M&V Report - Model-Based Predictive HVAC Control Enhancement Software

DR13SDGE0006 Report

Prepared by:

Emerging Technologies Program
San Diego Gas & Electric

October 2015

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Acknowledgements

San Diego Gas & Electric Emerging Technologies (ET) group is responsible for this project. It was developed as part of SDG&E's Emerging Technologies Program under internal project number DR13SDGE0006. kW Engineering conducted this technology evaluation with overall guidance and management from Kate Zeng, Matthew Smith and Christopher Roman. For more information on this project, contact Kate Zeng via email at kzeng@SDG&E.com.

EXECUTIVE SUMMARY

The goal of this Emerging Technologies study is to determine the electrical energy savings and demand response potential of a model-based predictive HVAC control enhancement software to an existing building energy management system.

TECHNOLOGY DESCRIPTION

The model-based predictive HVAC control enhancement claims to save energy by generating a predictive model of building operations, then optimizing heating, ventilation, and air conditioning (HVAC) system operations to meet these predicted loads. The specific model-based predictive HVAC control studied in this report provides a real-time prediction of a building's power profile for the subsequent 24-hour period, and updates this model every 4 hours. This predictive model informs how to most efficiently control HVAC system start-up and shut down times, and optimize heating, cooling, and airflow set points. The system seeks to achieve this goal in a three-step process:

1) The first step is to generate a generic building model that predicts the building's thermodynamic loads and the resulting energy consumption of HVAC systems based on variables including outdoor air temperature, humidity, building square footage, and building occupancy. This initial model utilizes numerous generic assumptions and is not building-specific, often leading to significant inaccuracies when first compared to the building's actual energy consumption.

2) To improve the generic building model, the system continually monitors building power consumption and compares the results to the expected power consumption from the model. Parameters of the model are adjusted based on the difference between the predicted building power consumption and the actual measured power consumption. Using this approach, the model 'learns' how the specific building operates and tunes the model parameters until an acceptable fit is achieved. This learning process typically takes 4-6 weeks depending on the variation in outdoor air temperature and occupancy observed during the learning period. After the 'learning mode' is complete, the model will predict future building power consumption 24 hours in advance, based on expected occupancy and weather profiles. The goal of generating this building model is to identify the pathway to the lowest HVAC operating cost for the building. This model is continually updated throughout the lifetime of the model-based predictive HVAC control system.

3) Once the model has completed the learning phase, the predictive controls are slowly transitioned into effect over a 4-6 week period. Based on the predictive model, the system optimizes air-side HVAC schedules and set points to achieve the most efficient operating point. The most efficient operating point is defined by minimizing overall energy cost. The system therefore considers factors including peak pricing, HVAC system part-load efficiency, and demand response capabilities in order to define the HVAC optimization sequence in a way that minimizes overall cost – not just overall energy consumption.

The system also uses predictive algorithms to intelligently reduce HVAC demand in response to an automated demand response (ADR) signal from the utility. The demand response algorithms includes the following general sequence:

1) The HVAC system is driven in a "pre-cool" mode prior to the DR timeframe to move the spaces toward the minimum acceptable zone temperatures.
2) At the start of the DR event, the HVAC system is set to supply air temp maximum, and supply air pressure minimum. There will be a gradual ramping of these parameters per standard system operations.
3) The optimization software will then dynamically pulse the units in a staggered manner to eliminate coincident cooling peaks from the air handlers. The term pulsing means resetting the unit to lower the supply air temperature and increase the supply air pressure to provide a calculated amount of cooling for a predetermined period of time. The software will then reset the natural drift of that space, so that the maximum acceptable space temperature is not breached within the DR period.
4) If at any time a zone approaches the maximum acceptable comfort temperature, that unit is removed from the DR algorithms and returned to full cooling.
5) Once the end of the DR event, all HVAC equipment is returned to normal operation in a staggered fashion to minimize any demand spikes at the end of the DR event.

PROJECT FINDINGS

This Emerging Technology report describes the data collection and analysis done to evaluate the energy savings potential of a model-based predictive HVAC control software and energy management service. As part of the project, kW Engineering performed a retrofit isolation analysis of the software installation at a large office building in SDG&E's service territory. The installation of this software enhances the existing air-side energy management controls by fine-tuning HVAC set points and operation based on predicted building loads.

kW Engineering's retrofit isolation analysis consisted of measuring whole-building HVAC power consumption through the utility interval meter for a period of 9 months prior to the retrofit and 7 months after the retrofit. Additionally, kW Engineering measured space temperature, humidity, and light levels in a sample of offices on each floor in order to confirm that occupant comfort is maintained before and after the software installation. Finally, interviews with facilities staff and building owners were conducted in order to identify, track, and address any changes to the building operations or occupancy that occurred during the baseline and post-installation monitoring periods.

This data was used, along with weather data from local weather stations, to develop a regression model of the baseline building operation and the building operation after the software was installed. These models estimate the annual HVAC energy consumption before and after the project implementation in order to estimate the energy savings associated with the predictive optimization system. kW Engineering ran uncertainty analyses on both models in order to ensure that the models provide reasonable estimates of the HVAC system operation and to determine the validity of the resulting energy savings.

Additionally, two demand response event tests were held on June 15 and July 22. The DR test on June 15 lasted 2 hours with the DR test on July 22 lasting 4 hours. kW Engineering used the Standard 10-in-10 Baseline methodology with the "Morning-of Adjustment" to determine the demand response potential of the model-based predictive HVAC control enhancement system. SDG&E provided 15-minute interval utility data for the months of June and July. This metered data was used to develop the building's baseline load and to determine the demand reduction from each of the two demand response events.

The following table summarizes the electrical energy and demand response savings associated with the predictive software installation at the office building in this study. We also performed the project cost effectiveness of the technology and provided the associated simple payback.

TABLE 1. SUMMARY OF ENERGY SAVINGS AND DEMAND REDUCTION

	Annual Energy Consumption (kWh/yr)	Average Maximum Peak Demand (kW)	Annual Energy Savings (kWh/yr)	Peak Demand Savings (kW)	Average DR Event Savings (kW)	Simple Payback Without Incentive (Years)
Baseline	779,983	241	-		-	
Predictive HVAC Control	696,706	231	83,277	10	14	6.5

PROJECT RECOMMENDATIONS

At the singular site analyzed in this project, energy and demand savings were achieved that can be directly correlated to the model-based predictive HVAC control enhancement system. However, the limited scope of this study prevents making any conclusive statements regarding the energy-saving and demand response potential of this system across numerous building types, climate zones, and HVAC system types.

Since this system demonstrated the potential for energy savings that go above and beyond current code or industry standard practices at a reasonable payback, it has the potential to be a successful measure through statewide customized incentive programs. However, insufficient information has been collected to provide a reliable prediction of energy savings beyond those calculated for this specific site. Therefore, we recommend incorporating this technology into statewide customized incentive programs but with added measurement and verification (M&V) requirements. Each individual application would require significant pre-retrofit and post-retrofit data collection and analysis in order to validate the savings. Insufficient data has been gathered to generate any predictive model or energy savings calculator. Further testing across a wider range of building types, HVAC systems, and climate zones would be required to determine if the energy savings could be predicted reliably without conducting the same level of M&V as was conducted in this study.

ABBREVIATIONS AND ACRONYMS

ADR	Automated Demand Response
ASHRAE	American Society of Heating Refrigeration and Air Conditioning Engineers
BTU	British Thermal Units
CT	Current Transducer
DDC	Direct Digital Controls
DR	Demand Response
DX	Direct Expansion
EMS	Energy management systems
ET	Emerging Technologies
HVAC	Heating, ventilation and air conditioning
IPMVP	International Performance Measurement and Verification Protocol
IWC	Inches of Water Column
kW	Kilowatt
M&V	Measurement and Verification
NREL	National Renewable Energy Laboratory
nRMSE	Normalized Root Mean Squared Error
PEO	Predictive Energy Optimization
SDG&E	San Diego Gas & Electric
SaaS	Software as a Service
SAP	Supply Air Pressure
SAT	Supply Air Temperature
TMY3	Typical Meteorological Year – 3rd series of data (most recent)
TA&TI	Technology Assistance and Technology Initiatives
VFD	Variable Frequency Drive

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INTRODUCTION

This report describes a retrofit isolation analysis performed by kW Engineering to evaluate the energy savings and demand response potential from the model-based predictive HVAC control enhancement software. This software package takes control of a select few air-side set points within a building's existing energy management system.

Upon installation, the model-based predictive HVAC control enhancement software will monitor environmental conditions both outside and inside the building, as well as the existing EMS' abilities and tendencies to react to changes in conditions. The theory behind installing the predictive software is that existing EMS systems are pre-programmed, and are reactive rather than proactive with respect to changing thermodynamic conditions. The predictive software is designed to anticipate climactic changes before they happen based on mathematical models, and make proper adjustments to the HVAC system in the most efficient and cost-effective manner.

The software in this study is a group of algorithms arranged to predict short term changes in weather, and building thermodynamic properties. The software initially takes 4-6 weeks to 'observe' the incumbent EMS' ability to react to environmental shifts, at which point the model begins to predict the power profile of the building over the next 24 hours. This 24 hour prediction is recalculated every 4 hours in order for the system to be responding to the most relevant target.

Model-based predictive HVAC control enhancement software is worth investigating due to the potential increases in efficiency, ability to predict and therefore preemptively respond to demand, and for the potential reduction in operating costs. As regulatory energy requirements become increasingly stringent, proactive approaches to energy management must become more prevalent.

As part of this technology assessment, the predictive software was installed in two large office buildings in SDG&E's service territory (CEC Climate Zone 07). One of the two participating facilities was selected for the retrofit isolation study, as the other facility had irregular occupancy due to tenant turnover and therefore did not provide consistent data for analysis.

In the building selected for study, kW Engineering performed long-term monitoring of the HVAC energy use and building's thermal conditions both before and after implementation of the predictive software in order to confirm the system's energy saving and demand response potential. Four types of information were collected and analyzed for this evaluation:

- HVAC power consumption data from a utility submeter that is dedicated to the HVAC systems. Equipment on this meter includes all water-cooled air handling units, cooling towers, and condenser water pumps. This data was used to generate baseline and post-implementation HVAC energy consumption profiles.
- Weather data from nearby weather stations was collected to give us information about outdoor air drybulb and wetbulb temperatures. This data was combined with the monitored HVAC power consumption in order to establish a weather and occupancy-based model of baseline and post-implementation HVAC power consumption.
- Logged temperature, relative humidity, and light output readings from each floor in the building. Meters were installed in occupied office areas and collected over eight months of data.

- Statements from building facilities staff regarding building occupancy profiles, acceptable temperature and humidity ranges for indoor spaces. This data was used along with the logged indoor temperature and humidity ranges to ensure that occupant comfort was maintained before and after implementation of the software.

The collected data was used to analyze how the investigated facility's HVAC energy use changed due to the model-based predictive HVAC control enhancement software.

BACKGROUND

Direct Digital Control (DDC) Energy management systems (EMS) are in common use in large commercial facilities. These complex systems not only control lighting and space temperatures throughout large buildings, they also deliver heating and cooling to the conditioned space more efficiently by implementing strategies like economizer cooling, and temperature and/or static pressure resets when outdoor and indoor temperatures permit. These DDC systems are a significant improvement over the previous generation of HVAC control, which consisted primarily of pneumatic controllers adjusting HVAC equipment in order to meet a fixed operational set point (such as a constant 52 °F supply air temperature set point, or a fixed duct static pressure).

Although the advent of the standalone DDC EMS is a marked improvement from previous control techniques, these systems still have shortcomings and room for improvement. In particular, the traditional DDC EMS is reactionary in its control of a building, in that the EMS reacts to changing weather or occupancy conditions and tries to optimize system operations accordingly, with as minimal of a delay as possible. Additionally, the EMS is typically programmed up front, then operated by on-site facilities staff thereafter. The primary focus of on-site facilities staff is usually to ensure occupant comfort – energy efficiency is a secondary or tertiary concern. Also, on-site staff are often not fully trained to operate the EMS, which can lead them to manually override the EMS controls if and when there are occupant comfort issues. In many cases, the automated control of the EMS is never restored after being transferred to manual override, thus nullifying any energy savings that the originally established automated controls provided.

The advent of new software packages that allow for remote monitoring and incorporate algorithms to predict upcoming building thermal and operational conditions indicates the potential to increase the energy-saving capabilities of traditional energy management systems. These new control methods allow for automated tuning of HVAC set points based on reliable predictions of upcoming building and outdoor air conditions – something a traditional EMS cannot do. This pre-emptive method for controlling energy consumption is focused on reducing energy costs by transferring the building load to the times of day when the plant is most efficient and energy costs are lowest. For example, a traditional EMS may control an HVAC system to maintain a constant internal temperature of 72 °F throughout the day. The result is that HVAC systems are more lightly loaded in the morning hours when outdoor temperatures are cooler, and become more heavily loaded in the afternoon as outdoor air temperature and humidity rise. A system with predictive optimization, however, may load the HVAC slightly more heavily in the morning and drive the space temperature down to 70 °F, then allow the space temperature to 'float' upward to 74 °F in the afternoon. The result of this 'pre-cooling' is that the load on the HVAC systems increases in the morning, but decreases in the afternoon as the temperature set point is allowed to float up. In theory, this results in an overall reduction in HVAC energy consumption because the load is transferred to morning hours when the HVAC equipment operates more efficiently under cooler outdoor air conditions, rather than loading the HVAC systems more heavily in the afternoon when higher outdoor air temperatures and humidity reduce HVAC equipment efficiency. This control approach, however, is only possible with reliable predictions of the upcoming weather, occupancy, and thermal conditions of a building, which the predictive optimization algorithms provide.

The opportunity to reduce energy consumption and peak demand through software-based enhancement of existing energy management systems is significant, given both the prevalence of existing EMS technologies and large percentage of building energy consumption associated with HVAC equipment. Based on a 2012 study conducted by PG&E, 69% of large commercial buildings use an energy management system[1]. The same study identifies an even greater presence in large office buildings, at 77% penetration. In California, HVAC accounts for approximately 40% of electrical energy consumption in Large Office building types[2], so even an incremental reduction in HVAC consumption due to improved control could yield a significant reduction in overall building energy consumption. Additionally, since HVAC loads typically peak during afternoons when outdoor temperatures are highest, improved operational efficiency would have an even greater effect on grid peak demand than on overall energy consumption.

EMERGING TECHNOLOGY/PRODUCT

The particular software studied in this report is one of a number of available model-based predictive HVAC control enhancement software packages. Some of the technologies currently on the market include:

- BuildingIQ – Predictive Energy Optimization (PEO) Software
- Enerliance – Load Based Optimization System (LOBOS)
- Optimum Energy – OptiCx
- QCoefficient - QCo

The particular cloud-based software studied in this report is installed on top of existing EMS controls and does not utilize any independent sensors or equipment. The software remotely manages building HVAC operations with the primary goal of reducing energy consumption and peak demand. In order to manage the systems, the software monitors EMS sensor readings and adjusts set points based on the algorithm’s prediction of the most efficient control approach for that day. The following data points are collected by the predictive software:

- Zone temperature or space temperature (return air temperature can be used a substitute if zone/space temp is unavailable)
- Supply air temperature
- Supply air temperature setpoint
- Duct static pressure
- Duct static pressure setpoint (If the unit has a VFD)
- Any power metering points
- Compressor stage
- Fan speed
- Outside air damper position

[1] Pacific Gas and Electric Company, Estimation of EMS Presence in Commercial Buildings in PG&E Territory and a Snapshot of Technologies in the EMIS Landscape, 2012. Web. http://www.etcc-ca.com/sites/default/files/reports/ET11PGE4221%20EMS%20Market%20Study.pdf.

[2] Itron, California Commercial End-Use Survey, 2006. Web. http://capabilities.itron.com/CeusWeb/ChartsSF/Default2.aspx.

- Outside air temperature
- Outside air humidity
- VAV space temperatures
- Zone humidity

Additionally, weather data from local weather stations and HVAC power consumption from the building's dedicated HVAC meter are used to develop the predictive model. This model defines the parameters that the optimization software uses to predict the building operations and to determine the optimal set points. The model is fine-tuned through a continually-updated regression analysis to ensure reliable predictions of building operations.

The software includes a graphical front-end that provides building operators with an at-a-glance look at the current set points and system operations. Should building operators identify any problematic set points, or if they begin receiving comfort complaints from occupants ("hot calls," or "cold calls"), they can contact the software provider to investigate the issue and modify set points if appropriate. This is a key difference compared to the approach that facilities staff may have taken using only their standalone EMS. Frequently, the issue would be 'solved' by manually overriding a set point, and leaving that set point in place until another occupant comfort complaint arose. With the model-based predictive HVAC control enhancement software in place, the software provider's staff, who are specialists in HVAC optimization, are in control of the set points and can more effectively adjust operations to meet occupant comfort needs while not eliminating the energy-savings components of the EMS. Additionally, if on-site staff do override systems, the software can detect this remotely and generate an alert if the override isn't removed in a timely fashion.

TEST SITE DESCRIPTION

OVERVIEW

Two commercial office buildings in the San Diego region (California Climate Zone 07) were selected by SDG&E for the study. The study called for selecting sites from a single property manager to more effectively preserve uniformity in conditions and minimize the number of variables affecting results. Thus, these sites are owned and operated by the parent corporation, and located within 30 miles of each other. Further they shared similarities in building size and HVAC equipment type.

However, one of the two sites selected for study became unoccupied during the baseline data collection period, and remained unoccupied throughout the testing. Therefore, conclusive data was only available for one of the two selected buildings. The following describes the test site information for the building included in this study.

TEST SITE – LARGE OFFICE BUILDING, SAN DIEGO, CA

The site selected for this study is a six-floor commercial office building located in San Diego, CA. The following table summarizes the characteristics of the building at the commencement of the baseline M&V data collection, prior to the predictive HVAC control enhancement software installation.

TABLE 2. EXISTING BUILDING CHARACTERISTICS

<table>
<tr><td>Building Type</td><td colspan="4">Large Office Building</td></tr>
<tr><td># of Floors</td><td colspan="4">6</td></tr>
<tr><td>Conditioned Area</td><td colspan="4">144,000 Square Feet</td></tr>
<tr><td>Vintage</td><td colspan="4">2001</td></tr>
<tr><td>HVAC Systems</td><td colspan="4">The HVAC systems include three 65-ton and three 72-ton Trane Intellipak packaged air handling units – one serving each floor. Each unit is equipped with a VFD-controlled supply fan, water-side economizers, water-cooled DX compressors, and hot water coils. The DX compressors are on a common condenser water loop which is served by a rooftop cooling tower that operates with a VFD-controlled fan.

Heating is provided by rooftop boilers that supply hot water to coils in each air handling unit and to some of the zone-level air distribution boxes. Hot water is distributed using two VFD-controlled pumps in a lead/lag configuration.

Fresh air is circulated through the building using one VFD-controlled supply fan and two constant-speed exhaust fans. Fresh air is supplied to a common plenum that each air handling unit pulls from.</td></tr>
<tr><td>Air Distribution</td><td colspan="4">Conditioned air is distributed through the building using VAV boxes with hot water re-heat coils. The one exception is the lobby area, which is served by a constant-volume box with hot water reheat.</td></tr>
<tr><td>HVAC Control</td><td colspan="4">HVAC operations are controlled by a Johnson Metasys control system. The system sets and monitors space temperatures and controls the HVAC operating schedule, supply air temperature, duct static pressure, condenser water temperature, and hot water supply temperature. Fresh air is provided to the building using a variable speed outdoor air fan which supplies air to a common plenum for each air handling unit.

The following observations of the baseline HVAC control capabilities were made:
- HVAC units are set to turn on and off based on a programmed operating schedule. There are no optimal start/stop controls.
- The supply fans operate using VFDs to maintain a constant duct static pressure (DSP). The DSP set point is different for each floor, and varies from 1.2 to 1.8 IWC.
- There is a supply air temperature reset in place, which varies the supply air temperature set point based on the measured return air temperature.
- Compressors are cycled on and off to maintain the supply air temperature set point.
- Each unit has a water-side economizer that uses condenser water to directly cool the air stream when the building load does not require the compressors to operate. This typically happens early in the morning, and when outside air temperatures are mild. While in water-side economizer mode, the cooling tower provides 59 °F water.
- Whenever any compressors are operational, the cooling tower operates to maintain a constant condenser water supply temperature of 80 °F.</td></tr>
<tr><td>Hours of Operation</td><td>Weekdays:
Saturdays:</td><td>5 AM – 6 PM
8 AM – 1 PM</td><td>Sundays:
Holidays:</td><td>OFF
OFF</td></tr>
</table>

ASSESSMENT OBJECTIVES

The primary objective of this technology assessment is to determine what, if any, energy savings and demand response benefits could result from implementing the model-based predictive HVAC control enhancement software on top of a pre-existing energy management system.

The main objectives of the project were as follows:

ENERGY EFFICIENCY OBJECTIVES

- Determine if the software system yields measurable and persistent energy savings across all building operating conditions.
- Confirm that the software system's set point adjustments did not infringe on occupant comfort.

DEMAND RESPONSE OBJECTIVES

- Determine if the EMS reliably received DR signal from the predictive software
- Determine if the EMS reduced the HVAC demand upon receipt of DR signal
- Determine how much HVAC demand was dropped during the test periods

To achieve these project objectives, significant testing of the baseline and post-implementation systems was conducted at the participating facilities. The team also developed and conducted a schedule of semi-automated DR tests. Following the tests, the team analyzed the monitored data to verify the implementation of the test signals and to quantify the energy and demand savings. The following sections provide detail on the testing approach.

TECHNICAL APPROACH/TEST METHODOLOGY

The following describes the field-testing and data analysis conducted to quantify the energy savings and demand response potential of the model-based predictive HVAC control enhancement software as part of this ETP assessment.

DATA ACQUISITION

The measurement and verification conducted in order to assess the potential of the predictive software followed International Performance Measurement and Verification Protocol (IPMVP) "Option B: Retrofit Isolation." According to IPMVP, this analysis method is most appropriate for projects where the affected systems are clearly defined, and the energy savings are too small to be detected using whole building data[3]. In this case, whole building electrical data was not available, so the retrofit isolation approach was selected as the most appropriate data collection approach.

The predictive software was installed to control the set points of all HVAC equipment in the building. The scope of the data collection therefore encompasses all of the HVAC. Therefore, the electrical energy consumption of all HVAC equipment was measured both before and after implementation of the software in order to assess the effect of the project. Data was collected over a period of multiple years. Therefore, it was critical to track any changes to the building operations during the monitoring period to ensure that the only variable changing in the analysis is the implementation of the studied technology – in this case, the predictive HVAC control enhancement software.

For this project, access was provided to sub-meter data for the meter that is dedicated to all HVAC systems in the building. Since the installed software only affects HVAC systems, assessing the savings on this meter alone is sufficient to determine the energy saving potential of this technology. The same approach to assessing whole building data, including normalizing for weather, determining uncertainty, and tracking any changes to building operations was used in the assessment of this meter in order to justify the energy savings claims.

Since the predictive software claims to save energy by modifying HVAC set points and allowing space temperatures to float above or below the set point, it was also important to confirm that occupant comfort was not affected by the installation of the new control software. Therefore, in addition to the HVAC-meter energy analysis, space temperature and humidity levels were monitored using stand-alone data loggers in a sample of locations throughout the building, both before and after implementation of the software. This data was used to determine whether any temperatures or humidity levels exceeded standard occupant comfort ranges as a result of the software installation.

The following sections provide further detail on each data source used in the M&V plan, including what data was collected and how the data is used in this ETS assessment.

[3] US Department of Energy, International Performance Measurement & Verification Protocol – Concepts and Options for Determining Energy and Water Savings, Volume 1. March 2002. Web. http://www.nrel.gov/docs/fy02osti/31505.pdf

UTILITY INTERVAL DATA

Utility interval data provides electrical demand in 15-minute increments. This data was collected from the building's HVAC meter in order to track the HVAC power consumption over time.

BASELINE DATA COLLECTION

To establish the baseline energy consumption, 18 months of interval data was collected from the site. Data collection began in May 2013, and the baseline monitoring period ended in October 2014 when the predictive HVAC control enhancement software was installed. This data was compiled with local weather data from the same period (discussed below) in order to establish a correlation between HVAC power consumption and ambient weather conditions.

Though over a full year of data was collected, not all of the data was used in the analysis. Investigation of the building operations via conversations with facility staff and building ownership identified significant changes to building operations that occurred during the baseline monitoring period. In particular, the following changes occurred:

- In August 2013, a new chief engineer took over at the building. He implemented numerous changes to operational set points and schedules in an effort to reduce the building's energy consumption. Data prior to August 2013, therefore, is not a valid representation of how the building was operating immediately prior to the PEO installation, and was removed from the analysis.
- Building facilities staff stated that all of the VAV controllers in the building were replaced 'sometime in 2013,' though the exact date was unknown. This replacement represents a significant improvement to the building and therefore all data from 2013 was removed from the analysis in order to ensure that the baseline was properly represented.
- Floor #5 in the building became unoccupied at the end of 2013. The floor has remained unoccupied since, and continues to remain unoccupied. This represents a significant change in building loads, so any data with Floor #5 still occupied is not considered a valid representation of the baseline. All data before January 2014 was therefore removed from the analysis.

The resulting baseline data collection period, once all time periods with significant changes to the building were removed, was from January 1st, 2014 to October 3rd, 2014.

POST-INSTALLATION DATA COLLECTION

After the installation of the predictive software on October 27th, 2014, an additional set of utility interval data was collected to confirm the post-retrofit HVAC energy consumption. Nine months of utility interval data for post-retrofit analysis was collected from November 1st, 2014 through August 3rd, 2015.

As in the baseline case, the building facilities staff, ownership, and software provider were polled to determine if there were any changes to the building operations or issues with the HVAC operations that should not be considered in the post-implementation analysis. The following information was provided:

- Facilities staff and ownership confirmed that the 5th floor has remained unoccupied during the entire post-retrofit monitoring period.
- Facilities staff confirmed no major changes aside from normal maintenance to any HVAC systems, nor any changes to building occupancy, schedules, or operations.

- The software provider staff stated that there were 'connectivity issues' with the system in December 2014. Since these start-up issues are not expected to persist throughout the useful life of the PEO software, this data was removed from the post-retrofit analysis.

Based on the above statements from facilities staff, ownership, and software provider, the post-retrofit data range used to test the software's performance was January 1st, 2015 to August 3rd, 2015.

The Results section of this report provides details of the data collected during both the baseline and post-retrofit monitoring periods.

METERING EQUIPMENT

HOBO-brand data loggers were installed to measure occupant comfort in a randomly selected office on each floor of the building, and to measure current from each component of the HVAC system. Measurements were taken during the same interval as the baseline and post-implementation measurement of the interval data, discussed above. The following provides additional detail on the information collected:

- **Current loggers**

  Current loggers are current transducers (CTs) that are connected to a data recording device. CTs are clamped around the wires of particular circuits within an electrical panel. Current loggers were hooked up to all HVAC equipment on-site, including the six air handling units, two condenser water pumps, and two cooling tower fans. Each measured circuit was also spot-checked with a multimeter to measure the power factor of the equipment and the voltage in order to calculate the total power. This data was used to independently confirm the accuracy of the interval meter that monitors this same equipment. The following graph shows how the power consumption from the dataloggers compared with the metered power. Although the fit is not exact, the data shows reasonable agreement between the datalogger power and the metered power.

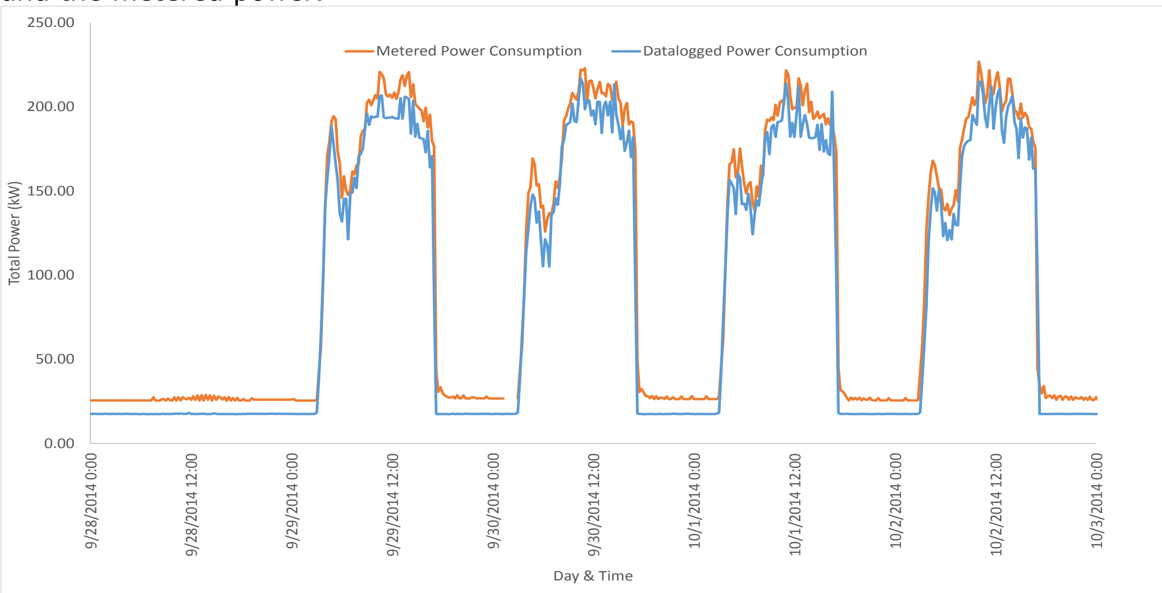

FIGURE 1. COMPARISON OF INTERVAL METER DATA TO STAND-ALONE DATA LOGGERS

- **Temperature loggers** recorded the indoor temperature and humidity in one randomly-selected office on each floor. These loggers were in open office areas, as close to the thermostats as possible. The purpose of these loggers was to track space temperatures both before and after the software installation, to confirm that occupant comfort was not affected by the software's energy-saving control adjustments.

LOCAL WEATHER DATA

Outdoor air temperature and humidity data in 15-minute increments was pulled from local weather stations (in this case nearby 'Montgomery Field' airport). This data was collected for the entire baseline and post-implementation monitoring period. The data was used to develop the regression model of baseline and post-implementation energy consumption, discussed in the Test Plan below.

INSTRUMENTATION PLAN

The following table summarizes the instrumentation used in this technology assessment.

TABLE 3. M&V INSTRUMENTATION

MONITORED VARIABLE	EXPECTED RANGE OF MEASUREMENT	MEASUREMENT EQUIPMENT	MEASUREMENT UNCERTAINTY	MEASUREMENT LOCATION
Total HVAC Power Consumption	0 – 1000 kW	Utility Meter	ANSI C12.20 0.5 accuracy class	Mechanical Room Meter
AC-1 Power	0 – 100 kW	ElitePro XC	1%	AC-1 Breaker
AC-2 Current	0 – 100 kW	HOBO	1%	AC-2 Breaker
AC-3 Current	0 – 100 kW	HOBO	1%	AC-3 Breaker
AC-4 Current	0 – 100 kW	HOBO	1%	AC-4 Breaker
AC-5 Current	0 – 100 kW	HOBO	1%	AC-5 Breaker
AC-6 Power	0 – 100 kW	ElitePro XC	1%	AC-6 Breaker
Cooling Tower 1 Current	0 – 50 kW	HOBO	1%	CT1 Breaker
Cooling Tower 2 Current	0 – 50 kW	HOBO	1%	CT2 Breaker
Condenser Water Pump 1 Current	0 – 50 kW	HOBO	1%	CWP1 Breaker
Condenser Water Pump 2 Current	0 – 50 kW	HOBO	1%	CWP2 Breaker
6^{th} Floor Space Temperature	62 – 85 °F	HOBO	+/- 0.63 °F	6^{th} Floor Open Office

5th Floor Space Temperature	62 – 85 °F	HOBO	+/- 0.63 °F	5th Floor Open Office
4th Floor Space Temperature	62 – 85 °F	HOBO	+/- 0.63 °F	4th Floor Reception Area
3rd Floor Space Temperature	62 – 85 °F	HOBO	+/- 0.63 °F	3rd Floor Reception Area
2nd Floor Space Temperature	62 – 85 °F	HOBO	+/- 0.63 °F	2nd Floor Break Room
1st Floor Space Temperature	62 – 85 °F	HOBO	+/- 0.63 °F	1st Floor Open Office

TEST PLAN

The above collected data was used to test two aspects of the predictive HVAC control enhancement software's performance – the annual energy savings and demand response potential. The test plan uses a regression analysis of HVAC interval data and outdoor air temperature to test the annual energy savings, and a standard "10-in-10" baseline methodology to test the demand response potential. Further details on each test plan are provided below.

ANNUAL ENERGY SAVINGS TEST PLAN

To test the annual energy savings, a statistical regression model was applied to the electrical sub-meter data that is dedicated exclusively to the HVAC equipment. This regression approach was applied to both the baseline and post-retrofit data. The statistical models were developed using the approach presented in LBNL-4944E, an April 2011 article from Lawrence Berkeley National Laboratory entitled 'Quantifying Changes in Building Electricity Use, with Application to Demand Response'[4].

Each regression model was developed using the following steps:

1) 15-minute utility interval data was collected from the HVAC sub-meter.
2) 15-minute outdoor air temperature and humidity data was collected from The National Oceanic and Atmospheric Administration (NOAA), collected at Montgomery Field Airport in San Diego, California.
3) A weekly occupancy schedule was developed based on posted building hours, EMS schedules, and discussions with facility staff.
    a. The schedules used in the model include occupied and unoccupied times for each day of the week, the number of weeks of operation per year, and any holidays when the building is typically vacant or lightly loaded.

[4] Mathieu, Johanna; Price, Phillip; Kiliccote, Sila; Piette, Mary Ann. 'LBNL-4944E: Quantifying Changes in Building Electricity Use, with Application to Demand Response.' Lawrence Berkeley National Laboratory. April 2011. Web. http://eande.lbl.gov/sites/all/files/LBNL-4944E.pdf

b. The observed weekly schedule is as follows:
    i. Weekdays 5 AM to 6 PM
    ii. Saturday 8 AM to 1 PM
    iii. Sunday and holidays OFF

4) TMY3 weather data for the same location, Montgomery Field Airport, was collected in order to annualize the energy savings.
5) Any periods of time during the data collection period that major changes to systems or operations occurred were identified. This data was removed from the analysis in order to provide a like-for-like comparison between the baseline and post-retrofit operating conditions. See the Utility Data Collection section, above, for specific data that was removed from this site's regression analysis. The final data used in the analysis is as follows:
    a. Baseline data from 1/1/2014 to 10/3/2014 (6,622 hourly data points)
    b. Post-retrofit data from 1/1/2015 to 8/3/2015 (5,159 hourly data points)
6) Using the data above, two statistical models were generated - one for the baseline data and one for the post-retrofit data. Both models were then applied to the TMY3 weather data in order to calculate the predicted baseline energy usage and predicted post-retrofit energy usage for an entire typical year.
7) Statistical analyses were conducted per ASHRAE 14 standards to determine the level of uncertainty in the models and in the overall savings claims. This analysis determines how well the model fits the actual data, and thus how reliably it can predict building power consumption. The lower the uncertainty in the model, the greater the accuracy of the energy savings predictions.

The Results section of this report, below, provides the verified energy savings and identifies uncertainty of the energy models.

OCCUPANT COMFORT TEST PLAN

To ensure that occupant comfort was not affected by the implementation of the new software, the following test plan was implemented.

1) Stand-alone space temperature sensors were installed in various occupied areas of the facility.
2) One sensor was installed on each floor, for a total of six temperature sensors in the building.
3) Space temperature sensors were placed in open office areas and, when possible, were located close to the EMS room temperature sensors.
4) Space temperatures were recorded before and after implementation of the project to ensure that there is no significant change to the room temperature as a result of the software's HVAC control.

The Results section below provides a summary of the measured room temperatures before and after the project implementation.

DEMAND RESPONSE TEST PLAN

Two demand response event tests were held on June 15 and July 22. The test date on June 15 lasted 2 hours and occurred from 3:00 PM – 5:00 PM. The test date on July 22 lasted 4 hours and occurred from 1:00 PM – 5:00 PM. The software provider gathered demand usage data from the building's EMS to develop a usage baseline and to verify the reduced load during the demand response event.

Additionally, metered data for the building was provided from SDG&E, which shows the building demand at 15-minute intervals for the months of June and July. This metered data was used to develop the building's baseline load and to determine the demand reduction from each of the two demand response events.

The methodology used to analyze the building data is the Standard 10-in-10 Baseline methodology with the Morning-of Adjustment, taken from the "Baselines for Retail Demand Response Programs" by Bruce Kaneshiro, CPUC. The two demand response events were analyzed using this method.

The Standard "10-in-10" Baseline is used by many demand response programs to determine incentives. This baseline is based on the hourly average of the previous 10 business days prior to the demand response event. The previous 10 business days include Monday through Friday, excluding holidays, and days when the customer was paid to reduce load for a demand response event, or days when rotating outages are called.

RESULTS

The following sections provide the results of all testing done to assess the annual energy savings and demand response potential associated with the model-based predictive HVAC control enhancement software at the investigated building.

ANNUAL ENERGY SAVINGS TEST RESULTS

As discussed in the Test Plan above, two regression models of the building's HVAC energy consumption were generated – one baseline model and one post-implementation model. These regression models predict HVAC energy consumption based on time of day and outdoor air temperature. The following summarizes the results of the collected data.

BASELINE RESULTS

The baseline monitored data shows a clear linear correlation between outdoor air temperature and HVAC power consumption during the building's occupied period, as seen in the graph below. This operation is expected in a comfort cooling HVAC system where outdoor air temperature drives the load. The baseline unoccupied load is relatively consistent at 50 kW and does not vary with outside air temperature, as expected.

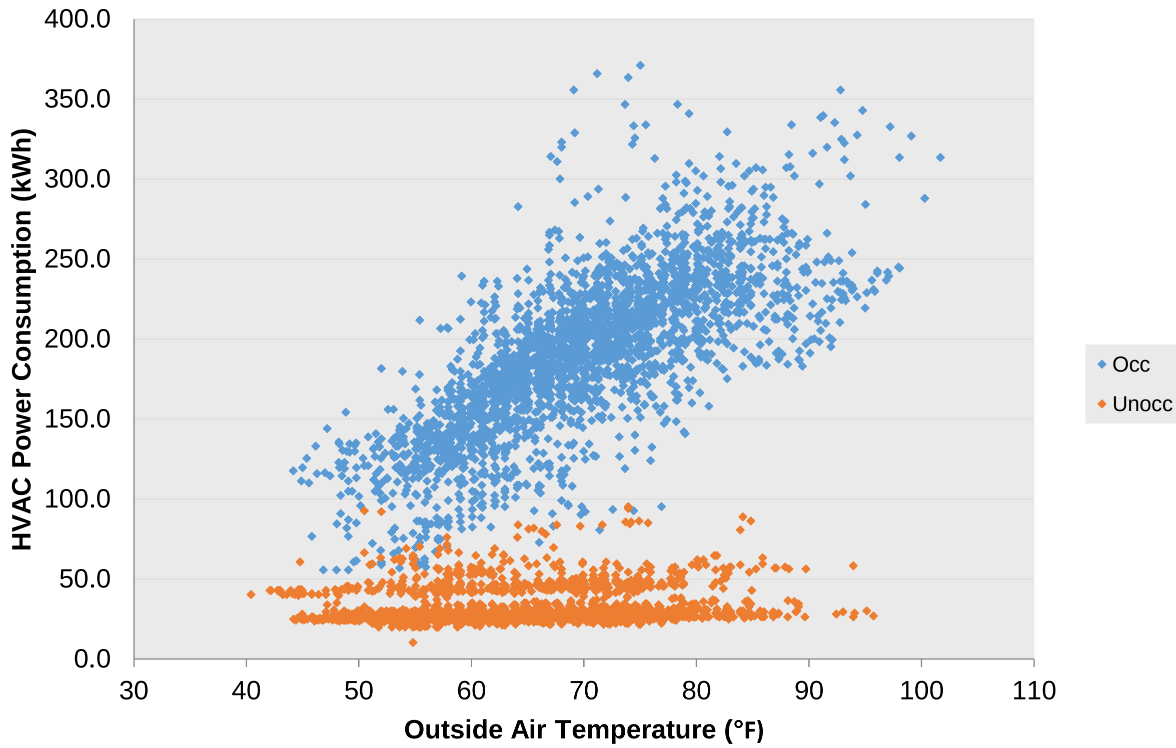

FIGURE 2. CORRELATION OF BASELINE HVAC POWER CONSUMPTION WITH OUTSIDE AIR TEMPERATURE

Based on the data presented above, there is a clear correlation between HVAC load and two variables – outdoor air temperature and building occupancy. Therefore, a multi-variant regression model was developed to predict the HVAC operation based on these two variables. The regression model predicts the HVAC power for every hour of the year based on outdoor air temperature and building occupancy status.

Baseline Regression Model Uncertainty Analysis

This regression model was tested against actual data to determine its accuracy. The following graph shows a comparison of the regression model and the measured data during a portion of the baseline monitoring period.

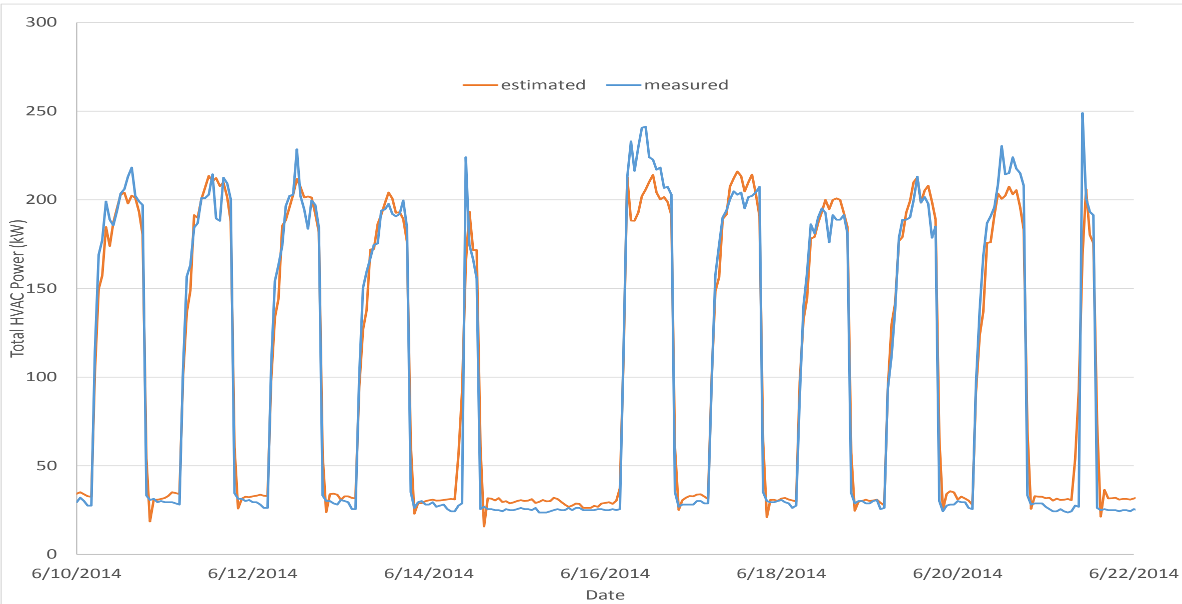

Figure 3. Correlation of Baseline Regression Model with Baseline Monitoring Data

As is evident from the graph, the regression model appears to follow the measured HVAC energy consumption quite accurately. However, visual evaluation of the model accuracy is not sufficient. The statistical metrics used to determine how well the model correlates to the real-world data include an R-Squared analysis and a normalized root mean squared error (nRMSE) calculation. The following table summarizes the uncertainty of the baseline regression model.

Table 4. Baseline Model Error Analysis

Model Designation	Number of Data Points	R-squared Error	nRMSE
Baseline	6,622	0.954	18.3%

The highest possible R-square error value is 1, which represents a perfect fit to the data. The nRMSE provides an aggregated estimation of the error across all data points. While these values are useful in determining if a model is reasonable, as is the case for this model based on the high R-squared error and relatively low nRMSE in this case, there is no standard to measure these values against. However, the uncertainty in this model and in the post-retrofit model will both be reflected in the uncertainty of the energy savings. Ultimately, the uncertainty of the final calculated savings will be compared against ASHRAE 14 M&V guidelines to determine if the models provide a reasonable estimate of the savings.

ANNUALIZED BASELINE ENERGY CONSUMPTION

The regression model used real-world weather and HVAC power consumption data collected during the monitoring interval. During the 9-month baseline monitoring period, the total energy consumption was approximately 655,560 kWh, and the maximum demand was 371 kW.

In order to estimate the baseline energy consumption for a typical year, which may have different weather patterns than 2014 when the data was collected, TMY-3 weather data was input into the regression model. TMY-3 data, compiled by NREL, provides hourly average weather data for a 'typical meteorological year' at a given location. This data set is the standard for energy efficiency analyses as it provides the most comprehensive and localized compilation of weather data. The resulting calculated energy consumption for a typical meteorological year is as follows.

TABLE 5. BASELINE ANNUALIZED ENERGY CONSUMPTION

MODEL DESIGNATION	ANNUAL ENERGY CONSUMPTION (KWH/YR)	AVERAGE MAXIMUM SUMMER PEAK (KW)
Baseline	779,983	241

POST-RETROFIT RESULTS

As with the baseline data, the post-retrofit HVAC power consumption data and outdoor air temperature data were used to develop a post-retrofit regression model. Again, the HVAC power consumption was plotted against outside air temperature to ensure that the same linear relationship still applied. As is evident from the graph below, the building HVAC power still shows a linear dependency on outside air temperature while the building is occupied. Therefore, the same analysis approach was expected to yield a regression model within a reasonable amount of uncertainty.

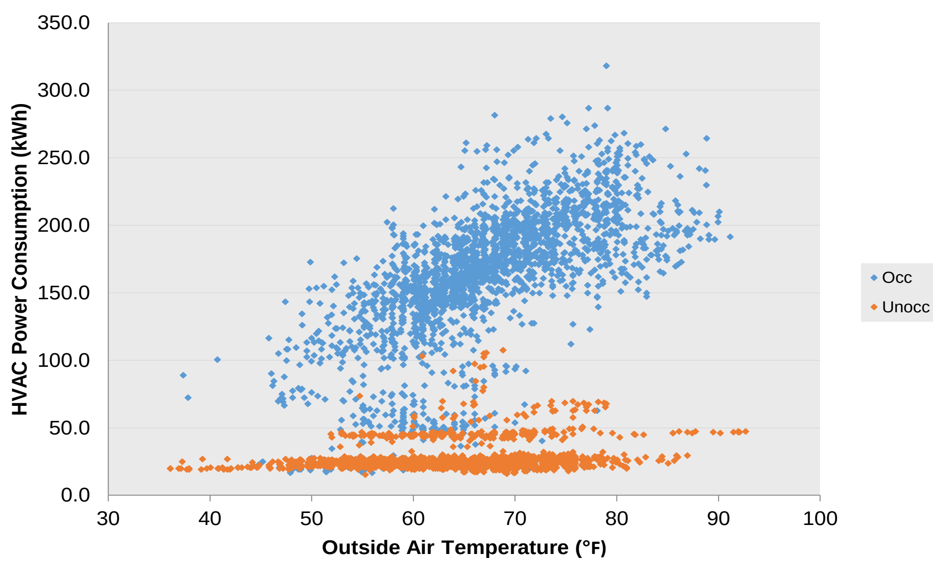

FIGURE 4. CORRELATION OF POST-RETROFIT HVAC POWER CONSUMPTION WITH OUTSIDE AIR TEMPERATURE

Post-Retrofit Regression Model Uncertainty Analysis

As expected, the post-retrofit regression model fit the real-world HVAC power consumption data within a reasonable margin of error. The graph below shows the model's fit to the data, and the table lists the same uncertainty measurements and standards used to assess the baseline model.

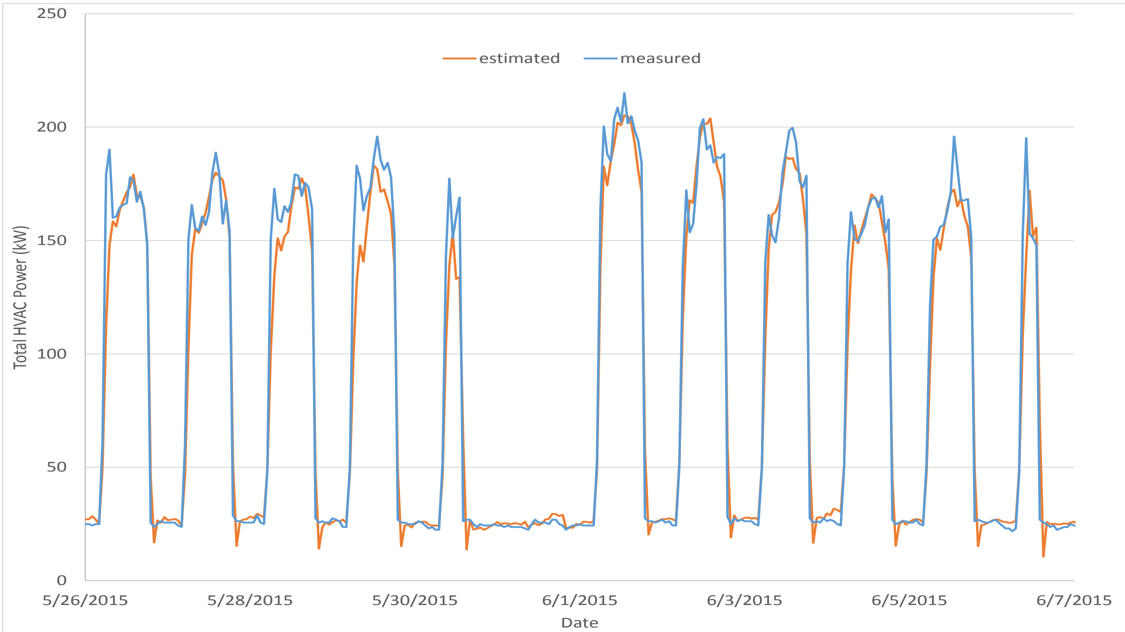

Figure 5. Comparison of Post-Retrofit Regression Model to Post-Retrofit Monitoring Data

Table 6. Post-Retrofit Model Error Analysis

Model Designation	Number of Data Points	R-squared Error	nRMSE
Post-Retrofit	5,159	0.952	19.5%

Note, as stated above, that these uncertainty values on their own do not definitively confirm that the model is a 'good fit.' The uncertainty of the final savings, calculated using this model and the baseline model, will ultimately determine if the models appropriately estimate the savings within a reasonable margin of error. Please see the Annual Energy Savings section, below, for a final assessment of the uncertainty.

Annualized Post-Retrofit Energy Consumption

Like the baseline model, the post-retrofit regression model was generated using real-world weather and HVAC power consumption data. During the 7-month post-retrofit monitoring period, the total energy consumption was approximately 444,600 kWh, and the maximum peak demand was 318 kW.

The same TMY-3 weather data used in the baseline was applied to the post-retrofit model in order to calculate energy consumption for a typical meteorological year, as seen below.

TABLE 7. POST-RETROFIT ANNUALIZED ENERGY CONSUMPTION

MODEL DESIGNATION	ANNUAL ENERGY CONSUMPTION (KWH/YR)	AVERAGE MAXIMUM SUMMER PEAK (KW)
Post-Retrofit	696,706	231

ANNUAL ENERGY SAVINGS

The difference between the baseline annual energy consumption and the post-retrofit annual energy consumption represents the annual energy savings for the predictive HVAC control software at this site. No adjustments to either model were required since there were no changes to the building loads or operation, other than the installation of the software, during the M&V period.

The predicted annual energy savings are 83,300 kWh, or 10.7% of the annual baseline usage. This savings estimate has a calculated uncertainty of 4.4% at 68% confidence. As discussed above, this uncertainty value is the result of the uncertainty in both the baseline and post-retrofit models. ASHRAE Guideline 14, which establishes uncertainty standards for energy efficiency M&V projects, states that for retrofit isolation M&V projects the uncertainty must be less than 50% of the annual reported savings[5]. The uncertainty of this final model is well within the ASHRAE Guidline 14 standards, and is therefore considered a reasonable estimate of the energy savings.

OCCUPANT COMFORT RESULTS

Space temperature data was collected during the entire monitoring period. This data was condensed into average weekday space temperature profiles both before and after implementation of the predictive HVAC control enhancement software. The graph below shows the baseline and post-retrofit space temperature data.

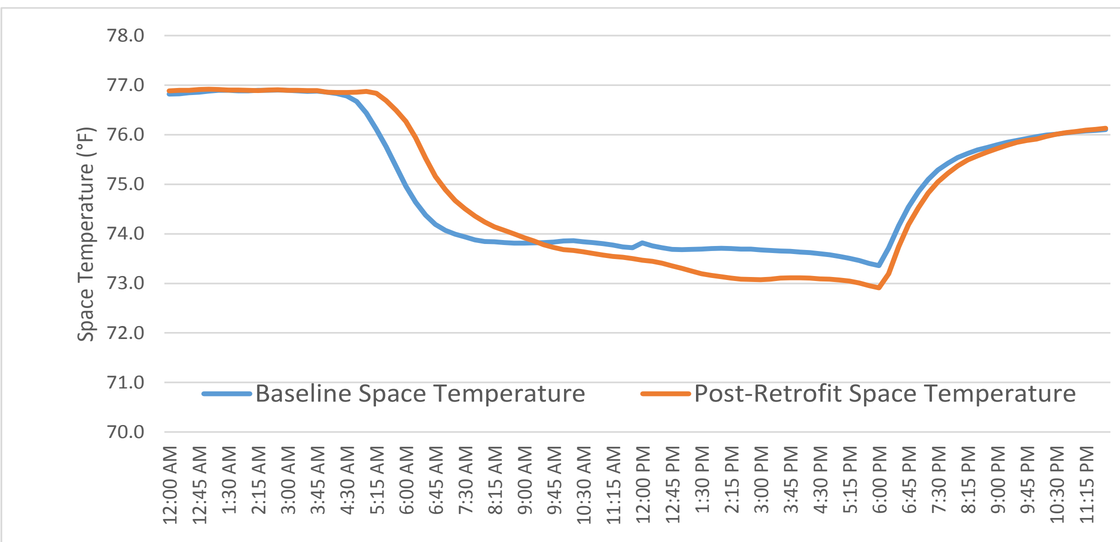

FIGURE 6. AVERAGE WEEKDAY SPACE TEMPERATURE PROFILES BEFORE AND AFTER PROJECT IMPLEMENTATION

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[5] ASHRAE Guideline 14-2014: Measurement of Energy and Demand Savings, American Society of Heating, Refrigerating and Air Conditioning Engineers.

As seen in the graph above, the average building space temperature is slightly higher in the post-retrofit system during the morning hours, and decreases below the baseline temperature in the afternoon. Although there are variations, the difference in space temperature is minimal and ranges from has increased in the post-retrofit system. Based on the data, the average temperature increases across all hours of the day, and the increase ranges from -0.6 °F to 1.3 °F.

In addition to the space temperature, the relative humidity was monitored inside the building. Based on the measured relative humidity and temperature, the humidity ratio was calculated. The following graph shows the average relative humidity and humidity ratio in the building before and after implementation of the predictive software system.

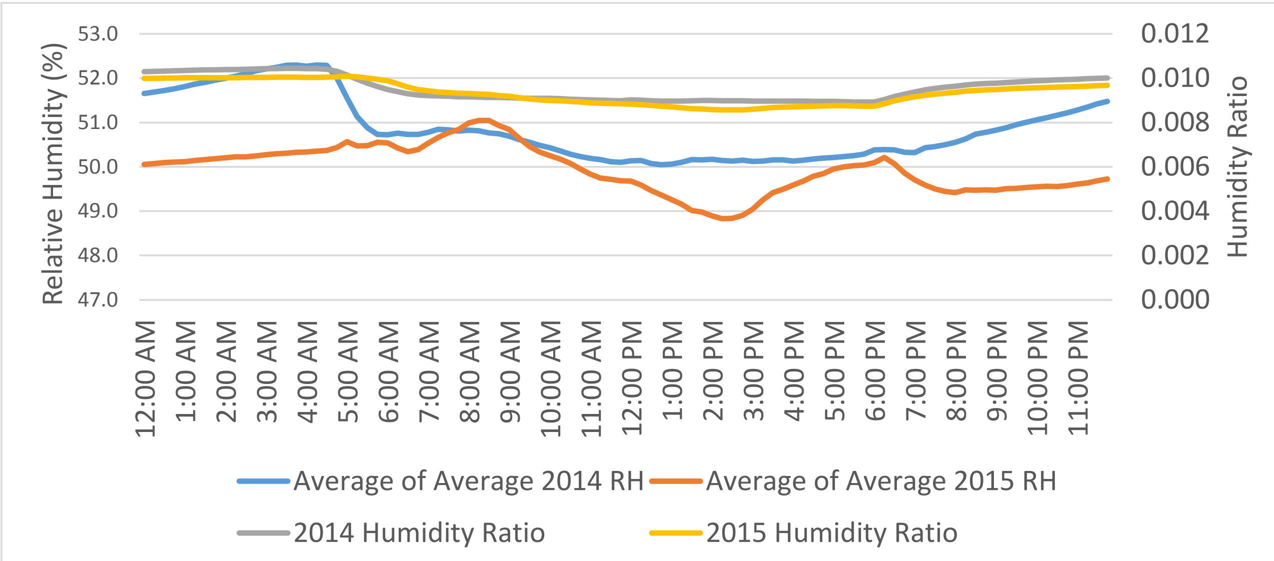

FIGURE 7. RELATIVE HUMIDITY AND HUMIDITY RATIO BEFORE AND AFTER SOFTWARE IMPLEMENTATION

DEMAND RESPONSE TEST RESULTS

As discussed in the Demand Response Test Plan above, the Standard 10-in-10 Baseline methodology with the "Morning-of Adjustment" factor was used to determine the demand response potential of the model-based predictive HVAC control enhancement software.

2-HOUR DEMAND RESPONSE TEST

Utility interval data was collected for 10 business days prior to the 2-hour demand response event which took place on June 15, and is presented in the table below. The kW hourly average is taken from SDG&E metered data for these 10 days, corresponding to every hour of the day that the demand response event occurred. The hourly averages of these 10 values are averaged to determine the baseline. The morning-of adjustment factor was applied for weather normalization purposes.

TABLE 8. STANDARD 10-IN-10 BASELINE WITH "MORNING-OF" ADJUSTMENT RATIO FOR JUNE 15TH

DATE	15:00 - 16:00	16:00 - 17:00
6/1/2015	202.72	200.80
6/2/2015	186.88	182.24
6/3/2015	192.00	180.96
6/4/2015	173.76	164.32
6/5/2015	179.52	163.20
6/8/2015	234.56	231.68
6/9/2015	230.08	216.00
6/10/2015	206.88	194.08
6/11/2015	205.92	198.24
6/12/2015	189.76	183.20
10-Day Average Baseline	**200.21**	**191.47**
Multiply by "Morning-Of" Adjustment Ratio	**1.17**	**1.17**
10-Day Average Baseline with "Morning-Of" Adjustment	**234.33**	**224.11**

The "Morning-Of" adjustment is incorporated to adjust baselines that are weather-sensitive and require weather normalization. The customer's morning demand for the four hours prior to the demand response event are averaged, and the morning demand for each of these same four hours is averaged across the 10 days leading up to the demand response event.

For example, if morning demand on the event day is much higher than the previous 10 days, the morning-of adjustment factor will adjust the baseline higher. The morning-of demand response average kW is divided by the prior 10-day demand response average kW to determine the morning-of adjustment factor for the standard 10-in-10 baseline. Any adjustment to the baseline is limited to plus or minus 40% of the existing baseline for Capacity Bid Programs or 20% for all other programs[6].

Interval data was used to determine that the morning hourly kW demand was higher than usual on the event days, and an adjustment factor was calculated to determine the baseline that was used in the calculations. As shown in Tables 8 and 9, a 17% morning of adjustment factor was applied to the two-hour test baseline, and a 10% morning of adjustment factor was applied to the four-hour test baseline.

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[6] Kaneshiro, Bruce. "Baselines for Retail Demand Response Programs." California Public Utilities Commission. March 12, 2009.

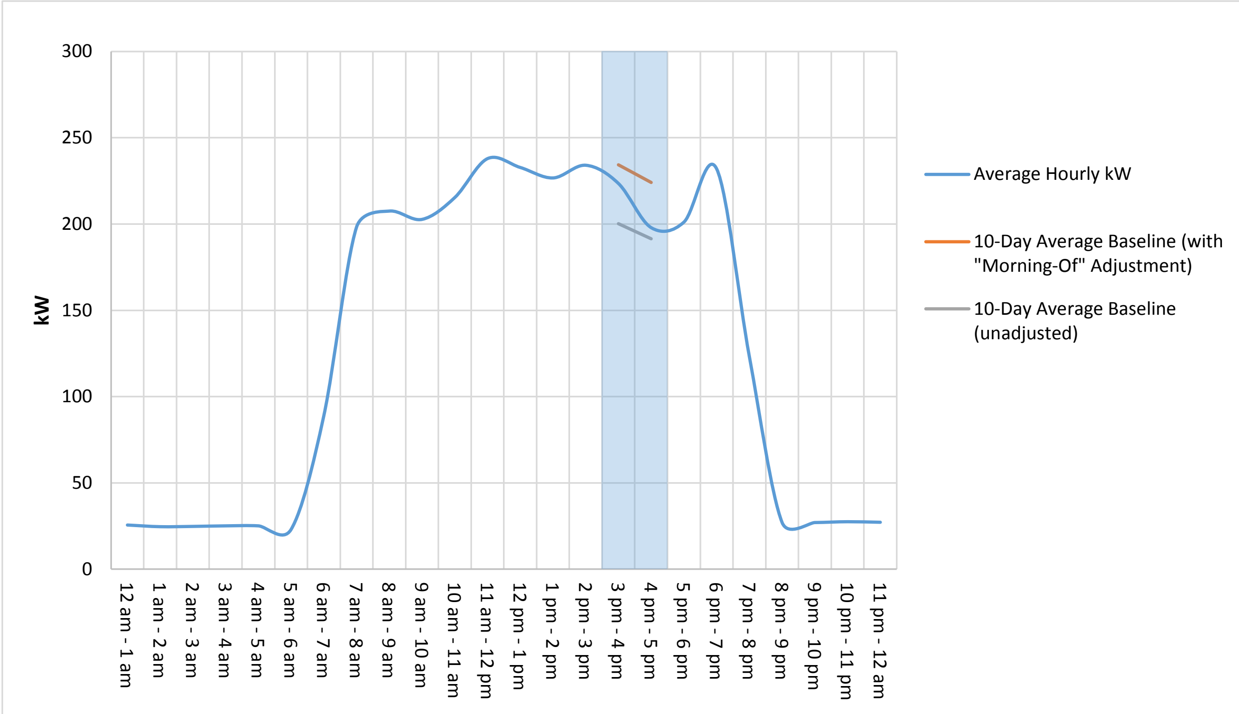

FIGURE 8. COMPARISON OF UNADJUSTED AND ADJUSTED 10-DAY AVERAGE BASELINES FOR JUNE 15TH

In the figure above, the morning-of adjustment factor was used to develop the "10-Day Average Baseline (with "Morning-Of" Adjustment) portion of the graph. This factor was multiplied by the 10-Day Average Baseline for each hour corresponding to the demand response event. As shown in Figure 7, the 10-Day Average Baseline with the morning-of adjustment factor was adjusted higher than the average baseline due to weather normalization. On the morning of the test event, building load was much higher compared to the previous 10 business days. If the morning-of adjustment factor were not used, the "Event Day Usage" would show an increase in demand relative to the baseline, rather than a decrease as compared to the adjusted baseline.

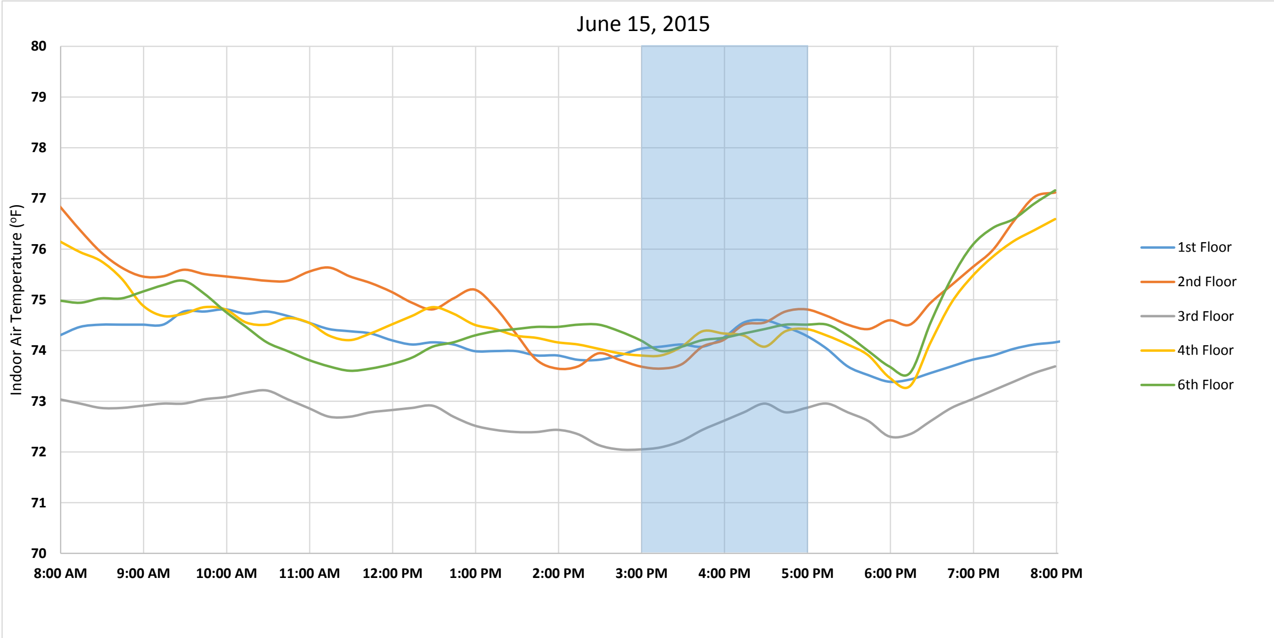

FIGURE 9. INDOOR BUILDING TEMPERATURES FOR EACH FLOOR ON JUNE 15TH

In the figure above, the temperature representative of each floor in the building was logged at 15 minute intervals. The 5th floor is not shown because it is an unoccupied floor. During the test event on June 15, the temperatures for the 2nd, 4th and 6th floors continued to decrease before gradually increasing. Meanwhile, the temperature seen at the 1st floor increased and decreased throughout the duration of the test event. The 3rd floor temperature steadily increased until approximately 4:30 PM at a temperature of 72.9°F, at which point it decreased before the demand response event had ended. The maximum temperature reached by any floor was seen on the 2nd floor, with a maximum temperature of 74.8°F. We believe that the indoor building temperatures for each floor could be raised further during the demand response event, while still maintaining occupant comfort that will result in additional DR savings.

4-Hour Demand Response Test

Similarly, data was collected for 10 business days prior to the 4-hour demand response event which took place on July 22. The kW hourly average was taken from SDG&E metered data for these 10 days, corresponding to every hour of the day that the demand response event occurred. The hourly averages of these 10 values were again averaged to determine the baseline for this test event, and the morning-of adjustment factor was calculated to determine the adjusted baseline.

Table 9. Standard 10-in-10 Baseline with "Morning-of" Adjustment Ratio for July 22nd

DATE	13:00 - 14:00	14:00 - 15:00	15:00 - 16:00	16:00 - 17:00
7/8/2015	193.28	195.2	193.76	180.64
7/9/2015	193.12	197.92	192.96	180.8
7/10/2015	183.36	180.32	184.48	175.68
7/13/2015	216.96	218.24	219.52	198.72
7/14/2015	216.32	216.96	196.16	187.2
7/15/2015	198.88	201.6	197.28	188.16
7/16/2015	201.44	204.16	189.44	185.6
7/17/2015	201.12	218.72	219.68	207.2
7/20/2015	307.04	269.76	249.12	239.52
7/21/2015	213.44	224.48	242.24	224.64
10-Day Average Baseline	**212.50**	**212.74**	**208.46**	**196.82**
Multiply by "Morning-Of" Adjustment Ratio	**1.10**	**1.10**	**1.10**	**1.10**
10-Day Average Baseline with "Morning-Of" Adjustment	**233.75**	**234.01**	**229.31**	**216.50**

On the morning of July 22, the event day demand was significantly higher than the demand during the same morning hours for the previous 10 business days. The 10-day average baseline was adjusted to reflect this. In the figure below, it is clear that without the morning-of adjustment factor, the event day usage would appear to be higher than the baseline usage during the majority of the demand response event.

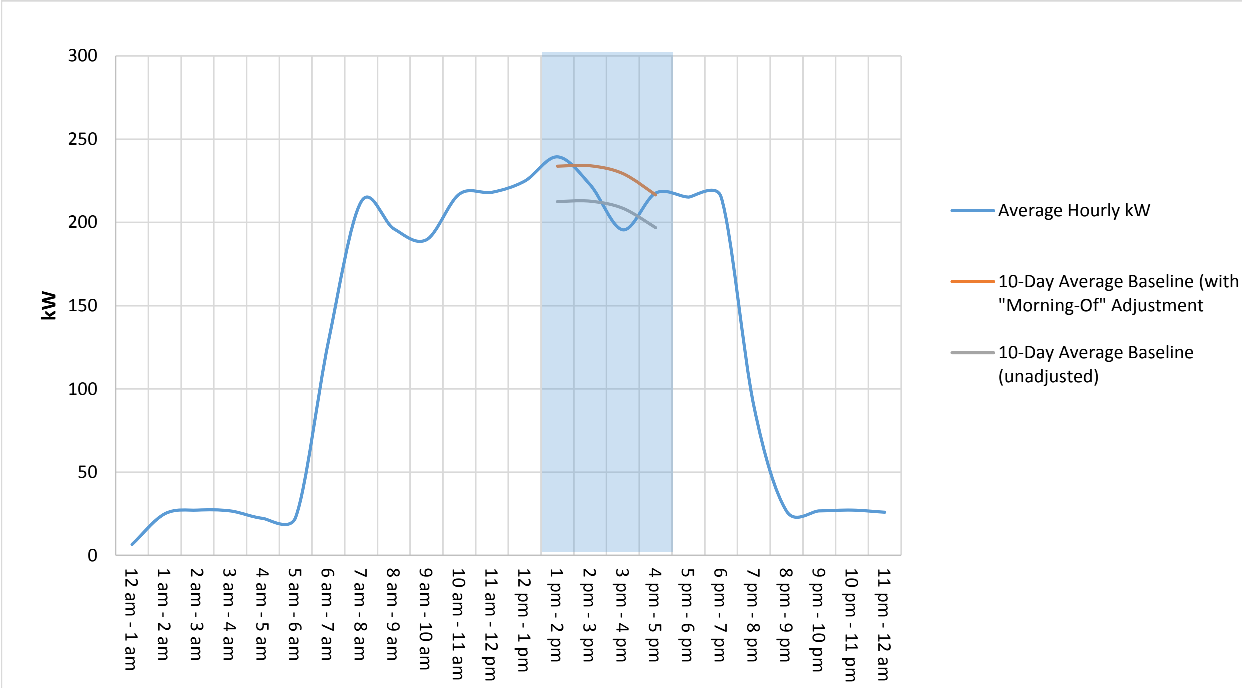

FIGURE 10. COMPARISON OF UNADJUSTED AND ADJUSTED 10-DAY AVERAGE BASELINES FOR JULY 22ND

With the morning-of adjustment baseline, the demand reduction for each event day was analyzed as shown in the following tables.

The interval data corresponding to the event day of June 15 shows that the actual kW read from the meter was higher than both the baseline kW and actual kW from the software provider's report. The morning-of adjustment factor was used to adjust the baseline from the metered data, because demand was higher on the morning of June 15 compared to the previous 10 business days.

TABLE 10. COMPARISON OF KW REDUCTION FROM METERED DATA VS. SOFTWARE PROVIDER REPORT FOR JUNE 15TH

TIME RANGE	15:00 – 16:00	16:00 – 17:00
Morning-of Adjustment Baseline (kW)	234.33	224.11
Actual kW on Event Day	223.52	197.92
kW reduction	**10.81**	**26.19**
% Reduction	**4.6%**	**11.7%**
Baseline kW from Provider's Analysis	181.86	176.76
Actual kW Reported by Provider	156.00	171.83
kW Reduction from Provider Data	**25.86**	**4.93**
% Reduction from Provider Data	**14.2%**	**2.8%**

The analysis shows that there is a 4.6% demand reduction during the first hour of the event and an 11.7% demand reduction during the second and final hour of the event. In comparison, the Building IQ data showed that there was a 14.2% demand reduction during the first hour of the event, and only a 2.8% demand reduction during the final hour of the event.

Similarly, the interval data corresponding to the event day of July 22 shows that the actual kW read from the meter was higher than the adjusted baseline for two out of the four hours during the test event. The morning-of adjustment factor was used to adjust the baseline from the metered data, because demand was higher on the morning of July 22 when compared to the previous 10 business days.

TABLE 11. COMPARISON OF KW REDUCTION FROM METERED DATA VS. SOFTWARE PROVIDER REPORT FOR JULY 22ND

TIME RANGE	**13:00 - 14:00**	**14:00 - 15:00**	**15:00 - 16:00**	**16:00 - 17:00**
Morning-of Adjustment Baseline	233.14	233.40	228.72	215.94
Actual kW on Event Day	239.36	222.56	195.52	217.60
kW Reduction	**-6.22**	**10.84**	**33.20**	**-1.66**
% Reduction	**-2.7%**	**4.6%**	**14.5%**	**-0.8%**
Baseline kW from Provider	198.49	191.21	183.16	185.45
Actual kW from Provider Report	172.27	167.76	182.79	174.98
kW Reduction from Provider Report	**26.22**	**23.45**	**0.37**	**10.47**
% Reduction from Provider Report	**13.2%**	**12.3%**	**0.2%**	**5.6%**

The analysis shows that the demand change for each hour of the demand response event was -2.7%, 4.6%, 14.5%, and -0.8% for hours 1-4, respectively. In comparison, the Building IQ data showed that the demand reduction for each hour of the event was 13.2%, 12.3%, 0.2%, and 5.6% for hours 1-4, respectively. While the SDG&E demand response document for calculating load reduction does not address the uncertainty associated with this methodology, it does state that one baseline may not fit a customer's entire usage pattern, and baselines do not work well with customers with highly variable usage patterns.

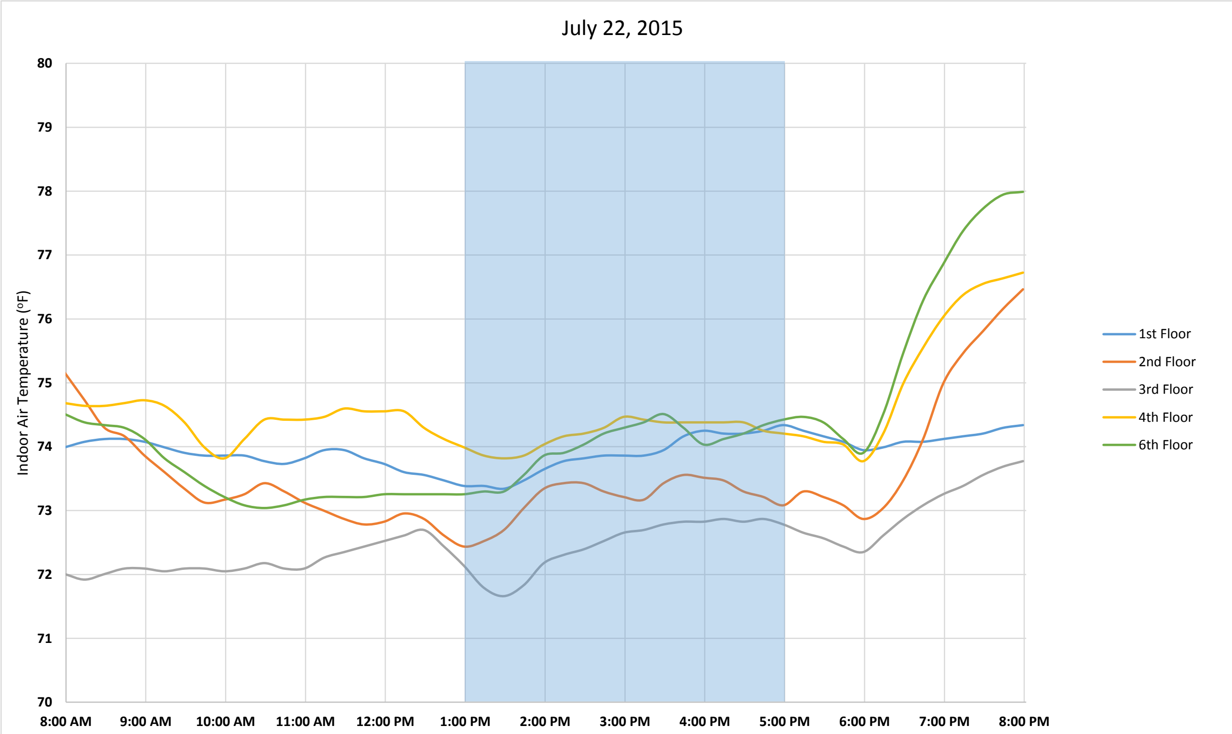

FIGURE 11. INDOOR BUILDING TEMPERATURES FOR EACH FLOOR ON JULY 22ND

In the figure above, the temperature representative of each floor in the building was logged at 15 minute intervals. The 5th floor is not shown because it is an unoccupied floor. During the test event on July 22, the temperatures for the 1st, 3rd, and 4th floors continued to decrease before gradually increasing. Meanwhile, the temperature of the 2nd floor steadily increased during the first hour of the event, after which point it continued to fluctuate for the duration of the event. The 6th floor temperature steadily increased until approximately 3:30 PM at a temperature of 74.5ºF, at which point it decreased before the demand response event had ended. The maximum temperature reached by any floor was seen on the 6th floor, with a maximum temperature of 74.5ºF. We believe that the indoor building temperatures for each floor could be raised further during the demand response event, while still maintaining occupant comfort.

In summary, the metered data shows higher actual building demand and differences in load reductions compared to what was recorded by the software provider. It is possible that there is additional equipment that is not being captured by the provider's metered data. However, demand reductions were verified for each hour of the June 15 test event using the Standard 10-in-10 baseline methodology combined with the morning-of adjustment factor. Demand reductions were also verified for two out of the four hours of the July 22 test event using this methodology. It may be necessary to perform additional test events in the future, for longer periods of time, to address any uncertainty or high variability in the building's usage pattern. Additionally, it is recommended that the indoor building temperatures for each floor to be raised further during the demand response event, while still maintaining occupant comfort, to obtain a more significant demand reduction.

PROJECT FINANCIALS

Based on the verified energy savings and costs supplied by the software provider, the cost-effectiveness of the model-based predictive HVAC control enhancement software was determined. For the purposes of this report, the cost-effectiveness is defined by the simple payback. The following tables innumerate the costs to the customer and the simple payback based on the calculated energy savings.

TABLE 12: PROJECT COST BREAKDOWN

Implementation Component	Type	Category	SaaS Yearly	5-Year Project	Explanation
Make Ready	Material	One Time	$1,500	$7,500	Computer appliance, site agent, connection to metering consumption and building control system
	Labor	One Time	$200	$1,000	½ Day Installation and Testing
	Expense	One Time	$200	$1,000	Travel and general admin
Initial Services	Labor	One Time	$900	$4,500	Configuration of AHU control points in software
	Labor	One Time	$600	$3,000	Project management, coordination with EMS vendor, building owner, facilities, and IT department
Technology Platform	Material	Annual	$3,700	$18,500	Software license annual cost – typically up front for the first 5 years of contract
Client Services	Labor	Annual	$7,000	$35,000	Remote energy management services including ongoing overview, optimization, anomaly detection, comfort tuning, and customer support
TOTALS			**$14,100**	**$70,500**	

The table above shows the project costs for the specific building studied in this report. According to the provider, customers typically enroll in a 5-year contract which includes all equipment, installation, software licensing, and client services. These 5-year costs are bundled and billed up-front. For this project, the total up-front cost was $70,500, which equates to $0.50 per square foot. After completion of the 5-year contract, the customer pays only the annual software licensing and remote energy management costs, which equates to $10,700 per year based on the table above.

Based on the costs listed above, and the verified energy savings, the project cost-effectiveness is summarized in the following table.

TABLE 13: PROJECT COST-EFFECTIVENESS

MEASURE DESCRIPTION	PEAK DEMAND SAVINGS (KW)	DR EVENT LOAD SHED (KW)	ELECTRICITY SAVINGS (KWH/YR)	TOTAL COST SAVINGS	MEASURE COST	SIMPLE PAYBACK (YEARS)	POTENTIAL UTILITY INCENTIVE	NET MEASURE COST	SIMPLE PAYBACK WITH INCENTIVES (YEARS)
Predictive HVAC Control	10	14	83,277	$10,826	$70,500	6.5	$18,192	$52,308	4.8

In the table above, the following assumptions are made:

- The blended electricity rate is $0.13 per kWh. Using a blended rate is likely to provide a conservative estimate of the annual cost savings because the predictive model-based HVAC control enhancement saves energy during daytime hours when electricity rates are typically higher than the blended rate.
- The measure will qualify for SDG&E's Energy Efficiency Business Incentives (EEBI) with a rate of $0.15 per kWh and $150 per kW. Please refer to the 'Conclusions' section for a recommended incentive program adoption.
- The measure will qualify for SDG&E's Technology Incentives (TI) with a rate of $300 per verified kW shed during a demand response event. Please refer to the 'Conclusions' section for a recommended incentive program adoption.
- The potential utility incentive for this project was determined by multiplying the energy, demand, and DR event savings by the corresponding incentive rates listed above: Incentive = (83,277 kWh x $0.15/kWh) + (10 kW x $150/kW) + (14 kW x $300/kW curtailed)

Additionally, note that the $70,500 measure cost above represents the initial cost of the system and 5 years of software licensing and service fees. This is the standard service contract length for the technology studied in this report, and also corresponds to the standard utility program incentive program duration of savings for reporting purposes. The customer will incur additional licensing and service fees beyond this initial 5-year period at a rate of $10,700 per year.

DISCUSSION

The following sections discuss the results of the baseline and post-retrofit measurement and verification study of the model-based predictive HVAC control enhancement software.

ENERGY SAVINGS

Based on the results of the measurement and verification of the predictive software installation, the system successfully reduced the annual HVAC energy consumption in the building. The software provider's website claims that savings of 10-25% in HVAC energy costs are achievable with the predictive HVAC control system. In this M&V study, the verified savings were 10.7%, which falls within the lower range of the provider's predictions. However, it is important to note that this study was limited to electrical savings because sufficient data to assess the gas savings was not available. Therefore, the actual building's on-bill savings may vary from the results presented in this report.

Although energy savings were verified in this study, it will be difficult to make any broad conclusions about the predictive HVAC control performance based on this individual test. Numerous factors affect the potential savings including the building type, operating profile, HVAC systems, and existing methods of HVAC control. In the building studied for this project, some energy-saving controls had already been employed, such as supply air temperature resets and water-side economizing, though some other typical energy reduction approaches, such as duct static pressure reset, were not implemented in the baseline. The savings are expected to vary dramatically based on the pre-existing energy efficiency controls that are utilized at the project site.

OCCUPANT COMFORT

The predictive HVAC control software analyzed in this study achieves energy savings by fine-tuning the air-side HVAC system operational set points based on predicted weather patterns. One concern with this control approach is that if the set points are modified too aggressively, occupant comfort may suffer. For this project, the occupant comfort was correlated to space temperature and humidity ratio, to correspond with the human occupancy comfort standards set forth in ASHRAE Standard 55-2013. As demonstrated in the M&V results, the space temperature varied slightly after the new software was installed, but not significantly enough to affect occupant comfort.

The following observations support the claim that space conditions have remained comfortable throughout the entire monitoring period.

- The space temperature variance ranged from -0.6 to 1.3 °F. The accuracy of the dataloggers used to measure space temperature is +/- 0.63 °F, and therefore the total uncertainty in the space temperature difference is +/- 1.26 °F. The maximum observed temperature increase was only slightly larger than the measurement error, indicating that the increase in temperature was not significant enough to differentiate it from the measurement error.
- According to the building engineer, there has been no increase in complaints of high space temperatures from occupants since the predictive HVAC control software was installed.
- ASHRAE Standard 55-2013, 'Thermal Environmental Conditions for Human Occupancy,' states that temperature can range from 67 °F to 82 °F and comfort can

still be maintained[7]. Additionally, this standard states that HVAC systems must be able to maintain a humidity ratio at or below 0.012. The pre-retrofit and post-retrofit data in Figure 7, above, show that the humidity ratio has been constant at approximately 0.010 throughout the entire monitoring period. At no point during the monitoring period was the indoor air temperature outside of this comfort range defined by ASHRAE Standard 55-2013.

Demand Response

The results of our study confirmed that the model-based predictive HVAC control enhancement software was able to reduce demand by approximately 6% on average, but it wasn't consistent as the results varied from -2.7% - 14.5% over the course of a four-hour test. The monitoring data showed that after an initial reduction in demand, the demand varied significantly over the entire 4-hour period. Although this is a very limited evaluation, this data shows that adjusting supply air temperatures and pressures as a demand reduction strategy can be unpredictable. The DR strategy to raise the set point temperature for the air conditioning systems can result in reduced demand, but it is not necessarily consistent throughout the event period. Experience and historical data can help improve what to expect when implementing this strategy.

Additional System Functionality

In addition to the energy savings and demand response potential that were measured in this study, the predictive HVAC control software includes other benefits that are difficult to quantify or isolate through an M&V process. In particular, the software provider acts as an energy agent to the customer by providing remote fault detection and on-call services to facilities engineers.

The building engineer at the location studied in this project stated during a telephone interview that the software provider contacted him on numerous occasions to inform him when supply air or return air temperatures exceeded their normal operating conditions. These remote observations allowed the building engineer to quickly assess and fix issues with his HVAC systems. Additionally, the building engineer noted that the provider was very responsive when he called them to report any hot calls in the building. The provider worked with the facilities staff to correct any issues that were causing hot calls without resorting to manual set point overrides.

Although no direct energy savings can be attributed to this service in this M&V study, both the remote fault detection and the on-call assistance with operational issues provide added benefit when compared to a traditional EMS, and should improve the persistence of energy savings by minimizing the frequency of manual set point overrides by facilities staff. By preventing manual overrides, the predictive HVAC control software should maintain control over set points more reliably.

Barriers to Implementation

Ultimately, the installed HVAC control software demonstrated energy savings and demand response potential. However, there were challenges with implementing the system.

The primary barrier to implementation was the need for, and challenges associated with, an outside network connection to the on-site EMS. During implementation at this project site, a change to the building's network communication protocols led the predictive software system to lose communication with the site's EMS. This lapse in communication spanned

[7] American Society of Heating Refrigeration and Air Conditioning Engineers, ASHRAE Standard 55-13 "Thermal Environmental Conditions for Human Occupancy." 2013.

numerous months, which significantly delayed project implementation. Since the end of the M&V testing, the facilities staff reported another change to the network settings from the building's IT department that has led to additional losses in communication with the system. These losses of communication have led to both project delays and reduced energy savings.

Another potential barrier to achieving persistent savings with this technology includes the reliance on the existing EMS. The predictive HVAC control software in this study does not include any sensors or control equipment – rather it 'piggybacks' on top of the existing EMS. While this can keep implementation costs down, it also means that the software's performance is only as good as the data it receives from the existing sensors. Depending on the vintage of the EMS, sensors may lose calibration or other aspects of the EMS may degrade prematurely, thus reducing the effectiveness of model-based predictive HVAC control enhancements.

Despite the observed and potential implementation barriers, in this particular case study the predictive HVAC control software was implemented successfully and demonstrated real, verified energy savings and demand response potential.

CONCLUSIONS

Based on the testing performed during this project, the following can be concluded:

- As shown in the Results and Discussion sections, there were verifiable electrical energy savings and demand response savings associated with the implementation of this particular model-based predictive HVAC control enhancement software. However, it is difficult to make any broad conclusions based on this data, because the savings are expected to vary significantly based on building types, climate zones, HVAC equipment sizing, and existing energy management capabilities.
- The predictive software set point adjustments did not infringe on occupant comfort. As demonstrated in the M&V results, the space temperature did show a slight increase after the software was installed but we confirmed that the post-install temperatures/humidity levels did not exceed applicable ASHRAE standard occupant comfort ranges.
- The EMS reliably received the DR signal from the predictive HVAC control software during all of the test periods. However, the project was delayed for a significant amount of time because the facility changed their network and the software lost all access to the facility data. This underlines the importance of a strong, reliable network connection as part of the communication chain.
- The predictive HVAC control software was able to reduce HVAC equipment demand during both a 2-hour and 4-hour simulated demand response event. These results will vary based on facility and existing HVAC equipment but will have issues if the cooling systems are undersized.
- The software was able to reduce demand by approximately 6% on average but it wasn’t consistent as the results varied from -2.7% to 14.5% over the course of a four-hour test. Additional DR savings could have been achieved if the customer was willing to be more aggressive with their set points during the event but the offset would have been occupant comfort.

Of particular importance to this study is the fact that the achieved energy savings demonstrate potential that goes above and beyond the current technology required by 2013 Title 24 building energy code. However, since the building included in this study did not meet all of the current Title 24 standards it cannot be concluded that 100% of the verified energy savings go above and beyond what code requires. Future studies should establish that the buildings are code compliant before implementation of the model-based predictive HVAC control enhancement software.

RECOMMENDATIONS

This field evaluation demonstrated the potential for this and other model-based predictive HVAC control enhancement software systems to yield energy savings that exceed Title 24 code requirements and allow for automated demand response. Therefore, this measure could be successfully adopted into the state-wide customized incentive programs, including SDG&E's Energy Efficiency Business Incentives program (EEBI) and SDG&E's Technology Incentive program (TI).

ENERGY EFFICIENCY BUSINESS INCENTIVES (EEBI)

This report recommends that SDG&E incorporate model-based predictive HVAC optimization software into its existing EEBI program. The following section details the recommended measure details, incentive classifications, and M&V requirements. Since this report concludes that the energy savings could vary widely based on the existing building conditions, building type, and climate zone, significant M&V would be required for each project to verify the savings. Since baseline and post-retrofit M&V data are used to establish the savings, it is difficult to isolate the above code savings from the on-bill savings. However, this technology should be targeted for installation on existing energy management systems that still have significant remaining useful life. Therefore, this measure would be treated as a 'retrofit add-on' (REA) project type within state-wide customized incentive programs, so the actual on-bill energy savings would be eligible for incentive. The following table summarizes the recommended incentive program, applicable measure information, and suggested M&V requirements for program participation.

TABLE 14. ENERGY EFFICIENCY INCENTIVE PROGRAM DETAILS

SDG&E Incentive Program	Energy Efficiency Business Incentives (EEBI)
Measure Type	Retrofit Add-On
Measure Name	Smart Controls/Energy Management System
Incentive Category	Targeted
Incentive Rate	$0.15 per kWh; $150 per kW
M&V Requirements	M&V should be conducted in accordance with IPMVP Option B: Retrofit Isolation Analysis. The following data points should be collected in 15-minute increments from the baseline and post-retrofit systems. Data shall be collected for a period no less than two months, and should be sufficient to cover the full range of outdoor air temperatures. Data should include: - Power consumption of all HVAC equipment, taken from utility sub-metering or stand-alone data loggers. - Outdoor air temperature from on-site sensors or local weather stations. This data should be used to develop a regression model that estimates the energy savings within ASHRAE 14 uncertainty standards. Note that alternative M&V plans under IPMVP Option B would be possible, and should be evaluated on a case-by-case basis.

Since the calculated simple payback for this measure is five years or less, including incentives, this measure would qualify for on-bill financing (OBF).

TECHNOLOGY INCENTIVES (TI) PROGRAM

This study also confirmed that the model-based predictive HVAC control enhancement software can successfully interact with utility automated demand response (ADR) servers and shed load. Therefore, this technology should be eligible for SDG&E's TI program, which incentivizes eligible customers to install the necessary technology to participate in ADR programs. The following additional conditions must be met in order for a specific technology or building site to participate in SDG&E's TI program:

- The installed technology must have Open ADR 2.0a certification in order to be eligible. The particular software studied in this report is ADR 2.0b certified, not ADR 2.0a. However, the software provider stated during a telephone interview that ADR 2.0a certification is forthcoming and expected by the end of 2015.
- The building must have a utility interval meter installed, capable of reporting power consumption data in 15-minute increments. At a minimum, all of the HVAC equipment must be energized through this meter, though whole-building interval data is preferred.

The TI incentive will be calculated based on real-world test data during a simulated demand response event. This is the same approach used to test the DR load shed potential of this technology, as described in the 'Demand Response Test Results,' above. This test data provides the estimated load shed capabilities of the system.

SDG&E's current TI program pays incentives of $300 per kW, as verified during the DR load shed testing. 60% of this incentive is paid up-front, and 40% of the incentive is paid at the end of one year of operation, and only if the real-world load shed meets the estimated load shed determined during the DR testing.

POTENTIAL NEXT STEPS

The building selected for study in this project did not meet all of the Title 24-2013 requirements prior to the model-based predictive HVAC control enhancement installation. Therefore, this study cannot identify what portion of the energy savings exceed code requirements. For utility incentive reporting requirements, the above-code savings must be demonstrated and calculated. Additionally, prior to removing the extensive M&V requirements for this measure, the savings must be demonstrated across a wider range of building types and climate zones in order to develop a more comprehensive model of the energy savings. Additional M&V efforts must be undertaken in order to achieve these goals.

If this measure is adopted into existing incentive programs, the verified savings of each project should be tracked and catalogued. In particular, the following information should be tracked:

- Annual energy savings in projects where the baseline system meets Title 24.
- Verified annual energy savings across a wider range of building types.
- Verified annual energy savings across a wider range of climate zones.

With this data, a clearer picture of what building characteristics most heavily influence the savings potential of the predictive software can be established. More clearly defining these parameters will yield more accurate models of the savings. Ultimately, with enough data, a reliable model could be developed that does not require significant monitoring data input. At this time, the technology would be ready for adoption into compliance tools, energy saving calculation software packages, and core incentive programs without the additional M&V requirements that are recommended in this report.

APPENDICES

APPENDIX A: ADDITIONAL M&V FIGURES

The following figures provide additional details on the measured data results. This information was included in the test plan but did not yield information that was pertinent to the final analysis.

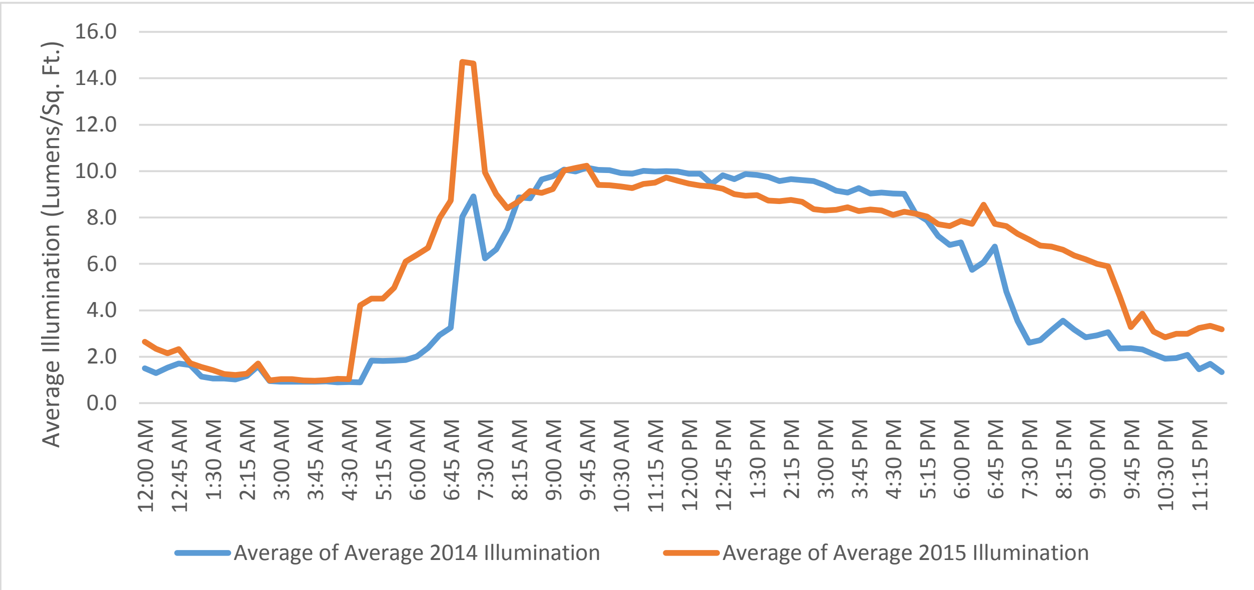

FIGURE 12. AVERAGE ILLUMINATION BEFORE AND AFTER PREDICTIVE SOFTWARE IMPLEMENTATION

Light levels were recorded to ensure that the measured reduction in HVAC power consumption did not correlate with reduced lighting levels in the spaces. Reduced lighting power consumption, indicated by reduced illumination levels, would lower the heat gain in the building and reduce the cooling load, yielding energy savings that are not directly attributed to the predictive HVAC control software. However, the data revealed no significant variation in light levels in the spaces during the monitoring period. Additionally, facilities staff confirmed that no lighting retrofits have been performed since the beginning of the data collection period. Therefore, no adjustments to the HVAC power consumption were made.

APPENDIX B: DATA AND CALCULATION FILES

The following data and calculation files were used to generate this report. All external data files will be made available upon request.

HVAC INTERVAL DATA

The following data files were used to build the regression models as well as in the demand response calculations.

DR13SDGE0006 - HVAC Interval Data -

DR13SDGE0006 - HVAC Interval Data -

REGRESSION MODEL CALCULATION FILES

The following files include the data used to generate the regression model, and the model simulation files from the modeling program, 'R.'

DR13SDGE0006 - Regression Model Data.zip

OCCUPANT COMFORT DATA

The following data was compiled from the stand-alone dataloggers that were installed throughout the studied building. This data includes space temperature, relative humidity, and light levels.

DR13SDGE0006 - Occupant Comfort D

DEMAND RESPONSE TEST DATA

The following data was used to determine the demand response savings during the 2-hour and 4-hour demand response tests. This sheet contains the overall peak demand savings calculations as well.

DR13SDGE0006 - Demand Response (

PROJECT FINANCIALS

DR13SDGE0006 - Project Financials.xls