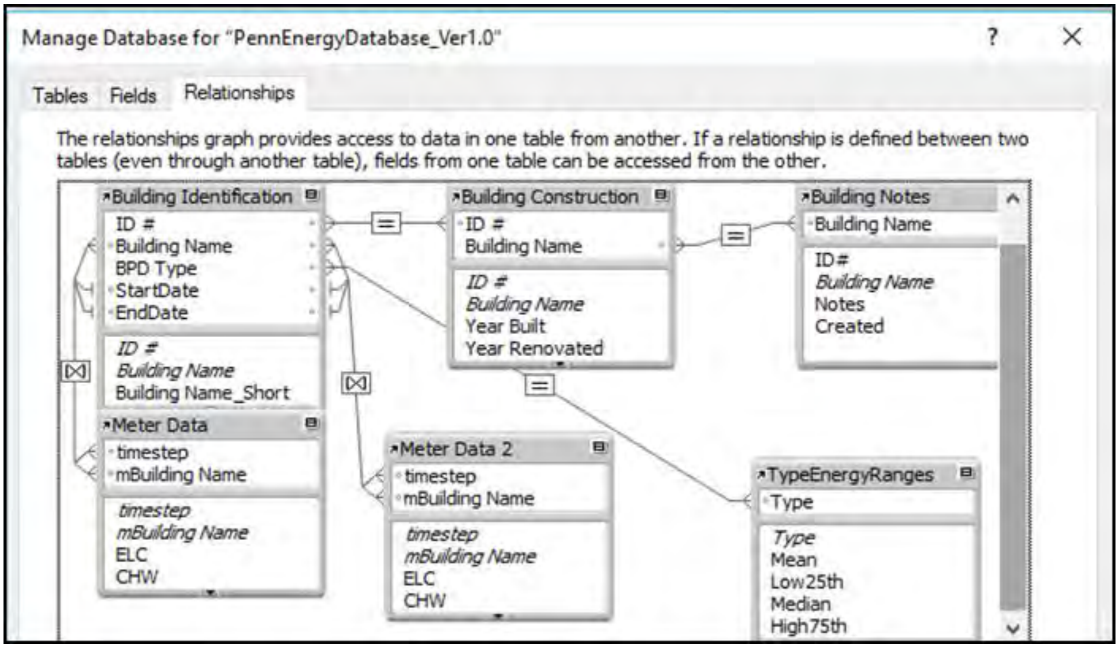


Figure 31- Defined relationships between tables determine how information on each relates for automatic filtering and aggregation

Once the basic structure of the database was developed, the cleaned and interpolated energy meter data was imported and several layouts were created to display varying levels of information. The remainder of this section will briefly discuss these reports, but they represent only a portion of the potential forms the information collected could be displayed. Ultimately the goal is to create a database that is web accessible, hierarchically password protected that could be used to easily navigate through multiple layers of information tailored to specific audiences. In addition to the annual reports that have been generated in the past, it is possible with this system to call upon a wider variety of analyses that are specifically tuned to the questions being asked as well as to the ones that haven't even been asked yet.

Figure 33, below, shows a version of an annual energy report that was generated using the CEBD database. This report was developed as a proof of concept to illustrate the ability of the Filemaker program to generate the same quality reports previously generated using Excel. This was tested by recreating the annual energy report, which was one of the final deliverables from the previous year. This version improves on the previous year by being increasingly flexible in terms of the speed at which the reports can be generated as well as being more able to easily query specific time frames for examination rather than being limited to a single fiscal year.

Annual Energy Report

Goddard Laboratories

Building Information

3710 Hamilton Walk, Philadelphia, PA 19104

Area Manager: John Blankemeyer

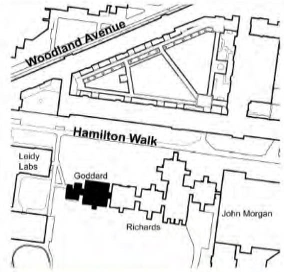
Building Manager: Amy Eader

Analysis Period

From: 7/1/2015

To: 6/30/2016

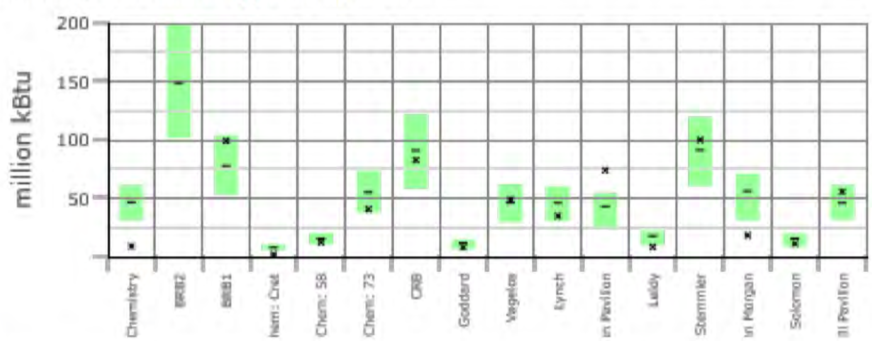
ID # 180



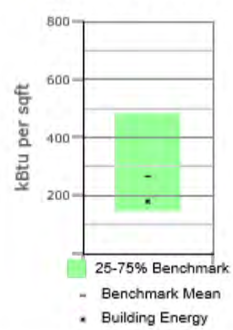
Type:	Laboratory: Chem/Bio 0-25	*Year Built:*	1964
Affiliation:	SAS	*Renovated:*	-
Area (gsft):	43,985	*Height (ft):*	109
Floors:	10		

Energy Consumed	**Source Units**	**kBtu**	**kBtu/sqft**
Elec:	715,552 *kWh*	2,441,562	55.5
Steam:	4,379,356 *kBtu*	4,379,356	99.6
CHW:	4,266,266 *kBtu*	1,096,727	24.9
Total:	*(site)*	7,917,645	180.0

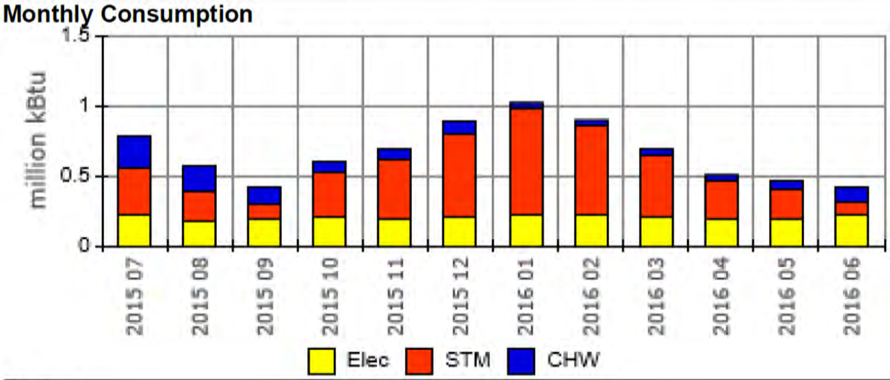
Buildings of Similar Type Comparison



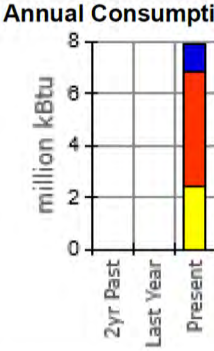
Regional Benchmark



Monthly Consumption



Annual Consumption



Notes

University of Pennsylvania / Facilities & Real Estate Services

Center for Environmental Building + Design

Figure 32- Example of an annual energy report

Further report layouts were developed to demonstrate the potential for customized reporting of energy information based on specific audiences or energy related queries. Figures 34 and 35 below show two additional reports that were created. Figure 34 shows a report that provides a quick summary of a building's energy usage. In addition to the basic building identification information and construction details, this report provides an annual summary, by fiscal year, of the total and normalized energy consumption in the building. This information is displayed graphically at an hourly resolution for the date range selected, and provides a portal showing the data points in table form. This layout is useful when querying a particular time period within the context of an entire year's consumption.

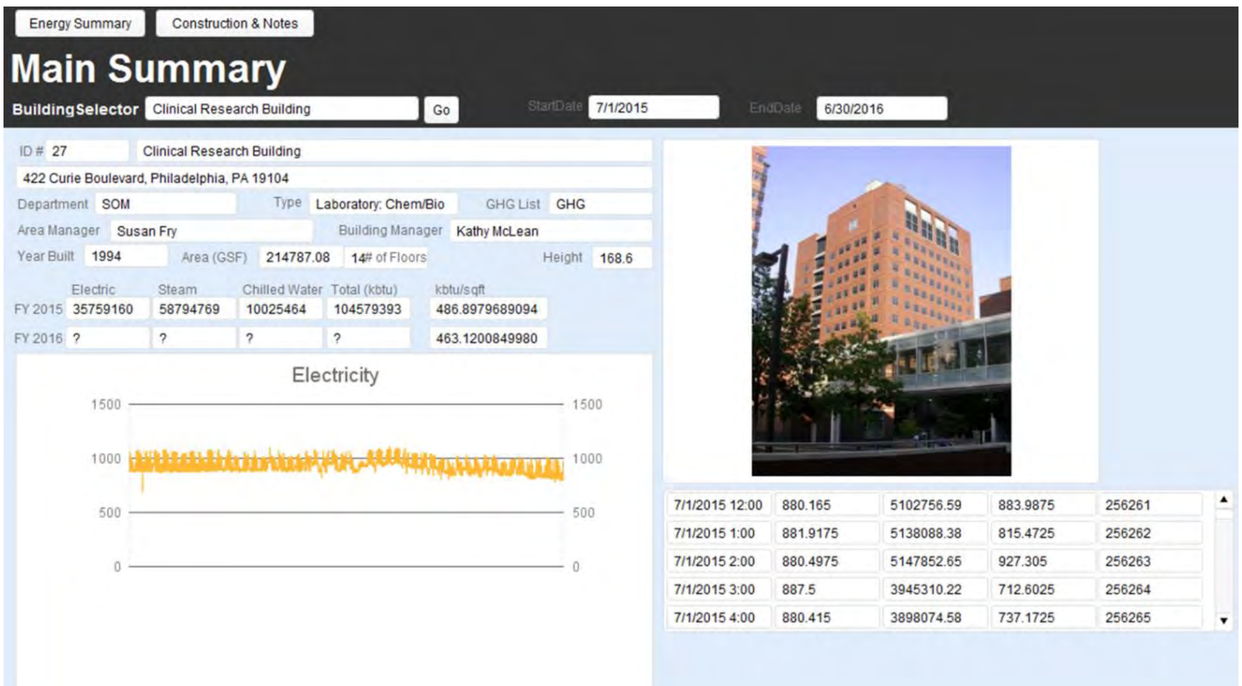


Figure 33- Example of a building summary report for a custom time frame

Figure 35 shows a broader overview of the building's energy consumption, providing aggregated energy information at the monthly level for all three utilities monitored in addition to the total. The monthly aggregation provides finer detail of how the building is using its energy based on the time of year. This is a level of resolution that would overwhelm the causal viewer and that the annual summary does not provide. Again, the data is provided in both table form as well as a chart.

It is important to note that these are just a sampling of the reports and analyses that the CEBD database can develop. One task that has already begun is a series of discussions with the building operators and decision makers regarding the information that would be useful to them in regards to energy consumption. The intent of these discussions is to ultimately create a hierarchical series of report layouts that would be accessible categorically based on end-user. Each report layout would contain useful information and analyses tailored to these specific audiences. Some possibilities include: views for internal benchmarking with estimates of expected usage versus actual usage; spatial data overlaid on maps; suggestions for potential issues present in individual buildings. The combination of these reports and layouts can serve as the primary portal for all energy and building information.

	Total Consumption (kbtu)				Normalized Consumption (kbtu/sqft)			
	Electric	Steam	Chilled Water	Total Energy	Electric	Steam	Chilled Water	Total Energy
Totals	27,720,658	50,827,769	4,270,446	82,818,874	136.0	249.3	20.9	406.3
2015 07	2,394,589	2,074,706	822,443	5,291,738	11.7	10.2	4.0	406.3
2015 08	2,381,654	2,116,772	670,539	5,168,966	11.7	10.4	3.3	406.3
2015 09	2,301,089	2,293,341	596,006	5,190,436	11.3	11.3	2.9	406.3
2015 10	2,382,365	3,685,932	260,630	6,328,928	11.7	18.1	1.3	406.3
2015 11	2,315,946	3,886,941	230,056	6,432,943	11.4	19.1	1.1	406.3
2015 12	2,395,571	4,108,441	221,108	6,725,120	11.8	20.2	1.1	406.3

Gross Square Feet: 203,852

Figure 34- Example of an energy focused report showing monthly consumption by utility type

4.3- DR-Advisor: A data-driven demand response recommendation system

To take advantage of real-time pricing and demand response (DR) programs, the commercial, industrial and institutional C/I/I consumers must monitor electricity prices and be flexible in the ways they choose to use electricity. The challenge for these large consumers of electricity is to be able to predict their aggregate power consumption accurately and quickly in order to take suitable load curtailment control actions. On the surface demand response may seem simple. Reduce your power when asked to and for financial compensation. However, in practice, one of the biggest challenges to end user demand response for large scale consumers of electricity is the following: upon receiving the notification for a DR event, what actions must the end-user take in order to achieve an adequate and a sustained DR curtailment? This is a difficult question to answer for the following reasons:

1. **Modeling complexity and heterogeneity**: Unlike the automobile or aircraft industries, each building is designed and used in a different way and therefore, it must be uniquely modeled. Learning predictive models of building dynamics using first principles based approaches (e.g. with EnergyPlus) are very cost and time prohibitive and require retrofitting the building with several sensors. The user expertise, time, and associated sensor costs required to develop a model of a single building are very high. This is because usually a building modeling domain expert typically uses a software tool to create the geometry of a building from the building design and equipment layout plans, and then adds detailed information about material properties, equipment, and operational schedules. There is always a gap between the modeled and the real building and the domain expert must then manually tune the model to match the measured data from the building.

2. **Limitations of rule-based DR**: The building's operating conditions, internal thermal disturbances and environmental conditions must all be taken into account to make appropriate DR control decisions, which is not possible with using rule-based and pre-determined DR strategies since they do not account for the state of the building but are instead based on best practices and rules of thumb. Rule based DR strategies have the advantage of being simple but they do not account for the state of the building and weather conditions during a DR event. Despite this lack of predictability, rule-based DR strategies account for the majority of DR approaches. The challenge is the increasing complexity of possible scenarios. There is a limit as to what can be pre-programmed and only a finite number of operations can be managed using this approach. There are also some operations that cannot be fully managed with a rules-based approach.
3. **Control complexity and scalability:** Upon receiving a notification for a DR event, the building's facilities manager must determine an appropriate DR strategy to achieve the required load curtailment. These control strategies can include adjusting zone temperature set-points, supply air temperature and chilled water temperature set-point, dimming or turning off lights, decreasing duct static pressure set-points and restricting the supply fan operation, etc. In a large building, it is difficult to assess the effect of one control action on other sub-systems and on the building's overall power consumption because the building sub-systems are tightly coupled. Consider the case of the University of Pennsylvania's campus, which has over a hundred different buildings and centralized chiller plants. In order to perform campus wide DR, the facilities manager must account for several hundred thousand set-points and their impact on the different buildings. Therefore, it is extremely difficult for a human operator to accurately gauge the building's or a campus's response.
4. **Interpretability of modeling and control:** Predictive models for buildings, regardless how sophisticated, lose their effectiveness unless they can be interpreted by human experts and facilities managers in the field. For e.g. artificial neural networks (ANN) obscure the physical features that control them and hence, are difficult to interpret by building facilities managers. Therefore, the required solution must be transparent, human centric and highly interpretable.

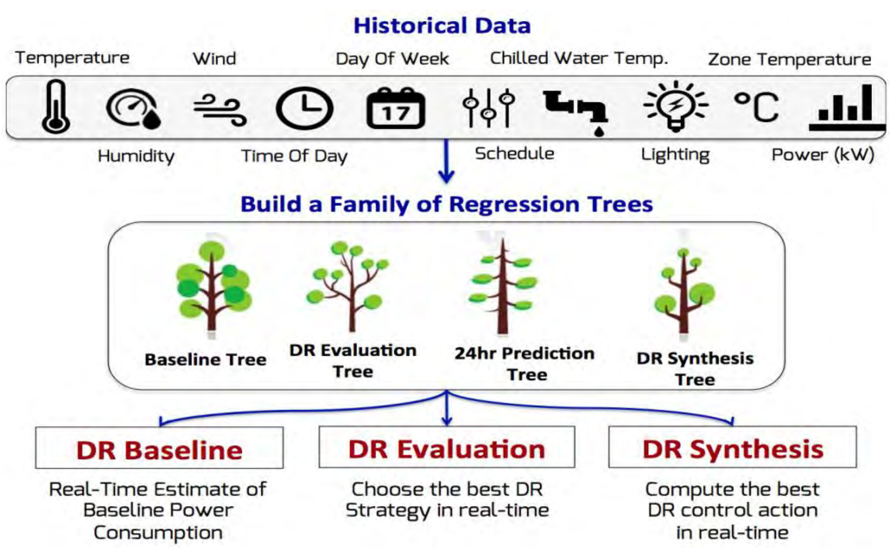


Figure 35- DR Advisor Overview

The goal with data-driven demand response is to make the best of both worlds; i.e. keep the simplicity of rule based approaches and the predictive capability of model based strategies, but without the expense of first principle or grey-box model development.

We present a method called DR-Advisor (Demand Response-Advisor), which acts as a recommender system for the building's facilities manager and provides the power consumption prediction and control actions for meeting the required load curtailment while maximizing the economic reward. Using historical meter and weather data along with set-point and schedule information, DR-Advisor builds a family of interpretable regression trees to learn non-parametric data-driven models for predicting the power consumption of the building (Figure 35). DR-Advisor can be used for real-time demand response baseline prediction, strategy evaluation and control synthesis, without having to learn first principles based models of the building. By using modified model based regression trees, we can also determine good demand response control policies for the duration of the DR event that achieve the required curtailment, without adversely affecting the system and causing any kick-backs.

The following are the key features of DR-Advisor:

1. DR Strategy Evaluation: Choose the best curtailment strategy from the available energy curtailment measures.
2. DR Strategy Synthesis: provides completely new strategies in real-time that did not exist before, while taking into account operations and occupant comfort.
3. Energy Analytics: Open-ended query response system for insightful analytics.
4. No expensive audits required.
5. Sustained load curtailment.
6. Demand response set-point recommendations.
7. No additional sensors required.
8. Outperforms fixed curtailment strategies.
9. Provides guarantees on comfort during the curtailment.

DR-Advisor uses a mix of several algorithms to learn a reliable baseline prediction model. For each algorithm, we train the model on historical power consumption data and then validate the predictive capability of the model against a test data-set which the model has never seen before. In addition to building a single regression tree, we also learn cross-validated regression trees, boosted regression trees (BRT) and random forests (RF). The ensemble methods like BRT and RF help in reducing any over-fitting over the training data. They achieve this by combining the predictions of several base estimators built with a given learning algorithm in order to improve generalizability and robustness over a single estimator. A boosted regression tree (BRT) model is an additive regression model in which individual terms are simple trees, fitted in a forward, stage-wise fashion.

DR-Advisor has been tested using historical weather and power consumption data from 8 buildings on the Penn campus (Figure 36). These buildings are a mix of scientific research labs, administrative buildings, office buildings with lecture halls and bio-medical research facilities. The total floor area of the eight buildings is over 1.2 million square feet and the size of each individual building is shown in Figure 37.

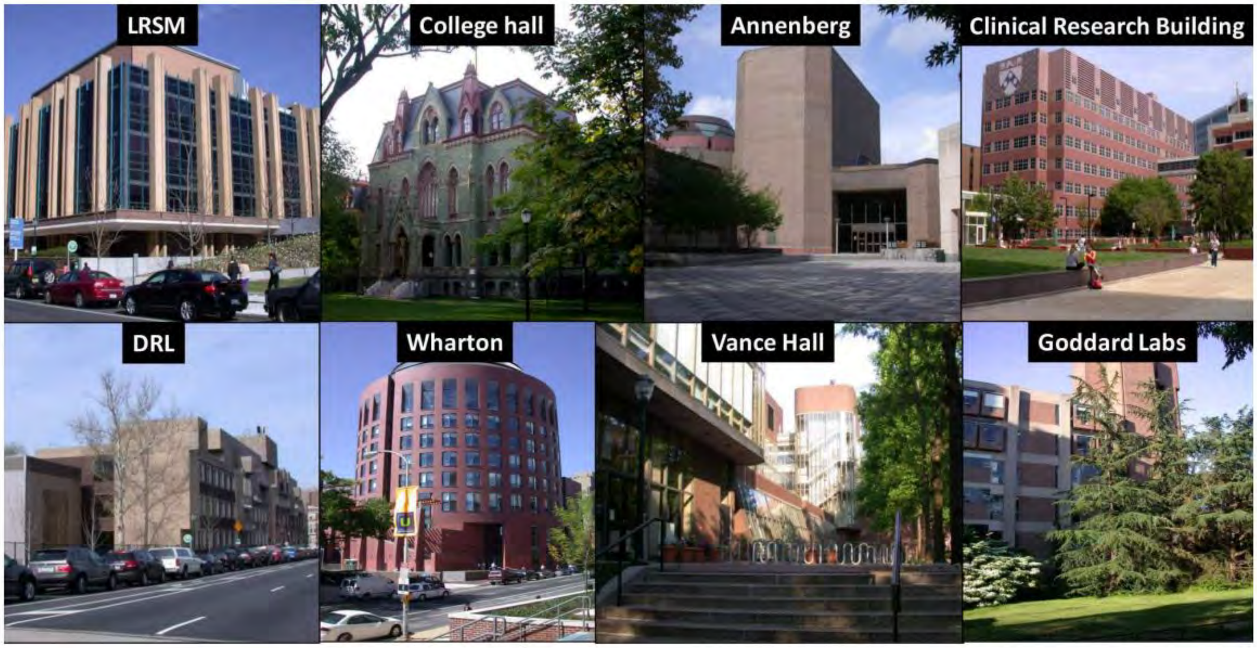


Figure 36- Buildings chosen for DR Advisor baseline prediction

For each of the Penn buildings, multiple regression trees were trained on weather and power consumption data from August 2013 to December 2014. Only the weather data and proxy variables were used to train the models. We then used the DR-Advisor to predict the power consumption of a test period, which lasted for several months in 2015. The predictions are obtained for each hour, producing a baseline power consumption estimate. The predictions from the test-set were then compared to the actual power consumption of the building during the test-set period. One such comparison for the clinical reference building is shown in Figure 38. The following algorithms were evaluated: single regression tree, k-fold cross validated (CV) trees, boosted regression trees (BRT) and random forests (RF). Our chosen metric of prediction accuracy is the one minus the normalized root mean square error (NRMSE). NRMSE is the RMSE divided by the mean of the data. The accuracy of the model for all eight buildings is summarized in Figure 37. We notice that DR-Advisor performs quite well and the accuracy of the baseline model is between 92.8% to 98.9% for all the buildings.

Building Name	Total Area (sq-ft)	Floors	Accuracy (%)
LRSM	92,507	6	94.52
College Hall	110,266	6	96.40
Annenberg Center	107,200	5	93.75
Clinical Research Building	204,211	8	98.91
David Rittenhouse Labs	243,484	6	97.91
Huntsman Hall	320,000	9	95.03
Vance Hall	106,506	7	92.83
Goddard Labs	44,127	10	95.07

Figure 37- Model Validation for Penn Buildings

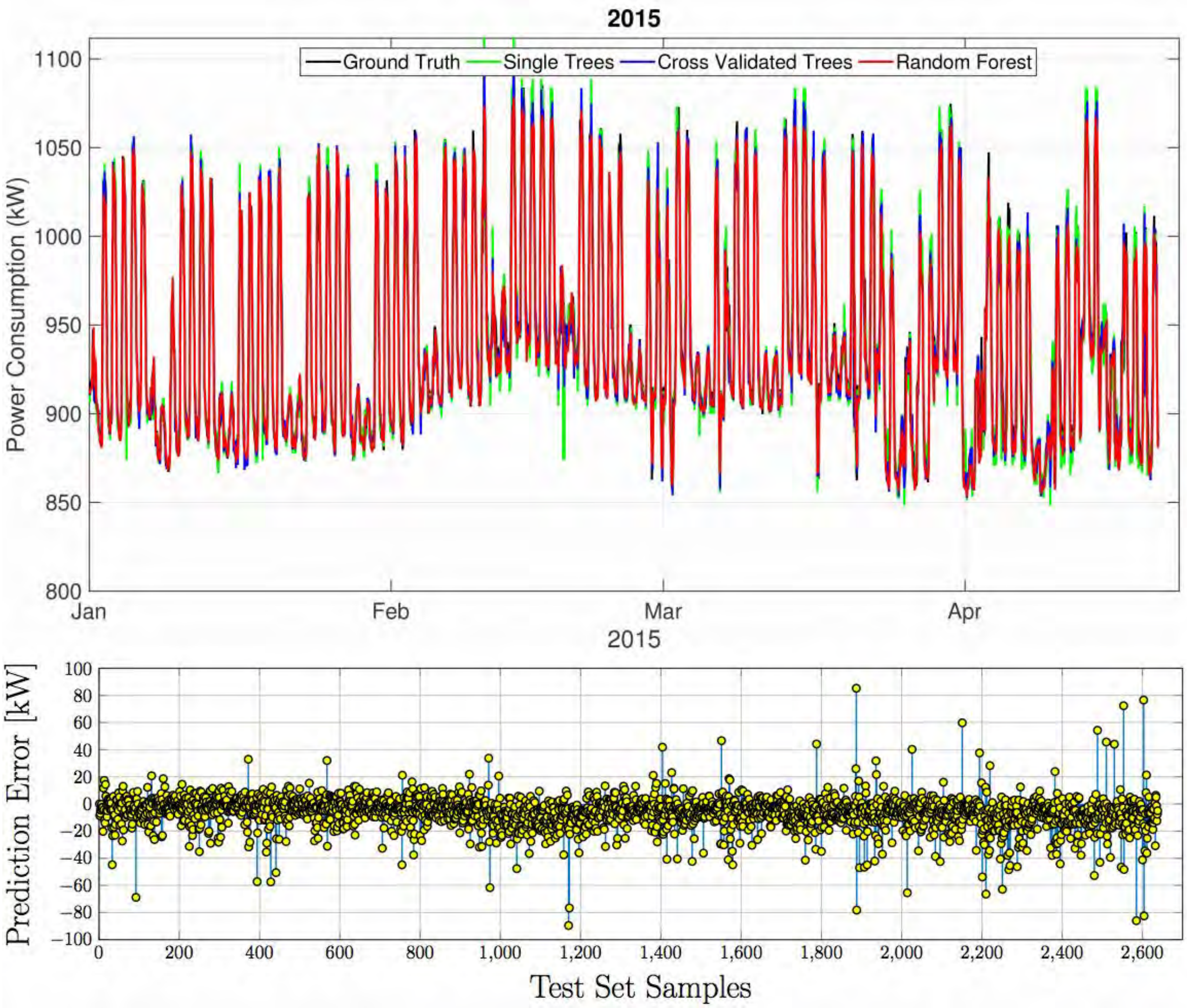


Figure 38- Model validation for Clinical Research Building

In order to implement the DR-Advisor at Penn, we will need regular, direct export of building meter data in a standardized, controllable format. This will simplify analysis and reporting and leverage the full power and functionality of DR-Advisor. The data will be used to develop data-driven predictive models for buildings which form the backbone of the Demand Response and Open-Ended Energy Analytics Engine recommendation applications:

These applications involve:

1. **Strategy Evaluation:** Predictive models to evaluate pre-determined and rule-based load curtailment strategies. These are queries of the form: *What is the expected power consumption of Building A (or a set of buildings) over the next time interval T; if Set-point S is changed to a value X?*
2. **Strategy Synthesis:** Providing recommendations about set-points values which takes into account the expected aggregate electricity load and thermal comfort inside the building. E.g. *What should be the value of set-point S for building A (or a set of buildings) over the time interval T?*
3. **Open-Ended Energy Analytics Engine:** Building a data-driven query-response system (with both graphic and voice user interface) which can answer open-ended questions about:
    a. **Data discovery and exploration:** What is happening?

b. **Reporting and analysis:** Why did it happen?
c. **Predictive analytics and modeling:** What could happen?
d. **Decision management and recommendations:** What action should be taken?
e. *The following are some more examples of the kind of queries supported by the energy-analytics system:*
   i. *What is the leading cause of peak power consumption of the building compared to the baseline?*
   ii. *Are there any anomalous building electricity consumption patters?*
   iii. *Which buildings on campus consistently consume the most power?*
   iv. *At what time is the peak expected to occur for Building A?*

If possible, the following data would be useful to enhance the capabilities of the DR-Advisor:

1. **Historical** time-stamped logs of Energy meter and SCADA/BMS data across different building types. Preferable in a common data format such as .dat, .txt or .csv.
2. **Live (read-only)** SCADA feed (initially from one building) to map to a sandbox simulated building, to test out controls (which will not be sent back to the real building).
3. **SCADA data** includes but is not limited to,
   i. AHU level sensor data (and set-points):
      1. Supply and return air temperature and flow,
      2. Damper position
      3. Reference pressure, supply static pressure, return static pressure
      4. Supply and return air relative humidity
      5. Heat exchanger inlet and outlet temperature data
      6. Fan speed
      7. AHU instantaneous power (if available)
   ii. VAV data and set-points:
      1. Reference temperature
      2. Damper position
      3. Re-heat status
      4. Outlet flow and temperature
      5. Inlet flow and temperature
   iii. Zone level data and set-points:
      1. Thermostat and humidity data
      2. Light levels (if available)
      3. People counter (if available)
      4. CO2 levels
   iv. Any sub-metered power consumption data.

5.0- Conclusions and Future Work

The work conducted by the Center for Environmental Building + Design this year represents the continuation of work that began in 2007 when the University signed the carbon reduction pledge with the goal of achieving carbon neutrality by 2042. Since then the CEBD has assisted Facilities and Real Estate Services with the analysis of the carbon produced by the University. As more than 80% of UPenn's emissions arise from energy used in facilities on campus, over the years these studies have increasingly focused on the energy used in buildings as the sector with the greatest potential for emissions reductions.

While initial efforts to understand how the buildings on campus were using energy by necessity relied heavily on building energy simulations and low-order models of building behavior it was clear that it was necessary to collect energy consumption information from individual buildings directly using electric, steam, and chilled water meters capable of taking frequent and regular readings. A program of meter installation and data collection began with the bulk of the individual building energy meters coming online in FY 2015. However, simply collecting the data is insufficient for several reasons.

Firstly, the data collected by the individual energy meters tends to be slightly messy. In FY15 as they were first brought online, many of the meters experienced a variety of issues involving calibration, reading incorrect units, or simply failing to collect sufficient data point due to connection failures or periods where they were disconnected for maintenance. As a result, while more meter data was available than even before, much of the efforts for the year were devoted to cleaning the data to remove outliers, identify the good data, and to develop a methodology for the interpolation of missing or removed data points in ordert o present a clearer picture of the actual energy consumption for each building over the course of the year.

While those steps were necessary to understand how much energy each building uses, this information is of limited use. While it identifies the largest consumers, it says little about the actual performance of these buildings based on their size, the type of building, the activities that occur within, or how external variables such as weather may affect performance. The second half of the work is to understand ***why*** the buildings are behaving as they do and if this pattern of behavior suggests a problem or potential for improvements. To accomplish this, a number of quantitative analyses can be used to compare the performance of a building against its own historical patterns of consumption or to establish a benchmark of performance based on the normalized energy consumption of peer facilities.

While some of this year's work improves the collection and cleaning of the meter, the bulk of the research conducted was focused developing the metrics, reports, and visualizations which transform the meter data into useful information which will help owners and operators of facilities to more effectively manage the building and plan for future energy reductions. This work can be divided into two categories: 1) developing new metrics / visualizations for energy data and 2) the collection of those metrics and visualizations into reports tailored for specific audiences and purposes. The ultimate goal of this work would be to integrate all of the metrics and visualizations into a reporting platform that would give individuals access to the information about the buildings they are interested in in the most useful form possible to assist them in decision making regarding facilities management.

The collection and cleaning of the meter data is a necessary step for all future analyses. Obtaining the data in FY15 was difficult, so for FY16 a procedure was developed that allows for the monthly transfer of the meter data in a standardized format. This removes the extraction issue and allows the data to be transferred electronically. After the data was collected, new parameters were used to identify outliers and missing data.

Regression analysis against weather and calendar based variables allowed for the interpolation of the missing and removed data points in order to present a complete picture of how energy was used in that building during the year. This methodology continues to be refined and this year the possibility of utilizing wireless data activity within each building as a proxy for building occupancy was explored and the feasibility of this methodology was established by confirming that the necessary data exists and can be collected. Early analysis of the potential for this data as a proxy for occupancy and it's capability to improve the ability to interpolate and predict electrical usage within a building seems impressive.

The second significant task accomplished in FY16 was the transfer away from spreadsheets as the primary aggregator of energy information for the generation of reports and comparative analysis of building energy consumption to a true database. The database offers several clear technological advantages for the handling of the meter information. One major limitation of spreadsheets is their inability to handle the large number of individual data points collected by the energy meters, which required the meter data to be separately aggregated into daily or monthly consumption before it could be used to generate reports.

The database structure, however, is capable of handling millions of individual records, which allows for the direct import of the meter data after cleaning and interpolation. Not only does this greatly reduce the time required and risk of errors being introduced via transcription errors, it also allows this finer grained detail to be used in generated reports. This opens the possibility for examinations of smaller increments of time such as daily, monthly, or quarterly which could be tailored to answer a much wider array of energy based questions. In addition to handling a larger quantity of data points, the database can also serve as an aggregator of multiple types of information including pictures, charts, construction information, and building history. While Excel primarily serves as a vehicle for quantitative analysis, the database can aggregate qualitative data as well, giving increased context and understanding to existing numerical analyses.

A final advantage of the database over spreadsheet is the ability to host it on the UPenn network or over the internet. Coupled with the ability to create password protected user accounts this will allow unprecedented access to the energy information generated by this work and eventually may allow users to access real-time energy analysis for the buildings they occupy or operate. This will allow the database to serve as the ultimate aggregator of building information, serving as both the receptacle for the data as well as the portal for its interpretation and distribution.

5.1- Proposed Future Work

There are several promising avenues for future research that would enhance the utility of the data gathered by the energy meters and aid in the decision making process regarding the management of facilities on the UPenn campus. These can be broadly divided into four categories: 1) further development of the database and its reporting capabilities, 2) the development of new and useful metrics which could provide unique and useful insights into the performance of individual buildings on campus, 3) development of graphic visualizations to make the data accessible to different users, such as DSim, 4) development of real-time tools, such as DR-Advisor, using data collected by the SCADA system.

Appendix

Table of Annual Energy Consumption by Building

ID	Building Name	FY15 Total	FY16 CHW	FY16 Elec	FY16 Stm	FY16 Total	Target	FY16 / sqft	Target/sqft
5	Anatomy Chemistry Building	13,907,886	1,705,480	1,725,188	5,620,107	9,050,774	30,901,097	70.6	241.2
10	Annenberg Center	13,463,510	2,241,045	4,155,397	8,951,209	15,347,651	8,383,040	143.2	78.2
15	Annenberg School	8,867,202	1,172,963	3,275,410	2,750,507	7,198,880	4,397,154	82.0	50.1
22	Biomedical Research Building 2	230,011,138	27,329,366	81,393,643	128,493,935	237,216,945	101,516,834	577.4	247.1
25	Fisher-Bennett Hall	11,777,458	2,068,569	3,724,309	8,161,054	13,953,932	3,716,669	188.1	50.1
27	Biomedical Research Building 1	104,579,393	10,813,671	40,094,856	48,563,683	99,472,211	53,073,887	463.1	247.1
30	Blockley Hall	21,201,627	1,131,411	8,069,795	10,966,056	20,167,262	22,132,585	116.7	128.1
45	APPC	6,899,530	555,966	5,886,378	4,475,335	10,917,679	2,505,848	218.3	50.1
50	Caster Building	6,180,881	106,227	870,912		977,139	1,234,266	39.7	50.1
55	Kelly Writers House	158,135	10,296	182,363		192,659	323,140	34.5	57.9
60	Chemistry Laboratories: Cret			686,579	1,152,172	1,838,751	5,269,902	86.2	247.1
65	Chemistry Laboratories: 1973	42,158,299	3,959,191	19,896,565	16,885,974	40,741,730	37,503,585	268.4	247.1
70	Chemistry Laboratories: 1958	7,481,181	1,746,394	1,254,318	9,423,079	12,423,791	10,206,462	293.6	241.2
75	The ARCH	2,665,150	672,450	1,632,866	1,141,373	3,446,689	1,668,852	119.6	57.9
80	Class of 1920 Commons	14,060,466	909,184	5,963,096	4,428,214	11,300,494	6,996,171	237.4	147.0
85	Class of 1923 Ice Rink	4,861,485		5,034,098		5,034,098	4,517,324	69.9	62.7
90	Class of 1925 House	6,291,177	312	803,531	5,050,199	5,854,042	1,153,674	143.6	28.3
92	Clinical Research Building	84,595,523	4,271,047	27,723,553	50,829,800	82,824,400	58,260,844	406.3	285.8
95	College Hall	9,446,618	1,933,089	3,604,141	4,211,833	9,749,063	5,493,263	102.8	57.9
100	Colonial Penn Center			237		237			57.9
103	Cyclotron	4,885,605	2,092,367	2,606,317	100,133	4,798,818	1,040,428	590.8	128.1
110	Dietrich Graduate Library	22,650,059	2,302,985	0	12,556,876	14,859,862	9,527,361	83.3	53.4
115	DuBois College House	3,690,978		1,283,164	5,797,883	7,081,048	2,587,158	77.5	28.3
130	Graduate School of Education	18,234,050	779,143	3,098,195	2,708,295	6,585,633	2,323,054	142.0	50.1
135	English House	10,120,753		2,637,938	8,428,474	11,066,411	1,905,156	164.4	28.3
140	Evans Building	22,020,430	3,037,850	7,813,903	15,823,155	26,674,909	5,506,461	223.3	46.1
145	Fox-Fels Halls	1,847,982	93,362	2,531,837	601,393	3,226,593	1,377,566	135.6	57.9
155	Franklin Building	32,397,987	3,381,547	13,758,974	17,113,514	34,254,035	5,813,565	341.2	57.9
160	Franklin Building Annex	5,510,375	756	3,405,497	1,391,457	4,797,710	2,237,279	124.2	57.9
165	Weiss Pavilion	3,040,457	699,763	9,660,922	2,278,978	12,639,664	2,069,100	383.0	62.7
170	Fisher Fine Arts Library	3,764,996	910,478	2,358,048	3,763,103	7,031,629	3,516,123	106.8	53.4
173	Schattner Center	19,043,443	2,976,945	5,828,184	9,565,402	18,370,531	3,290,480	257.4	46.1
176	Pottruck Health and Fitness	18,210,155	1,400,748	0	13,645,339	15,046,087	10,023,347	94.1	62.7
180	Goddard Laboratories	9,883,443	1,096,898	2,441,853	4,379,499	7,918,250	6,478,936	180.0	147.3
185	Grad Rsch Wing Moore School		2,209,662		6,769,497	8,979,160	5,344,166	212.7	126.6
190	Sansom Place West	13,358,628	1,371,927	3,757,454	10,742,649	15,872,031	6,604,536	68.0	28.3
205	Harnwell College House	14,709,178	702,843	5,732	7,931,147	8,639,723	8,720,419	28.0	28.3
210	Harrison College House	14,882,759	2,066,142	155,604,214	9,672,341	167,342,696	8,739,213	541.9	28.3
215	Hayden Hall	7,401,097	3,190,583	2,047,335	2,671,171	7,909,089	3,146,865	145.5	57.9
220	Rodin College House	19,236,426	1,508,825	8,065,461	17,807,873	27,382,159	8,721,435	88.9	28.3
225	Hill College House	19,120,192		4,598,573	11,013,685	15,612,258	5,323,005	83.0	28.3
227	Vagelos Laboratories	53,679,179	6,777,560	17,639,285	24,635,152	49,051,998	29,625,356	473.2	285.8
230	McNeil CEAS			549,209		549,209	738,572	43.1	57.9
235	Hollenback Center	11,405,520	308	2,801,380		2,801,688	3,730,725	47.1	62.7
241	Carolyn Lynch Laboratories	47,144,634	6,031,196	0	28,779,043	34,810,238	30,537,367	274.9	241.2
245	Houston Hall	16,819,862	2,529,297	10,130,846	9,299,479	21,959,621	12,603,880	256.1	147.0
246	Singh Center for Nanotechnology	29,698,435	1,437,332	12,047,371	10,158,879	23,643,582	10,082,317	300.4	128.1
250	Hutchinson Gymnasium	21,108,499	1,485,419	4,185,314	16,899,193	22,569,926	6,768,214	209.1	62.7
253	Institute of Contemporary Art	3,435,506	981,912	1,104,521	2,036,379	4,122,812	772,505	151.0	28.3
255	Irvine Auditorium	11,219,940	1,657,540	0	6,571,804	8,229,344	5,494,122	117.1	78.2
260	Johnson Pavilion	51,291,908	8,530,370	26,937,781	38,737,611	74,205,762	23,806,080	459.1	147.3
265	Lerner Center	2,121,218	311,672	643,482	1,244,851	2,200,005	1,482,609	74.3	50.1
270	King's Court	5,010,022		912,105	2,172,554	3,084,659	1,815,898	48.1	28.3
280	LRSM	23,990,855	3,743,113	6,981,400	17,039,889	27,764,402	11,907,151	298.7	128.1
284	Lauder-Fischer Hall	3,798,671	375,288	1,421,353	845,310	2,641,951	1,223,762	108.2	50.1
285	Gittis Hall	3,127,552	488,826	4,140,400		4,629,225	1,680,003	138.0	50.1
286	Tanenbaum Hall	17,645,165	1,683,690	9,829,349	2,326,680	13,839,720	5,983,043	123.5	53.4
288	Golkin Hall	17,050,545	355,063		15,645,380	16,000,444	2,050,092	391.0	50.1
290	Leidy Laboratories of Biology	7,873,616	1,290,074	4,641,562	2,420,724	8,352,359	9,771,587	125.9	147.3
293	Levine Hall	13,148,935	1,673,902	3,344,679	9,891,477	14,910,057	4,709,400	158.6	50.1
295	Levy Center for Oral Health	26,158,773	9,244,933	7,924,549	13,871,863	31,041,344	4,357,234	328.4	46.1
300	Hecht Tennis Center	2,502,719		3,455,291		3,455,291	3,655,849	59.3	62.7
305	Silverman Hall	9,885,733	1,081,518		3,947,160	5,028,678	5,111,352	49.3	50.1
310	Claudia Cohen Hall	8,349,624	1,459,753	2,608,276	4,299,600	8,367,629	4,677,440	103.6	57.9
320	Mayer Residence Hall	4,947,873	158,053	1,257,212	902,286	2,317,551	2,038,991	32.2	28.3
325	McNeil Building	19,093,217	1,433,307	7,009,108	7,699,354	16,141,769	6,031,237	134.1	50.1
330	Stemmler Hall	98,018,843	13,066,690	24,218,996	63,159,777	100,445,463	60,540,814	400.2	241.2
335	John Morgan Building	31,723,489	6,000,591	5,236,106	8,734,140	19,970,836	31,096,141	94.6	147.3
340	Meyerson Hall	19,102,820	1,276,017	4,002,951	2,118,476	7,397,444	4,706,995	78.7	50.1

ID	Building Name	FY15 Total	FY16 CHW	FY16 Elec	FY16 Stm	FY16 Total	Target	FY16 / sqft	Target/sqft
345	Moore School Building	8,004,779	1,530,664	3,478,760	2,572,837	7,582,261	6,287,019	152.7	126.6
350	Morgan Building	5,030,248	73,110	484,552	1,088,467	1,646,129	1,120,474	85.1	57.9
380	Sansom Place East	23,675,282	7,404,882	6,583,489	19,920,700	33,909,071	7,904,560	121.4	28.3
385	Claire M. Fagin Hall	28,821,958	2,759,087	8,128,769	8,658,880	19,546,736	8,296,560	118.0	50.1
390	3537 Locust Walk			0	87,705	87,705	325,572	15.6	57.9
405	Civic House	148,435		159,908		159,908	358,980	25.8	57.9
410	3905 Spruce Street	250,002		274,220		274,220	787,440	20.2	57.9
412	Parking Garage, 32nd & Walnut			552,509		552,509	0	4.0	
415	Jaffe History of Art Building	1,598,991	115,175	137,729	481,353	734,257	755,715	56.3	57.9
420	3808-3810 Walnut Street			493,274		493,274	880,370	32.4	57.9
450	Palestra	20,876,169	5,032	2,700,882		2,705,914	5,822,449	29.1	62.7
456	Skirkanich Hall	14,049,916	1,957,925	6,241,971	6,269,324	14,469,219	7,342,800	249.5	126.6
460	Carriage House	2,667,699	8,991	512,656	1,092,547	1,614,194	446,814	209.2	57.9
470	Presidents House		134	1,747,485		1,747,618	807,300	125.3	57.9
475	Solomon Laboratories	8,647,540	2,849,353	3,194,862	5,053,134	11,097,350	8,515,413	192.0	147.3
490	Quadrangle	17,913,816	2,187,108	11,136,212	25,696,589	39,019,909	14,619,238	75.5	28.3
500	Richards Medical Research Lab	27,367,954	1,121,761	5,718,941	6,846,488	13,687,190	4,937,483	127.8	46.1
510	David Rittenhouse Laboratory	27,419,425	2,544,065	17,588,588	30,413,416	50,546,069	30,821,403	207.6	126.6
515	Hillel at Steinhardt Hall		283,824	1,725,207	774,270	2,783,301	5,218,500	78.4	147.0
525	Charles Addams Fine Arts Hall	14,131,157	2,208,224	3,319,946	7,939,421	13,467,590	2,217,094	304.3	50.1
532	Bookstore		7,468,909	0	21,928,064	29,396,973	#DIV/0!	#DIV/0!	57.9
535	Steinberg Hall - Dietrich Hall	16,840,171	2,331,478	7,790,159	8,386,152	18,507,789	9,005,275	103.0	50.1
550	Stiteler Hall	13,171,826	781,852	6,020,293	4,297,119	11,099,264	1,983,960	280.3	50.1
555	Stouffer College House	15,517,831	1,934,046	6,250,995	6,766,954	14,951,995	3,749,390	112.9	28.3
560	Sweeten Alumni House	763,761	15	56,593		56,609	723,750	4.5	57.9
565	3216 Chancellor Street	7,101,366		2,230,390	4,563,962	6,794,351	2,057,245	423.1	128.1
570	Towne Building	54,765,165	4,297,885	8,472,842	44,327,023	57,097,750	9,886,715	334.4	57.9
575	University Museum	15,718,925	3,870,914	13,184,285	16,634,547	33,689,745	5,083,274	187.6	28.3
577	Penn Museum Parking Garage			1,556,274		1,556,274	0	7.0	
580	Van Pelt - Dietrich Library Center	38,370,012	5,163,457		15,956,926	21,120,383	10,744,881	105.0	53.4
585	Van Pelt Manor	4,854,715	624	2,289,079	3,134,890	5,424,594	2,159,290	71.1	28.3
590	Vance Hall	22,626,474	1,845,745	9,687,727	14,842,408	26,375,880	5,335,951	247.6	50.1
595	Ryan Veterinary Hospital	59,363,903	0	18,144,545	37,234,554	55,379,100	25,719,330	370.4	172.0
600	Veterinary Medicine Old Quad	49,829,992	15,981,666	8,346,420	33,854,351	58,182,437	15,428,400	648.6	172.0
605	Weightman Hall	9,287,802	0	6,512,966	0	6,512,966	4,094,310	99.7	62.7
610	Steinberg Conference Center	23,304,793	3,083,828	9,606,871	8,050,106	20,740,804	7,576,300	130.9	47.8
615	Dunning Coaches' Center	4,437,190	440,652	0	3,465,106	3,905,758	943,770	239.6	57.9
617	Huntsman Hall	78,141,176	7,971,094	24,313,889	45,607,495	77,892,478	16,032,014	243.4	50.1
620	Williams Hall	12,664,815	1,468,401	4,319,278	5,731,185	11,518,865	6,379,083	90.5	50.1
630	Hill Pavilion	52,706,020	4,959,516	21,513,438	29,299,861	55,772,816	31,330,358	439.9	247.1
9855	Locust Walk, 3615			26,332	404,784	431,116	780,955	32.0	57.9
9883	Locust House			19,803		19,803	520,058	2.2	57.9
9999	Module 6 Parking Garage			4,386,237		4,386,237	0	14.9	