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FINAL PROJECT REPORT

Automated Cloud-Based Continuously Optimizing Energy Management System

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PREPARED BY:

Michel Kamel	Mary Ann Piette	Richard Schorske	Michael Sontag
Dotty Hage	Marco Pritoni	Sam Irvine	E3
MelRok	LBNL	ZNE Alliance	

Primary Authors

Amir Ehyai
Project Manager
California Energy Commission

Agreement Number: EPC-16-034

Virginia Lew
Office Manager
ENERGY EFFICIENCY RESEARCH OFFICE

Jonah Steinbuck, Ph.D.
Director
ENERGY RESEARCH AND DEVELOPMENT DIVISION

Drew Bohan
Executive Director

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PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission, and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation, and bring ideas from the lab to the marketplace. The EPIC Program is funded by California utility customers under the auspices of the California Public Utilities Commission. The CEC and the state's three largest investor-owned utilities—Pacific Gas and Electric Company, San Diego Gas and Electric Company, and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

For more information about the Energy Research and Development Division, please visit the CEC's research website (www.energy.ca.gov/research/) or contact the Energy Research and Development Division at ERDD@energy.ca.gov.

ABSTRACT

The *Automated Cloud-Based Continuously Optimizing Building Energy Management System* (ACCO-BEMS) cost-effectively overcomes limitations of existing Building Energy Management Systems through cloud-based and automated control of energy-related building devices, systems, and sensors. Developed by MelRok in collaboration with the DOE Lawrence Berkeley National Laboratory, ACCO-BEMS has been used at Pomona College to catalyze reductions of building energy use through its automated optimization of energy controls, fault detection, and automated work order dispatch. This includes a novel occupant counting technique based on a number of devices connected to the Wi-Fi network (such as cell phones, computers).

Keywords: California Energy Commission, Pomona College, ACCO-BEMs, Building Energy Management Systems, Cloud Control, HVAC, measurement and verification, occupancy sensing, Wi-Fi occupancy, energy efficiency, business case, machine learning, self-driving buildings.

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Introduction

Achieving—and sustaining—building energy efficiency gains has been a challenge for building managers for decades. Even when buildings are properly constructed and calibrated to optimize their efficiency upon initial commissioning, maintaining optimum settings in the face of changes in mechanical system performance, occupancy and weather shifts, Building Energy Management software limitations, and imperfect maintenance is a persistent challenge that undermines efficiency gains over time. In a 2009 study of 24 university buildings in California by Mills et al, the building systems were observed to "drift" substantially from their optimum performance – leading to more than 40 percent waste in the building's total energy consumption.

Project Purpose

The Automated Cloud-Based Continuously Optimizing Building Energy Management System (ACCO-BEMS) Project was developed as a partnership between the Zero Net Energy Alliance, MelRok IoT, Lawrence Berkeley National Laboratory, Pomona College, E3, Correlate, HELiOS Energy Efficiency Exchange, and Ecoshift Consulting to substantially reduce energy use and maintain optimum performance in diverse buildings and large campuses, with Pomona College as the initial test case. This project explored substantially and sustainably reducing energy use in diverse buildings and large campus environments with automated, cloud-based systems, including: heating, ventilation, and air conditioning, lighting, and legacy control systems.

The Automated Cloud-Based Continuously Optimizing Building Energy Management System (ACCO-BEMS) platform goal is to enable substantial energy efficiency gains, (by 20 percent or more), and to improve the ability of energy managers to monitor and optimize a large portfolio of buildings, automating previously manual tasks using context-sensitive algorithms.

Project Approach

The team, led by Zero Net Energy Alliance with Melrok, Inc., and E3 providing measurement and validation, used the ACCO-BEMS in 10 campus buildings. The ACCO-BEMS was designed to effectively optimize the management of building sensors, energy consuming devices, and existing energy management systems.

This innovative system allows buildings to run more efficiently through automated, cloud-based, and continuous optimization of building systems, including heating, ventilation, and air conditioning (HVAC), lighting, and legacy control systems.

The team implemented the ACCO-BEMS in two phases: a continuous commissioning phase, and a cloud control phase encompassing 10 buildings on the campus. Half of these buildings had retro-commissioning with energy efficiency measures conducted before activating the cloud-based ACCO-BEMS controls, while the remaining buildings did not undergo retro-commissioning before cloud control activation.

The project team facilitated the following efforts including designing the audit and profile of the campus buildings, connecting the energy systems and cloud based-analytics, installing occupancy sensing devices with Wi-Fi data, measuring and validating the project effectiveness, and facilitating a technical advisory committee to provide input on project progress.

Project Results

Savings on the continuous commissioning phase of the project (before the cloud control features of ACCO-BEMS) averaged 7.3 percent per commissioned building, or 10 percent of total energy for the five buildings. Savings during the cloud control phase of ACCO-BEMS were more challenging to calculate because of COVID-related campus closures. However, comparison of energy use during daytime weekday hours with cloud control ON to that of daytime weekday hours with cloud control OFF in the months after the start of the pandemic demonstrated up to 25 percent decrease in energy use compared to hours with cloud control OFF. The energy decrease for hours with cloud control ON was about 16 percent on average per building.

The teams found that the ACCO-BEMS is estimated to reduce costs of energy audits and re-commissioning by 35 percent+ by eliminating manual building energy management systems reprograming and manual adjustments on energy-consuming devices; yielding enhanced occupant comfort and indoor air quality with better temperature control. ACCO-BEMS also enables real-time automated demand response capability in buildings where it is used, resulting in almost 2 gigawatt hours (GWh) of annual energy savings in Pomona College alone. The potential for energy savings in the other six co-located Claremont Colleges approaches 6 GWh annually.

Knowledge Transfer

The project team facilitated a technical advisory committee to provide input on project progress, publication of peer reviewed papers, participation in outreach events, and the founding of the Aliso Canyon Partners Network. This Network shared information and resources about the automated building energy management systems capabilities to Energy Service Companies and large campuses in the Aliso Canyon area that were prioritized for electricity demand reductions by Southern California Edison.

Benefits to California

Benefits of scaled use of ACCO-BEMS across California are likely to include reduced energy use and associated greenhouse emissions, reduced building operational costs, and improved occupant comfort and indoor air quality.

ACCO-BEMS is estimated to reduce costs of energy audits and re-commissioning by 35 percent or more by eliminating manual building energy management systems reprograming and manual adjustments on energy-consuming devices.

Significant savings from the ACCO-BEMs platform were identified for the 263 buildings and more than 17 million square feet of floor area owned and operated by the participating institutions in the Aliso Canyon Partners group. Electricity savings of more than 14 GWh per year were identified representing 7,394 kilowatts (kW) of peak demand savings. Furthermore, fuel savings of more than 16 billion British thermal units (Btu) per year were identified. Collectively these savings represent emission reductions of 67,184 million tonnes of carbon dioxide equivalents per year and annual cost savings of more than $2.5 million.

In addition to sustained energy savings, ACCO-BEMS enables real-time automated demand response capability in buildings where it is used. Pomona College peaks at more than 4 MW load, with the rest of the Claremont colleges peaking at 10 MW. Deploying ACCO-BEMS across all the colleges could enable more than 1MW of automated demand response potential.

CHAPTER 1: Introduction

Project Overview

In a study of 24 university buildings in California (Mills, 2009), buildings were observed to "drift" from their optimum performance achievable through continuous commissioning. This drift can lead to more than 40 percent waste in the building's total energy consumption. Even so, the return on investment in costly manual interventions to correct drift is not compelling for most building owners, given that re-commissioning may need to be repeated as often as every few months to sustain the savings. Unfortunately, conventional building energy management systems (BEMS) fail to optimize energy use because pre-determined settings become rapidly obsolete, and most BEMS are not able to continuously and automatically optimize set points for key systems, such as variable frequency drives, valve positions, and damper positions. Conventional BEMS also do not respond dynamically to changes in building schedules and room occupancy, and they are not cognizant of current and forecasted environmental factors and grid conditions that would enable optimization of energy use.

To address these challenges, the Automated Cloud-Based Continuously Optimizing Building Energy Management System (ACCO-BEMS) has been designed to continuously optimize the management of building sensors, energy consuming devices, and existing energy management systems through an artificial intelligence (AI)-enabled analytics engine that uses: 1) a universal cloud-connected gateway; 2) extremely wide networking bandwidth, 3) high-level encrypted security; 4) elastic cloud storage and processing capacity; and 5) real-time access to web-resident live databases to optimize for environmental and device-level attributes. Furthermore, the system has been integrated with open source Wi-Fi occupancy sensing technology developed by Lawrence Berkeley National Laboratory (LBNL) as part of this grant engagement.

This project developed and demonstrated an AI-enabled software platform that allows buildings to run more efficiently through automated, cloud-based, and continuous optimization of building systems, including heating, ventilation, and air conditioning (HVAC), lighting, and legacy control systems. These features were implemented at Pomona College in 11 campus buildings, half of which had the ACCO-BEMS platform installed as a new building energy management system, while the remaining buildings had the ACCO-BEMS platform interface with the existing building management system and controllers.

LBNL developed and deployed software using Wi-Fi data to estimate building occupancy in buildings at Pomona College. Occupancy data was used in retrospective analysis, to understand past energy use and the underlying drivers. Despite the importance of occupancy, energy information systems for buildings do not typically track occupants' presence or location (Price et al., 2015). Conventional occupancy sensors (for example, infrared, ultrasound, or CO2) have been expensive to install and to connect to a central information system, especially in an existing building, and have often had questionable reliability. However, there is considerable potential to deploy less costly occupancy sensing that "piggy-backs" on existing Wi-Fi systems and provides enhanced reliability. Occupancy data can be used in real-time applications, including building controls that enable dynamically adapting static schedules to respond to occupancy data (Pritoni, 2017; Balaji et al., 2013; Storey & Montgomery, 2014; Henderson, 2016; Sensible Building Science, 2015). Occupancy data can also be used in retrospective analysis, to understand past energy use and the factors driving it, such as measurement and verification (M&V) or fault detection and diagnostics. (Price et al., 2015; Pritoni, 2017)

To address the occupancy data gap, LBNL identified several potential data sources for implicit occupancy sensing in buildings, and found that data from Wi-Fi systems offers the best single opportunity for the following reasons: (Pritoni et al., 2017)

- It is the most widespread single method available—applicable to nearly any building type
- It is relatively easy to implement from an IT perspective
- The concept of Wi-Fi device counts being correlated to occupancy is easy for people to understand, even for those with limited network technology experience
- Wi-Fi technology is served by a modest number of key manufacturers (for the commercial sector at least), thus simplifying integration
- Wi-Fi device counts are notable for a low latency of detecting arrival and departure of devices.

In light of the potential for ubiquitous occupancy sensing to support deployment of automated BEMS at low cost and high reliability, the project sought to integrate deployment of the two systems and assess their potential contributions to energy savings and occupant comfort.

Project Goals and Objectives

The goals of the project were to:

1. **Substantially and sustainably reduce energy use in diverse buildings and large campuses** by continuously assessing real-time building performance versus energy baselines and building energy modeling algorithms – and by automatically adjusting energy use of critical systems through ACCO-BEMS technology.
2. **Demonstrate seamless cloud-based integration of ACCO-BEMS with existing building energy management controls and devices** – by connecting islanded and proprietary systems to an energy internet of things (Energy IoT) gateway for real-time data access and continuous control.
3. **Use a Wi-Fi based technology to estimate occupancy in buildings**.
4. **Reduce operational and maintenance costs of buildings** by automating energy management systems and fault detection; and by providing access to real-time data on occupancy and environmental conditions, automated system adjustments, and energy use.
5. **Accelerate use of ACCO-BEMS and related efficiency measures in the Aliso Canyon** impact area via the *Aliso Canyon Energy Partners' Network* to achieve deep

and sustained energy reductions – with an initial focus on: 1) major higher education campuses; 2) major retail chains; and 3) multi-building corporate headquarters.

The Objectives of the project were to:

1. **Reduce energy use by 20 percent+ in 11 mixed use buildings** – including 10 buildings at the Pomona College campus.
2. **Demonstrate automated control and optimization** of chillers, air handlers, variable air volume terminal units, variable frequency drives, economizer vanes, environmental and occupancy sensors, light and plug load controllers, and thermostats.
3. **Reduce costs of energy audits and re-commissioning by 35 percent+** by eliminating manual BEMS reprograming and automatically reporting faulty sensors and devices.
4. **Estimate energy savings and auto demand response potential of ACCO-BEMS** by analyzing 12 months of Smart Meter data in 150 buildings, through the development of the Aliso Canyon Energy Partner's Network (ACEPN).[1]

Technological Advancement and Breakthroughs

Multiple technological advancements and breakthroughs were identified and developed throughout the project implementation. The ultimate outcomes of the engagement represent the ability to automate management of building energy usage, signifying the paradigm shift from existing building energy management systems – which typically rely on manual interventions and recalibration to correct faults and re-calibrate system set-points. In addition to identifying energy efficiencies in the range of 20 percent+, the ACCO-BEMS platform improved the ability of energy managers to monitor and optimize a large portfolio of buildings, automating previously manual tasks using self-driving building algorithms.

Further, LBNL developed the COUNT software for data collection, and also developed the automatic data cleaning pipeline for estimating occupancy from Wi-Fi data. In addition, three applications were created:

1. Improving HVAC schedules
2. Enabling dynamic ventilation rates
3. Forecasting future loads more accurately

Wi-Fi occupancy data was used to:

- Track key building occupancy metrics, essential for accurate energy benchmarking and modeling.
- Provide data for dynamic building operation, at much lower cost than physical sensors.

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[1] California Public Resources Code, Section 25711.5(a) also requires EPIC-funded projects to lead to technological advancement and breakthroughs to overcome barriers that prevent the achievement of the state's statutory and energy goals.

Pre-optimization Energy Survey

Pomona College campus, like so many other campuses and commercial buildings, lacked needed insight into their building operations. It was thus necessary to audit and profile those buildings to understand how they operate and to create a baseline for comparison.

Augmented Level I American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE)-compliant energy audit reports were executed. The Pomona College Fiscal Year (FY) 2018, which starts July 1, 2017, and ends June 30,2018, was chosen as the baseline year. In addition to identifying the baseline, an M&V plan was prepared.

MelRok conducted an ASHRAE level I assessment of the buildings on the campus of Pomona College used in this project. The maintenance staff of the facilities was interviewed, and the facilities' critical energy equipment and power distribution networks were surveyed. Table 1 is a summary of monthly Energy Use Intensity (EUI) in thousand British thermal units per total square feet (kBTU/(ft^2-T)) for FY 2018, the baseline year.

Table 1: Summary FY 2018 Monthly EUI for All ACCO-BEMS Buildings

	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
JC Cowart IT Building	69.09	65.19	74.68	73.11	79	73.13	69.82	61.99	73.89	66.19	69.34	67.85
Mudd Science Library	10.36	12.99	15.81	14.23	12.73	11.54	11.77	12.11	13.35	13.25	13.22	11.96
Alexander Hall	13.59	16.91	13.36	13.97	13.81	11.21	12.08	12.03	14.45	12.57	12.6	12.85
Smith Campus Center	27.46	23.37	30.46	29.16	29.28	27.35	29.28	29.11	32.83	30.23	29.7	28.79
Carnegie Building	9.64	10.27	11.38	11.94	13.36	12.04	13.74	14.58	14.47	13.55	13	9.78
Crookshank Hall	6.07	6.55	7.19	7.54	8.07	7.52	8.26	8.24	8.92	7.81	7.51	5.84
Hahn Building	65.71	73.57	62.67	58.01	39.88	26.95	26.99	41.09	49.25	43.15	39.4	49.18
Mason Hall	9.31	9.74	9.81	10.45	11.45	10.13	11.26	11.84	12.32	10.91	10.7	9.7
Pearsons Hall	10.21	10.43	11.37	12.31	13.56	13.29	1.25	14.35	15.29	13.46	13.25	10.32
Thatcher	NaN	NaN	NaN	NaN	NaN	NaN	0.03	48.28	56.83	39.06	40.61	24.74

Note: kBTU/(ft^2-T) and FY 2018 – MelRok.

The findings of the survey were documented in the *ACCO-BEMS Initial Audit Report* and only a summary is presented in this report. The detailed report provides an executive summary of each building that includes the building's energy use, cost, and emissions summary along with the building's EUI relative to a comparable building's Energy Star score. In addition, Energy Improvement Measures recommendations were made. The report lists the major HVAC and lighting equipment, the power distribution and metering infrastructure, and an audit of each building's BEMS. Examples of the summary information are presented in Table 2 and 3.

Table 2: Example of 2018 Energy Use, Cost and Carbon Footprint Summary

	Unit	Alexander Hall	% of Campus
Total Energy Usage (kWhr)	kWhr	760,798	1.7%
Total Owned Site Green Power (	kWhr	0	0.0%
Total Purchased Green Power	kWhr	0	0.0%
Total Purchased Electric Power	kWhr	347,304	1.5%
Total Site Electric Usage	kWhr	347,304	1.5%
Total Gas Usage	Therms	14,109	2.0%
Total Energy Usage (kBTU)	kBTU	2,595,950	1.7%
Total Electric Usage	kBTU	1,185,050	1.5%
Total Gas Usage	kBTU	1,410,900	2.0%
Total Utility Cost	$	$46,159	1.6%
Total Electric Cost	$	$34,730	1.5%
Total Gas Cost	$	$11,428	2.0%
Total Emissions	Metric Ton CO_2e	172	1.7%
Total Electric Emissions	Metric Ton CO_2e	97	1.5%
Total Gas Emissions	Metric Ton CO_2e	75	2.0%

2018 documented for each building for the baseline year, FY 2018 - MelRok

Table 3: Example of Energy, Cost and Emissions Intensities for Each Building

		Alexander Hall	
	Unit	Actual	EnergyStar
Area	ft^2	32,776	
% Green Power	%	0	
Site EUI (kBTU/ft2)	$kBTU/ft^2$	79.2	59.6
Electric EUI	$kBTU/ft^2$	36.2	
Gas EUI	$kBTU/ft^2$	43.0	
Source EUI (kBTU/ft2)	$kBTU/ft^2$	158.7	141.4
Electric EUI	$kBTU/ft^2$	113.5	
Gas EUI	$kBTU/ft^2$	45.2	
Total Utility Cost Intensity	$\$/ft^2$	$1.4	
Total Electric Cost	$\$/ft^2$	$1.1	
Total Gas Cost	$\$/ft^2$	$0.3	
Total Emissions Intensity	Metric Kg CO_2e/ft^2	5	
Total Electric Emissions	Metric Kg CO_2e/ft^2	3	
Total Gas Emissions	Metric Kg CO_2e/ft^2	2	

For the baseline year, FY 2018

Source: MelRok

Summary of the energy use for each building is shown in Table 4.

Table 4: Summary of EUI for Each Building

	Building Name	Type	Area (ft^2)	Source EUI ($kBTU/ft^2$)	Site EUI ($kBTU/ft^2$)	% of Campus Energy
1	Alexander Hall	Other Education	32,776	159	79	1.7
2	Seely G Mudd	Other Education	21,806	145	65	1
3	JC Cowart IT	Data Center	12,206	N/A	N/A	1.7
4	Smith Campus Center	Lifestyle Center	74,127	298	128	6.3
5	Thatcher Music Hall	Performing Arts	30,850	133	418	2.7
6	Hahn Hall	Other Education	21,186	560	230	3.3
7	Pearsons Hall	Other Education	18,230	268	189	2.3
8	Mason Hall	Other Education	33,190	137	75	1.7
9	Crookshank	Other Education	17,403	233	183	2.1
10	Carnegie Hall	Other Education	18,064	131	66	0.8
	Sum		**279,838**			**23.6**
	Average			**229**	**159**	

Source: MelRok

Alexander Hall: Alexander Hall consists of administrative halls totaling 32,776 square feet (ft^2). Alexander Hall was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 158.7 $kBTU/ft^2$ and Site Energy Use Intensity of 79.2 $kBTU/ft^2$. The Source and Site EUIs are both close to the national average for an Other Education facility. The building represents approximately (~) 1.7 percent of the total energy consumed by buildings on campus, ~ 1.6 percent of the total campus energy utility costs and accounts for ~ 1.7 percent of the campus' emissions associated with building energy consumption.

Seely G Mudd: Seely G Mudd consists of two coupled buildings totaling 21,806 ft^2 used primarily as surge space; that is, as a back-up facility for other facilities that are being renovated. The building was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 145 $kBTU/ft^2$ and Site Energy Use Intensity of 65 $kBTU/ft^2$. The Source and Site EUIs are both close to the national average for an Other Education facility. It should be noted that the 'Other Education' type in Portfolio Manager describes buildings used for other educational purposes not described in other available property uses (specifically college/university). However, the type 'College/University' typically refers to a campus and not individual buildings. The building represents ~ 1.0 percent of the total energy consumed by buildings on campus, ~ 1.0 percent of the total campus energy utility costs and accounts for ~ 1.0 percent of the campus' emissions associated with building energy consumption.

JC Cowart IT: JC Cowart Information Technology (IT) consists of a complex of buildings totaling 12,206 ft^2 and used as a data center. The building was placed under the 'Data Center' Energy Star property type. Data Centers do not use source and site energy use intensity but instead use Power Usage Effectiveness, which is equal to (total facility energy)/(IT equipment energy). However, because IT equipment energy cannot be inferred from existing power measurements, the Power Usage Effectiveness cannot be calculated. The building represents ~ 1.7 percent of the total energy consumed by buildings on campus, ~ 2.6 percent of the total campus energy utility costs and accounts for ~ 2.0 percent of the campus' emissions associated with building energy consumption.

Smith Campus Center: The SCC consists of a U-shaped building totaling 74,127 ft^2 with offices and ballrooms used primarily for student activities and meetings. In this audit, the building was considered under the 'Lifestyle Center' Energy Star property type, with a benchmark Source Energy Use Intensity of 298.4 kBtu/ft^2 and Site Energy Use Intensity of 128.2 kBtu/ft^2. The Source and Site EUIs are both above the national average for an Other Education facility (~ 1.5 times). It should be noted that the 'Lifestyle Center' type in Portfolio Manager describes buildings used for mixed use commercial development that includes retail stores and leisure amenities with access from the outside and not connected by internal hallways. The building represents ~ 6.3 percent of the total energy consumed by buildings on campus, ~7 percent of the total campus energy utility costs, and accounts for ~ 6.6 percent of the campus' emissions associated with building energy consumption.

Thatcher Music Hall: MelRok conducted an ASHRAE level I assessment of Thatcher Music Hall on the campus of Pomona College. Facilities staff were interviewed, and the facility was walked to assess the existing conditions, evaluate the utility distribution networks for potential future sub metering, and to identify opportunities for energy savings. Thatcher Hall is a 30,850 ft^2 music hall facility with two floors above-grade and a basement below grade. The building falls into the 'Performing Arts' Energy Star property type, with a benchmark national median Source Energy Use Intensity value of 133 kBtu/ft^2 and national median Site Energy Use Intensity value of 417.6 kBTU/ft^2. The Source and Site EUIs are both well above the national average for a Performance Art building (~ 3 times and 5 times). This reflects the all-electric nature of the building, and probably also aging equipment and embedded inefficiencies. The building represents ~ 2.7 percent of the total energy consumed by buildings on campus, ~ 4.2 percent of the total campus energy utility costs, and accounts for ~ 3.3 percent of the campus' emissions associated with building energy consumption.

Hahn Hall: Hahn Hall consists of a building totaling 21,186 ft^2 used primarily for classrooms and offices. The building was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 560 kBtu/ft^2 and Site Energy Use Intensity of 230 kBtu/ft^2. The Source and Site EUIs are both above the national average for an Other Education facility (~ 4.5 times). It should be noted that the 'Other Education' type in Portfolio Manager describes buildings used for other educational purposes not described in other available property uses (i.e., college/university). However, the type 'College/University' typically refers to a campus and not individual buildings. The building represents ~ 3.3 percent of the total energy consumed by buildings on campus, ~ 3.8 percent of the total campus energy utility costs and accounts for ~ 3.5 percent of the campus' emissions associated with building energy consumption.

Pearsons: Pearsons Hall consists of a building totaling 18,230 ft^2 used primarily for classrooms and offices. The building was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 267.7 kBtu/ft^2 and Site Energy Use Intensity of 188.6 kBtu/ft^2. The Source and Site EUIs are both above the national average for an Other Education facility (~ 2 times). It should be noted that the 'Other Education' type in

Portfolio Manager describes buildings used for other educational purposes not described in other available property uses (i.e., college/university). However, the type 'College/University' typically refers to a campus and not individual buildings. The building represents ~ 2.3 percent of the total energy consumed by buildings on campus, ~ 1.5 percent of the total campus energy utility costs, and accounts for ~ 2 percent of the campus' emissions associated with building energy consumption.

Mason Hall: Mason Hall consists of a building totaling 33,190 ft^2 used primarily for classrooms and offices. The building was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 136.8 kBtu/ft^2 and Site Energy Use Intensity of 75.1 kBtu/ft^2. The Source and Site EUIs are both close to the national average for an Other Education facility. It should be noted that the 'Other Education' type in Portfolio Manager describes buildings used for other educational purposes not described in other available property uses (i.e., college/university). However, the type 'College/University' typically refers to a campus and not individual buildings. The building represents ~ 1.7 percent of the total energy consumed by buildings on campus, ~ 1.5 percent of the total campus energy utility costs and accounts for ~ 1.6 percent of the campus' emissions associated with building energy consumption.

Crookshank: Crookshank consists of a building totaling 17,403 ft^2 used primarily for classrooms and offices. The building was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 233.2 kBtu/ft^2 and Site Energy Use Intensity of 182.6 kBtu/ft^2. The Site EUI is higher than the national average for an Other Education facility. It should be noted that the 'Other Education' type in Portfolio Manager describes buildings used for other educational purposes not described in other available property uses (i.e., college/university). However, the type 'College/University' typically refers to a campus and not individual buildings. The building represents ~ 2.1 percent of the total energy consumed by buildings on campus, ~ 1.2 percent of the total campus energy utility costs, and accounts for ~ 1.8 percent of the campus' emissions associated with building energy consumption.

Carnegie Hall: Carnegie Hall consists of a building totaling 18,064 ft^2 used primarily for classrooms and offices. The building was placed under the 'Other Education' Energy Star property type, with a benchmark Source Energy Use Intensity of 130.5 kBtu/ft^2 and Site Energy Use Intensity of 66.3 kBtu/ft^2. The Source and Site EUIs are both higher than the national average for an Other Education facility. It should be noted that the 'Other Education' type in Portfolio Manager describes buildings used for other educational purposes not described in other available property uses (i.e., college/university). However, the type 'College/University' typically refers to a campus and not individual buildings. The building represents ~ 0.8 percent of the total energy consumed by buildings on campus, ~ 0.7 percent of the total campus energy utility costs and accounts for ~ 0.8 percent of the campus' emissions associated with building energy consumption.

Summary of Recommendations

A list of energy savings recommendations was presented for each building, which formed a starting point for quick energy improvement measures implemented in the optimization period. The measures recommended included the following:

Review the EMS schedule on weekends to explore any possible reductions in duty cycles or temperature/flow rate setbacks. Leverage use of virtual occupancy sensors to confirm schedules.

- Change the logging (trending) configuration of the EMS to allow logging of critical points. The power consumption of the electric chiller, heater and air handlers can also be sub-metered to confirm duty cycles and detect anomalies.
- Reset supply air temperature based on ambient conditions and building demand.
- Review the EMS set-points to eliminate any simultaneous heating and cooling.
- Verify operation of economizer.
- Verify operation of variable air volume terminal units.
- Reset chilled water temperature.
- Reset heating hot water temperature.
- Add flow control on chilled water pumps.
- Reset condenser water temperature on the closed loop that services the chiller.
- Reset cooling tower temperature based on load and flow-based chiller demand.
- Include occupancy information in the control logic when available.

Pre-optimization Analysis

An analysis of the energy use of buildings was conducted to evaluate the performance of buildings prior to any optimization efforts. The same methodology and performance parameters are used to evaluate the performance of buildings post optimization and to estimate the savings.

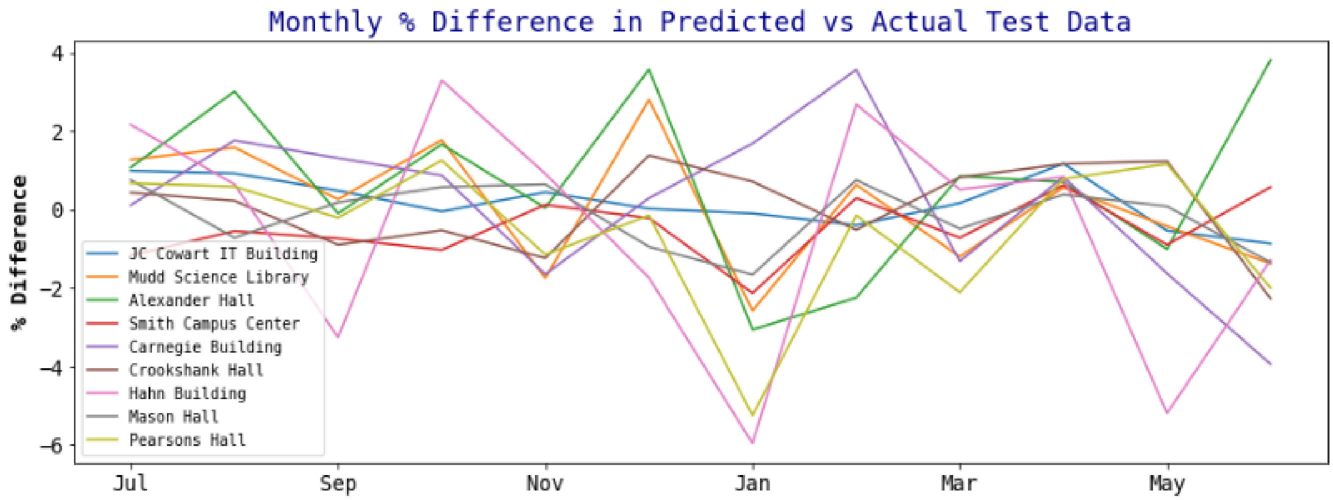
The method consists of selecting key performance indicators and developing an empirical model for the energy performance of the buildings for FY 2018, the pre-optimization base year. While a list of equipment-level and subsystem level key performance indicators were presented in the *ACCO-BEMS Pre-optimization Analysis Report*, only building level key performance indicators are being used to evaluate the energy savings resulting from ACCO-BEMS. Specifically, the weather normalized energy use pre- and post-optimization is used to estimate changes in energy usage.

An empirical energy model was created for each building, using the FY 2018 energy data as a baseline.

Independent variables included hourly environmental data, date and time, holiday calendar, and session calendar. No energy-related metrics were used as independent variables for the regression. Furthermore, no occupancy data was used in the regression, as there was none available for the pre-optimization period. Occupancy data is being automatically estimated in real-time during the course of the work using LBNL's virtual occupancy sensors.

A random sample of data points from FY 2018 was used to train the model, while the remaining data points were used to test the model. The Training Sample consisted of 70 percent of the FY 2018 data. The error between the predicted and actual energy for the random data points used to test the model are shown in Figure 1.

Figure 1: Difference Between Predicted and Measured Monthly Energy per Building

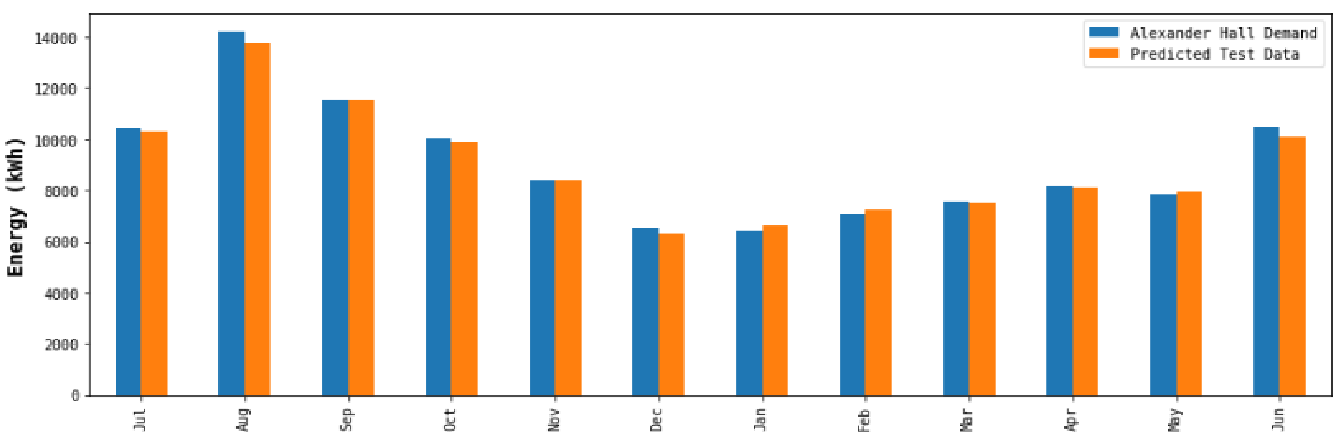


For the data used to test the empirical energy models

Source: MelRok

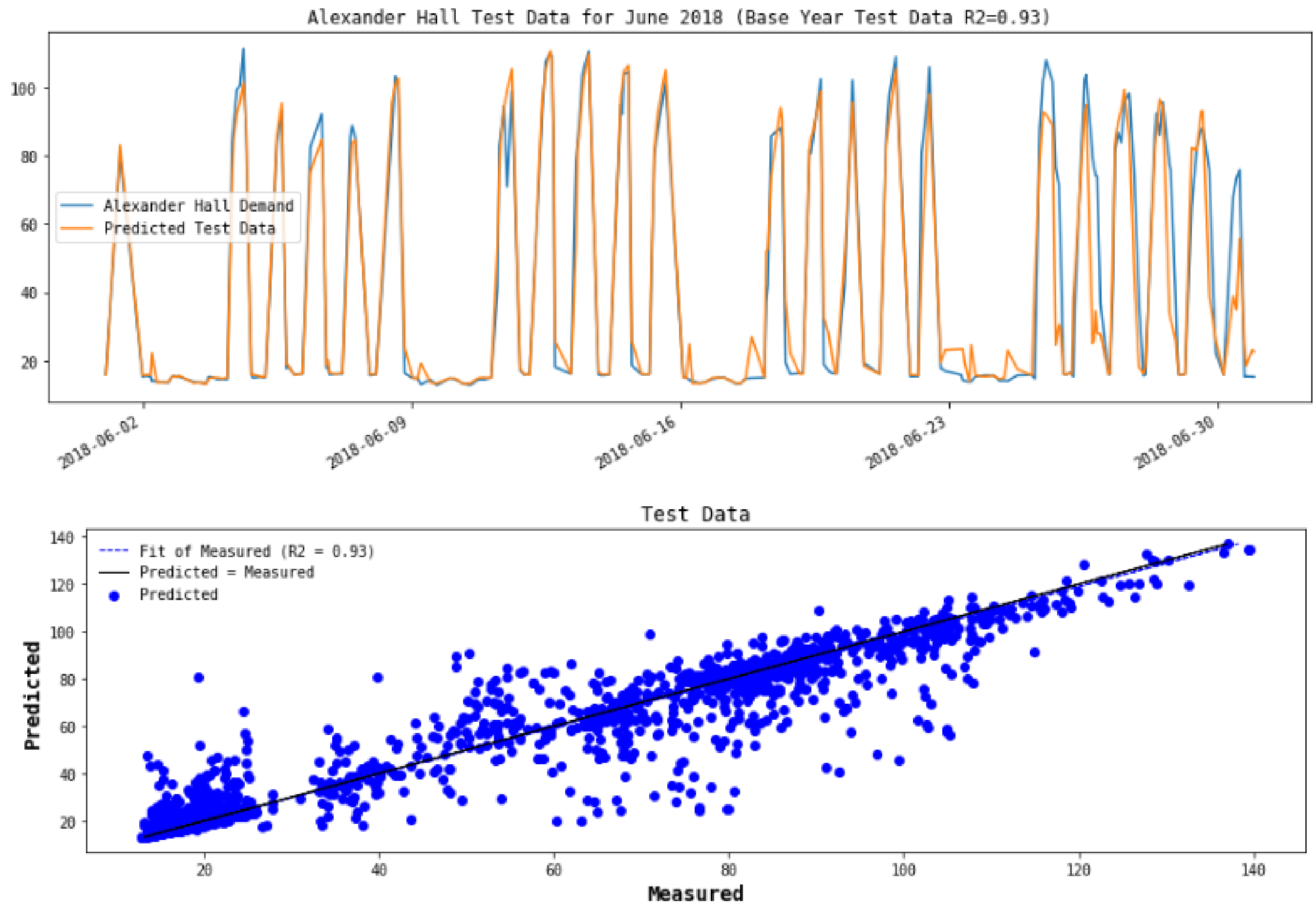
Results of predicted versus measured test data for Alexander Hall are shown in Figure 2 and Figure 3.

Figure 2: Monthly Predicted and Actual Energy Use for Data Used to Test Alexander Hall Energy Model



Source: MelRok

Figure 3: Measured versus Predicted Energy Use for Data - Alexander Hall



Source: MelRok

In summary, an hourly baseline model was generated for each building to be used for measurement and verification of ACCO-BEMS performance. The models correlated well with the test data for each building.

Measurement and Verification Plan

A M&V Plan was submitted as part of the project deliverables. The plan specified four phases for the project:

1. Preparation Phase: M&V instrumentation is completed.
2. Pre-Trending Phase: A 12-month monitoring and installation phase during which the unaltered behavior of all systems is recorded while the Touch Gateway and sensors are being installed.
3. Commissioning/Tuning Phase: ACCO-BEMS is sequentially activated, and commissioning efforts are implemented based on the ACCO-BEMS findings.
4. Post-Trending Phase: 12-month post-implementation monitoring phase where the performance of the ACCO-BEMS is assessed.

The plan called for calculating the energy savings based on annualized energy savings, as indicated below:

$$Annualized\ Facility\ Savings = Base\ kWh - Post\ kWh$$

The 12-month pre-trending period is used to establish a normalized baseline and establish multi-variable models of the buildings' energy use. In the post-commissioning portion of the project, MelRok made adjustments based on real-time measured energy and mechanical data, as well as information derived from multi-variable models of the facility and facility systems.

The M&V plan called for augmenting existing building sensors with a network of ethernet-linked sensors enabling access to all critical energy information. A MelRok Touch Gateway was installed in each building to connect energy meters, energy management systems, critical energy systems, energy sensors, and actuators to the cloud-based continuous energy optimization engine.

The International Performance Measurement and Verification Protocol (IPMVP®) defines standard terms and suggests best practice for quantifying the results of energy efficiency investments. Accordingly, the Melrok team used the IPMVP Option C method to assess the performance of the ACCO-BEMS platform using analysis of the whole facility sub-meter data and regression analysis of measured data. Option C quantifies savings by measuring energy use at the whole facility or sub-facility over a given reporting period. Measurements are recorded continuously throughout the length of the reporting period. Adjustments can be routine or non-routine.

In the case of the Pomona College analysis, baseline models calculated in the pre-optimization analysis was used to assess the impact of ACCO BEMS on the whole building energy.

The existing sub-meters were surveyed, and additional meters needed to provide more visibility into each building's equipment level energy usage were installed. The list of additional meters is provided in Table 5. As always, a main challenge when installing new meters is their commissioning. MelRok's commissioning software was used to review the meter data. Anomalies were highlighted that were either related to hardware installation or the load itself.

All anomalies were resolved through fieldwork by the Pomona College energy manager and its main electrical contractor, LVE. Some of the common anomalies included:

- Voltage Phase A, B, C were wrongly labeled on the panel.
- Current Transformers were connected to the wrong reference channel on the meter.

A full list of the submeters monitored is included in Table 5 for reference.

Table 5: List of Additional Sub-Meters Installed at Each Building

Name	Building Name	Channels
MCCA PowerScout	Smith Campus Center	3
AH4 PowerScout	Smith Campus Center	3
AH2 PowerScout	Smith Campus Center	3
MCCA1 Touch Pro	Smith Campus Center	12
MCC C4 Touch Pro	Smith Campus Center	12
MCC C3 Touch Pro	Smith Campus Center	24
MCCA Touch Pro	Oyster House	12
MCC North Touch Pro	Oyster House	24
Chiller 2 PowerScout	Oyster House	3
Main Panel Touch Pro	Thatcher	24
Main Panel 2 Touch Pro	Thatcher	12
MCCA & Main Panel Touch Pro	Seeley G Mudd	24
Panel G Touch Pro	Mason	24
Panel F Touch Pro	Mason	24
Panel HA Touch Pro	Cowart IT	12
B2 Level Touch Pro	Cowart IT	12
Panel PA Touch Pro	Crookshank	12
Panel AA Touch Pro	Crookshank	24
MCC R Touch Pro	Alexander Hall	12
Chiller 1 PowerScout	Alexander Hall	3

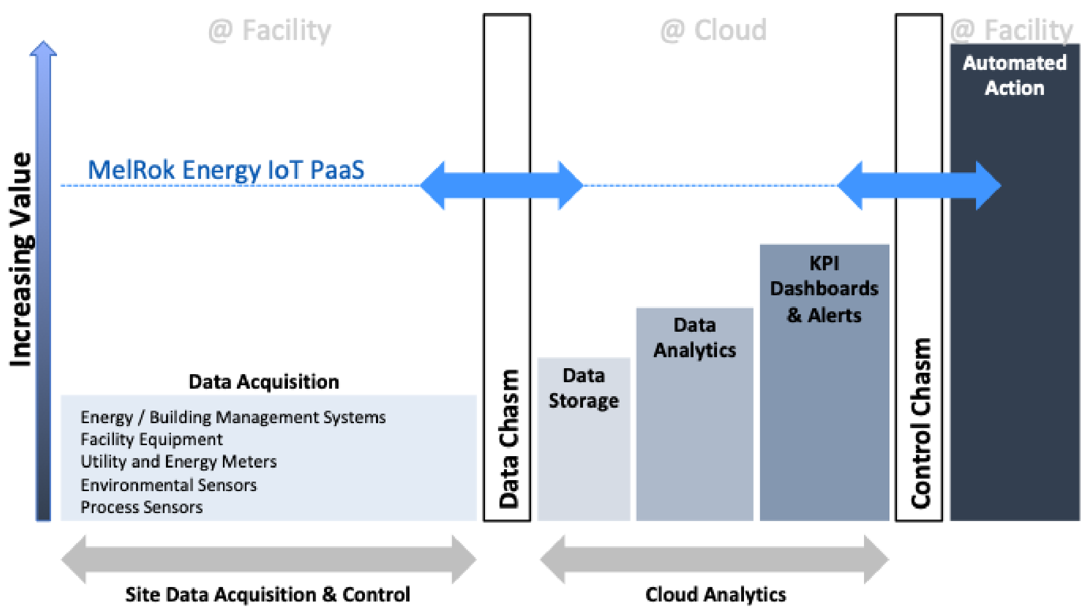
Source: MelRok

CHAPTER 2: Connected Energy Systems and Cloud-Based Analytics (MelRok/LBNL, 8/2)

Introduction

Cloud-based analytics and control of building energy management systems (BEMS) require the crossing of two chasms, illustrated in Figure 4. The first is a data chasm between the building's systems and the cloud storage. The initial challenge with the data chasm is the multitude of physical interfaces and communication protocols needed to connect to site equipment. The second challenge with the data chasm is identifying and tagging the data that is being collected. The lack of a standard naming convention for BEMS systems and points, as well as the lack of a standard way to represent associations between building systems, make it hard to put the collected data to good use. The second chasm is a control chasm, with a gap in automated action resulting from the findings of cloud-based analytics and optimization. ACCO-BEMS strives to cross these chasms with automated tagging and real time collection of BEMS data, coupled with the secure and real-time messaging of control points from the cloud to the systems in the buildings.

Figure 4: Data and Control Chasms in Cloud-Based Analytics and Control Processes



IoT = internet of things, PasS = platform as a service, KPI = key performance indicator
Source: MelRok

Connecting to Meters and Controllers

At the core of the ACCO-BEMS platform is MelRok's Touch Gateway that ensures two-way secure communication with the energy meters and BEMS controllers.

There are three distinct sources of data for ACCO-BEMS:

1. Energy meter data
2. Building energy management system data
3. LBNL's Virtual COUNT sensor data

The same platform, shown in Figure 5, is used to acquire data from the three distinct sources. The COUNT infrastructure is described later in this chapter.

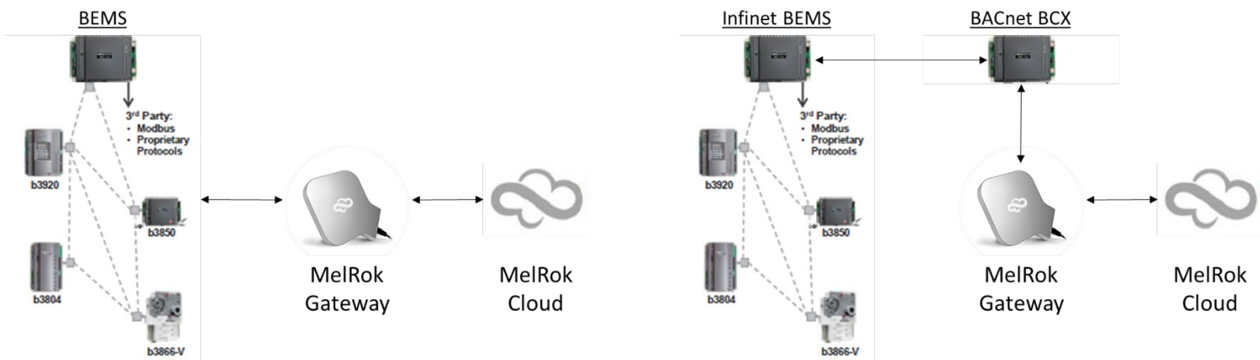
Figure 5: Components of Energy and BEMS Telemetry Platform

Source: MelRok

The Touch Gateway connects with the meters via Modbus TCP, Modbus RTU (RS 485), Pulse counter, or BACnet/IP. Most energy meters installed at Pomona College communicate using the Modbus protocol, while the Btu meters typically communicate using the BACnet/internet protocol (IP). The Touch Gateway can connect to as many meters as needed, limited only by the network's bandwidth and the requirement to sample all meters within a minute.

The Touch Gateway is also used to communicate with the BEMS controllers. At Pomona College, there are two types of communication protocols being used by the BEMS. The first is BACnet, which is a standard protocol that enables devices from different manufacturers to communicate seamlessly. The second is called Infinet, a legacy proprietary and unpublished (i.e., not documented) protocol developed and used by Schneider Electric.

Figure 6: MelRok Gateway Communication with BACnet (left) and Infinet (right) Schneider Electric Network Controllers



Source: MelRok

In buildings with BACnet BEMS, communication between the MelRok Touch gateway and the BEMS was straightforward. The MelRok gateway uses the BACnet protocol to read from and write to the BEMS over IP connections. This was the case in two of the buildings at Pomona College: Seely G Mudd Science Library, and JC Cowart IT Building. BACnet allows for the automated discovery of BACnet devices. When installed, the Touch Gateway scans the BACnet IP network to create a list of all BACnet devices existing in the same IT subnet. The Gateway then sequentially interrogates each BACnet device for the list of points managed by the device. The points represent input and output channels on the device, as well as variables that are defined and stored in the device. These devices can be BEMS field controllers, variable air volume controller/actuators, variable field drive controllers, chiller controllers, and others.

In buildings with Infinet controllers, the Touch gateway cannot communicate directly with the Infinet controllers. The project team implemented a work around using a second Schneider BACnet controller to mirror the points of the Infinet controllers. A program was written in the Infinet controller to push the values of each point to a corresponding point on the BACnet host.

Once the values of points (objects) are pushed to the Schneider BACnet network controller, they become accessible like any BACnet object (point). Thus, the BACnet network controller acts as a host for objects from Infinet controllers. To write to an Infinet object, instead of using a push function, an import statement would enable communication from the BACnet to the Infinet object. MelRok has successfully communicated with both BACnet and proprietary Infinet to collect and push data at one minute intervals.

The status of all connected devices is monitored by the MelRok platform and displayed on a network-monitoring dashboard, with email notifications pushed out in case of lost connectivity. This ensures that all meters are kept online and in case of any downtime, work orders are generated, and the issues resolved.

Mapping of BEMS data

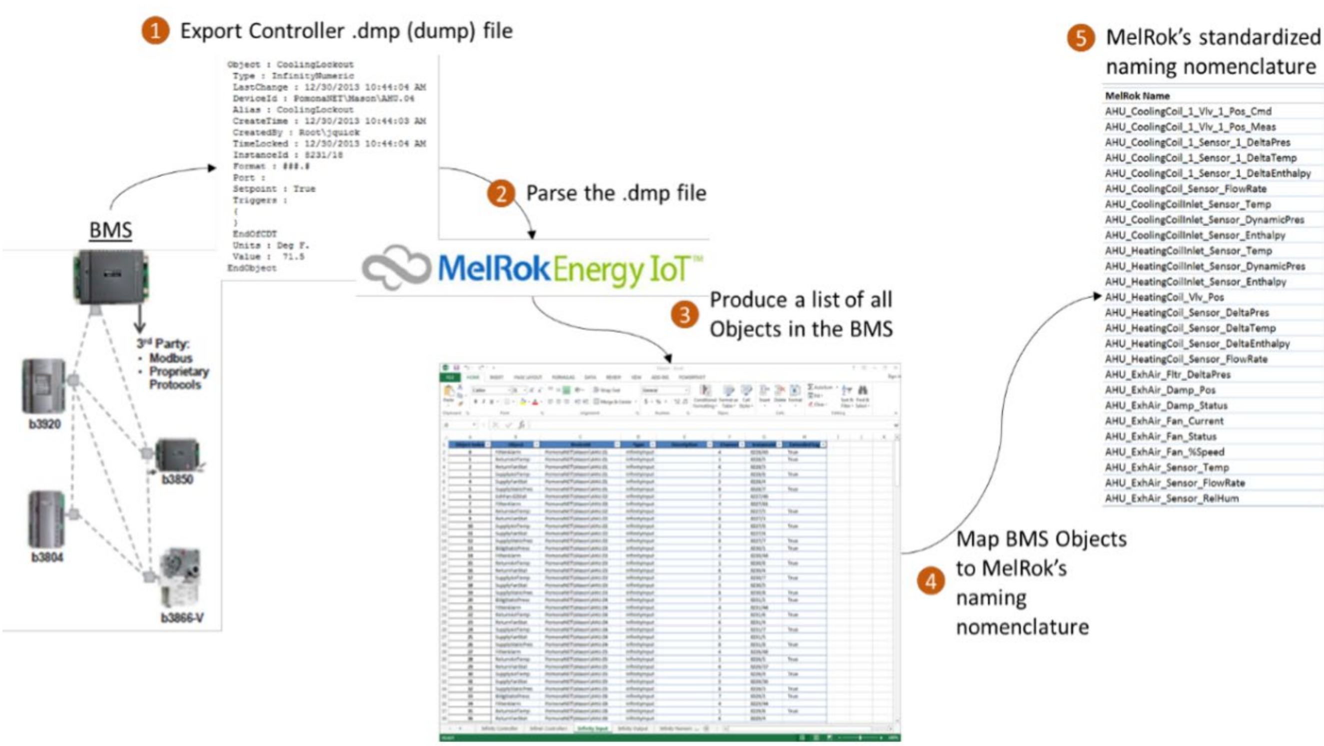
One of the biggest challenges in analyzing data from the BEMS is to map a non-standardized naming convention to a standard nomenclature. Each one of the BEMS points is given a name by the person who setup that object in the field controller. These names do not follow a standard nomenclature and are often hard to interpret. However, understanding what every point represents is key in proper diagnosis and optimization of the BEMS.

Once the BEMS points are uploaded to the cloud, MelRok proceeded with the tagging of the points to a standard naming convention. A MelRok-specific naming convention is used, simplifying the process of mapping them to any other standard convention in the future. In the absence of such mapping, from a non-standardized naming convention to a standardized nomenclature, it is virtually impossible to automate analytics.

The MelRok mapping process, illustrated in Figure 7, consisted of the following steps:

1. Exporting the configuration of the BEMS network to a text file (e.g., .dmp file)
2. Parsing the .dmp file using MelRok's automated parsers to obtain the list of points associated with each controller. The parsing process also identifies each object's equipment type, component, device, sensor, and action. A Global Unique Identifier to each point is assigned to each point.
3. Triggering a mapping engine to link each point to a specific metric in MelRok's standard nomenclature. The mapping engine uses metadata associated with each BEMS point, including the type of controller, controller name, point name, point format, and point values to best determine what each point represents.

Figure 7: MelRok's Mapping Process



Source: MelRok

For buildings using BACnet/IP protocol, 75 percent of BEMS input and output points were successfully automatically mapped, including the majority of critical points. In the buildings that use the older proprietary Infinet protocol, 40 percent of the inputs and output objects were mapped through the automated mapping process. All data is logged into the MelRok cloud in real-time regardless of whether it was tagged or not. MelRok mapped manually the points that failed the automated mapping. Almost 4,000 (measurement and control) points are being logged from the ACCO-BEMS buildings, from a total of about 339 BEMS controllers.

ACCO-BEMS Cloud Infrastructure

Energy and BEMS data is uploaded by the Touch gateway every minute to the MelRok cloud. If cloud connectivity is lost, the Touch Gateway stores the data locally and uploads the data once the connection is re-established.

Control of the building energy management system is affected by changing the value of the controller Output ports and by changing the value of the thresholds, set points, used by the controller's logic programs.

The ACCO-BEMS cloud infrastructure stack includes:

Infrastructure

- AWS Cloud
- Microsoft SQL Server
- Apache Spark
- Apache Ignite
- Apache Kafka
- Apache Cassandra
- Kubernetes
- Jupyter

Infrastructure Monitoring

- FluentBit - Log collection
- Grafana Loki - Log aggregation
- Grafana - Dashboards
- CoreOS Prometheus - Metrics and alerting
- CoreOS Clair – Container scanning
- Sysdig Falco – Intrusion detection

The data is directed by load balancers to different collector services, after which it is placed in Kafka, a subscription platform that manages all of the streaming data and makes it available to the different cloud apps. All cloud apps that need access to real time data obtain it from the Kafka platform.

Cloud apps include applications to:

- Decrypt, resample, and aggregate the incoming data
- Calculate the violations, faults and alerts
- Optimize set points for cloud control of BEMS and HVAC equipment

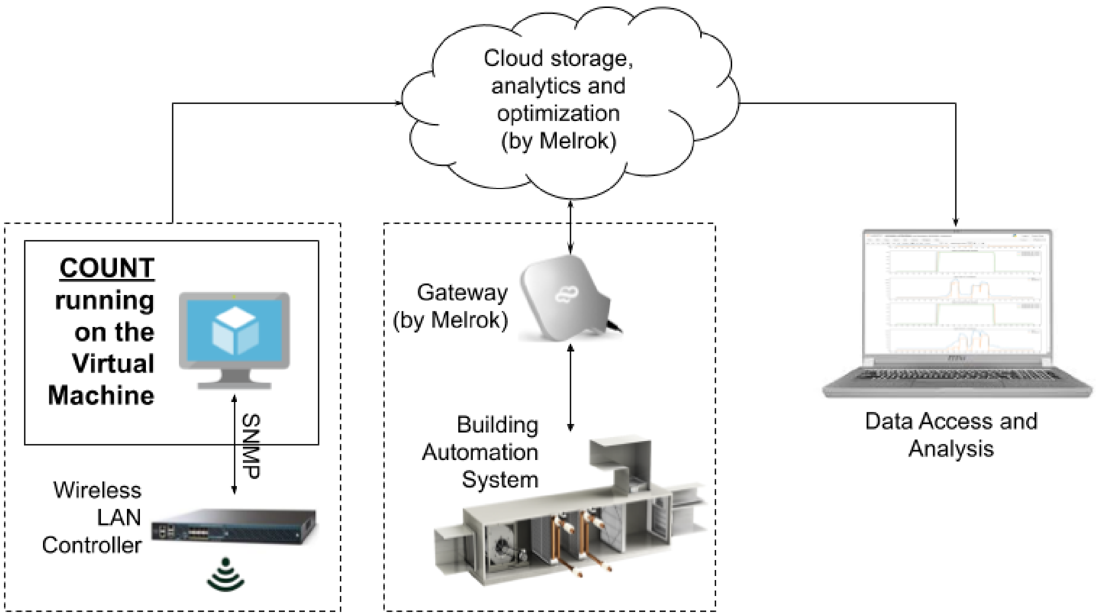
The ACCO-BEMS platform uses Cassandra distributed database for the storing of energy and BEMS data.

Occupancy Sensing Using Anonymized Wi-Fi Data

The Pomona College modern Wi-Fi network supports the wireless connectivity needs of about 1,700 students, plus faculty, staff, and visitors. More than 1,000 Wi-Fi access points report to a central Cisco Wireless Local Area Network controller. As part of this project, LBNL developed the COUNT software to query the Wi-Fi controllers every minute to obtain the number of devices that are connected to each of the 1,000+ access points during that minute. Once this raw device count has been obtained, the software anonymizes this data by removing any information (such as MAC address) that can be used to identify an occupant and performs data processing and cleaning. This results in an "estimated occupant count" at an access point level, and also at a building level. To store this data, researchers used the MelRok infrastructure described above, because storing all the data in one location allows easy integration with the control algorithms and visualization applications.

The architecture of the COUNT software is shown in Figure 8. COUNT was deployed on a Linux Ubuntu 16.04 virtual machine, hosted locally at Pomona College. The virtual machine has direct access to the Wireless Local Area Network controller and can also push data (outbound only) to the MelRok cloud platform. The data are encrypted using Advanced Encryption Standard, which is a symmetric key algorithm, before sending to the MelRok cloud. This estimated occupancy data, stored in the MelRok cloud database along with the BEMS and meter data, can be accessed via a REST application programming interface and/or over the MelRok Web Interface. COUNT was developed with the Python programming language (version 3.6) and has two main modules: one module queries the campus Wireless Local Area Network controller using the Simple Network Management Protocol and saves the data collected to a local buffer to prevent data loss. The second module reads the data from the database and tries to push it to the MelRok cloud; upon a successful push, the data are removed from the buffer. The decoupling of the software modules prevents loss of data in case of loss of network connectivity between the virtual machine and the MelRok application programming interface (which did in fact occur in the course of the project). In this case, the second module detects an unsuccessful data push to the MelRok application programming interface and will NOT delete the data from the buffer database. The software attempts to push the data to the application programming interface again, once the network connectivity is re-established.

Figure 8: Architecture of the COUNT software

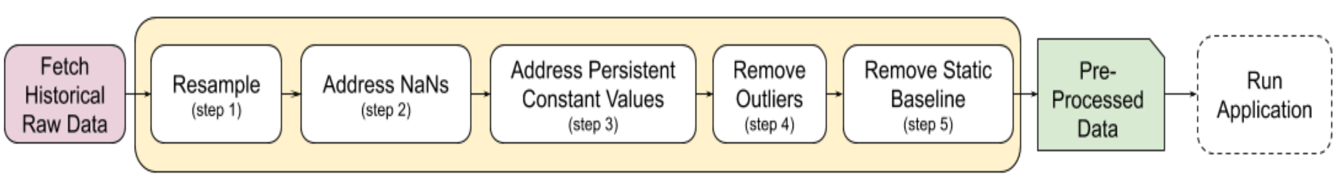


Source: MelRok

Figure 9 describes the steps involved in processing the raw data to obtain estimated occupancy counts. Normalizing irregular sampling frequency (due to network delays), handling null and zero values (due to missing data from access points or disconnected access points or no devices connected to an access point), removing outliers, and removing static devices (devices that are always connected to an access point for example printers, or VoIP phones) are some of the issues addressed in this process.

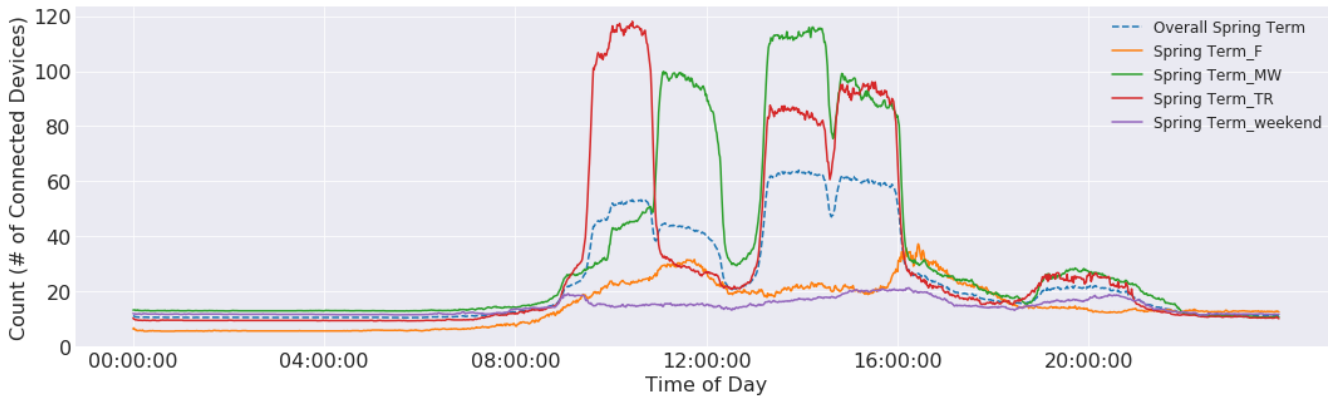
Figure 10 illustrates the daily average occupancy counts for different groups of days in a week (based on course schedules) in a Spring term for a building that contains mostly classrooms and lecture halls, where student presence drives the occupancy. The most obvious pattern is the drop in count at 12:00 p.m. across all the different days of the week, which is when the students head out for lunch. Further, for each hour, there is a significant difference in occupancy each day, due to irregular class schedules. This contrasts with the fixed HVAC operation every weekday. This difference is the main motivation to use this occupancy count in the HVAC control algorithm.

Figure 9: Data Engineering Pipeline to Process the Raw Wi-Fi Device Count Data



Nan = Not a number
Source: MelRok

Figure 10: Average Occupancy Patterns During Days in the Spring Term for a Campus Building



Source: MelRok

Cloud Analytics and Control

The ACCO-BEMS platform comes with out-of-the-box tools that facilitate the work of portfolio and energy managers. One of the main advantages of ACCO-BEMS is that it abstracts the make, model, architecture, and nomenclature of BEMS implementations to present all information in a uniform way and on the same dashboards.

The key to ACCO-BEMS success are the out-of-the-box features that come with it from dashboards, and fault detection to on-demand commissioning and cost reports.

Dashboards

The data can be viewed in tabular and timeline formats, with many embedded visualization tools such as heat maps, box plots, profile plots, scatter plots, and load duration curves. Data can be easily filtered, sorted, and downloaded.

Real-Time Sensor Anomalies

Results of real-time fault detection of sensor and equipment anomalies on dashboards with ease of drilling into the relevant data. Sensor faults include frozen sensors (static data), missing data (non-reporting sensors), out-of-range data (function of metric type and units), and short-cycling sensors ('hunting' in BEMS terminology). The most common sensor failures are frozen sensors, followed by short-cycling sensors. Missing data is often the result of network outages, with two Touch failures reported due to power-outage-related voltage spikes. When a Touch gateway is down, the points being acquired by the Touch are re-routed to another Touch gateway. The re-routing is currently a manual process and automating the process would be a beneficial feature.

Real-Time Equipment Fault Detection

Built-in fault detection algorithms consist of seven categories of failures, with plans for adding an additional eight categories. The failure categories include simultaneous heating and cooling, inconsistent temperatures, failure to heat, failure to cool, defective dampers, and ventilation failures. Results of the fault detection are displayed on a dashboard, with bar charts highlighting the times the failure was detected. Timeline charts of the relevant metrics are also displayed on the same dashboard page for quick diagnosis of the problem. The fault detection algorithms are calculated in real-time at one-minute intervals. When a problem is detected, it is first flagged as a violation. Violations that last 15 minutes are tagged as faults. Faults that last two hours or more are then tagged as Alerts.

On-Demand Commissioning

A set of auto commissioning modules are included that analyze spatially and time resolved BEMS data to detect problems and inefficiencies. Commissioning actions sift through one-minute data from all systems in a building to detect feedback that does not match control commands, metrics that are not set back at night, metrics that have no reset strategies, and terminal units that supply excessively hot air (in violation of Title 24). Other commissioning modules exist that look for simultaneous heating and cooling in ventilation loops, where the air handler is cooling, and all downstream terminal units are reheating the air. Modules also exist to evaluate un-used free cooling opportunities.

Data Science Sandbox

The ACCO-BEMS platform includes a sandbox for easy data science exploration using python. A series of built-in and well-documented python modules facilitate the retrieval of data from the MelRok platform and arranges the data in structured and easy to use python objects for user-driven custom analysis. This sandbox is used by LBNL's analysis of COUNT data, and by Pomona staff for custom management and analysis of their data.

Automated Controls Capability

The ACCO-BEMS automated control capability is managed by python-driven code deployed on MelRok's cloud. There is currently no user-access to the code, and user management of automated cloud control is limited to activation and de-activation of cloud controls down to the level of individual equipment metrics.

The ACCO-BEMS platform is also an automated demand response platform, and automated demand response strategies can be programmed into the platform. Furthermore, manual cloud control can be affected on any BEMS control point. The platform allows the user to select the value to send to any of the tagged control metrics and set the BACnet priority for each control command. Users need not know the BACnet ID of each point or the IP address of the controllers. The path is automatically determined by the ACCO-BEMS platform, and the control messages routed to the appropriate device and register.

Cost Considerations

Important to the scaling of the ACCO-BEMS platform are the costs associated with the hardware, setup, and ongoing software as a service. The project's scope of work entailed tasks that may not be necessary in all applications, such as detailed audits, extensive analysis, detailed metering, regular meetings, and reports. In a commercial deployment of ACCO-BEMS, the main cost components would be:

Gateway: One gateway is recommended per building to ensure that read and write operations to all meters and controllers can be done every minute. It was determined that one gateway can handle about 1000 points a minute, with the number ranging from 700 to 2500 depending on the latency of the BEMS systems and network. The gateway prices typically range from $500 to $1500, depending on the input/output ports needed. If only Ethernet communication is needed, then a $500 gateway will suffice.

Setup: Setup costs are a large function of the BEMS protocols. The setup of BACnet BEMS is largely automated and requires minimal human intervention. Setup of Infinet and other proprietary or serial devices is a labor-intensive process. BACnet systems can be setup for under $1,000 per building (including tagging), while setup of serial and proprietary systems can exceed $5,000 per building.

Cloud services: Ongoing cloud fees can be minimal once the setup is complete. ACCO-BEMS deployment helped the project team calculate infrastructure costs and benchmark performance and scalability of the cloud infrastructure. It is expected that most commercial buildings will be able to deploy ACCO-BEMS for a $50 to $150 monthly fee, with a rule of thumb of $1/kft^2 per month.

Lessons Learned

The project team identified a number of lessons in the process of deploying the ACCO-BEMs system and developing the COUNT Wi-Fi Occupancy tools, including:

Interfacing with Legacy Systems

Interfacing with legacy systems proved to be a challenging task. The main issue is the fact that these systems use a serial protocol that is Master/Slave, meaning only one device can interrogate other devices on the network. The solution that mirrors the serial points is dependent on the serial communication to and from that single device. The serial communication networks are sensitive to digital noise, wire quality, and are often not well managed compared to IT-based networks. The communication is also subject to the controller's "mirroring" program to run continuously and push/pull data to the BACnet controller. It is important to constantly monitor the status of the points to quickly detect any failure in communication that is due to issues with the wire or a stalled mirroring program or both. For new BEMS installations and upgrades, the use of IP-based and published protocol systems is critical for ease of integration.

Tagging of Points

The tagging process exposes points that most probably were previously never monitored or trended or both. It is important not to assume that the point names accurately reflect what they are monitoring or controlling. There were several examples of points that were mislabeled in the BEMS, and the mislabeling was never detected. While the tagging to a standard naming convention accurately reflected the point's name, the data was not consistent with expectations. An example was the mislabeling of chilled water inlet and outlet in the BEMS. Inspection of the data post tagging demonstrated that the water out of the chiller was warmer than the water into the chiller. After confirming that the tagging was accurate, it was determined that the labeling of the inlet and outlet chilled water in the BEMS was an error. There were similar examples with the naming of temperature sensors, electric panels, etc.

Scalability of Cloud-Connectivity Platform

Connectivity to BACnet, Modbus and other published protocols was demonstrated to be relatively straightforward and automated for the most part. The main challenge in scaling cloud-logging all BEMS and meter points, necessary for cloud-based controls, is the interfacing with the IT staff. In the Pomona case, there was significant reluctance by IT staff to permit cloud connectivity to building systems, stemming mainly from the lack of familiarity with the proposed solution and its cybersecurity measures. In addition, energy management issues do not occupy a high priority with IT staff, relative to other day-to-day tasks. As a result, extremely long times (in the order of weeks and months in some cases) were needed to obtain the required authorization to install a Gateway on the customer's local area network. This experience points the need to future cross-training between energy and IT staff as building systems become more software-driven and cloud-integrated.

Surfacing of Hidden Problems

While connectivity to all BEMS points is critical for cloud-based optimization, it highlights a number of existing failures that have previously been unnoticed. Some of these failures are logical, such as the mislabeling of points (discussed previously), or when a control program freezes randomly. Other failures are physical in nature, with broken communication wires, defective sensors, or defective actuators. One of the main challenges in ACCO-BEMS implementation was the time required to process the deluge of work orders related to failures that were detected by ACCO-BEMS after obtaining real-time connectivity to BEMS controllers and sensors. This is likely to be more a prevalent issue in older buildings and campuses where facility technicians are spread thin and deferred maintenance is an issue, and less of an issue in more recently built commercial office environments.

COUNT Implementation Challenges for Future Deployments

Data privacy and cybersecurity concerns were critical concerns for the IT/network administrators, especially as it related to occupancy sensing through Wi-Fi. Integrating the Wi-Fi COUNT software as an app of ACCO-BEMS will avoid duplications in the IT authorization process.

CHAPTER 3: Continuous Optimization of BEMS

Introduction

The ultimate goal of the ACCO-BEMS platform is to optimize the control of building energy systems from the cloud. The project team's approach consisted of the following steps towards achieving cloud control:

- Deploying the ACCO-BEMS platform to monitor performance of energy systems
- Launching ACCO-BEMS in continuous optimization mode to identify defective sensors, actuators, and faulty sequence of operations
- Conducting a data-driven retro-commissioning effort
- Fixing or replace any defective sensors and actuators
- Activating real-time cloud optimization of the BEMS to optimize the sequence of operations

The goal of the retro-commissioning effort was to fix any issues, specifically hardware failures, with buildings' sensors, actuators, and EMS controllers prior to start of continuous optimization. This step enabled ACCO-BEMS to automatically detect the state of the actuators and sensors, identify faulty equipment and sensors, and optimize the sequence of operations.

A data-driven approach to commissioning was used, where the ACCO-BEMS platform was used to detect faulty equipment and faulty sequence of operations. In addition, part of the commissioning effort was to review the BEMS network architecture and control logic of the BEMS controllers, so as to best identify how cloud optimization could be integrated with each controller.

Cloud-Guided Optimization

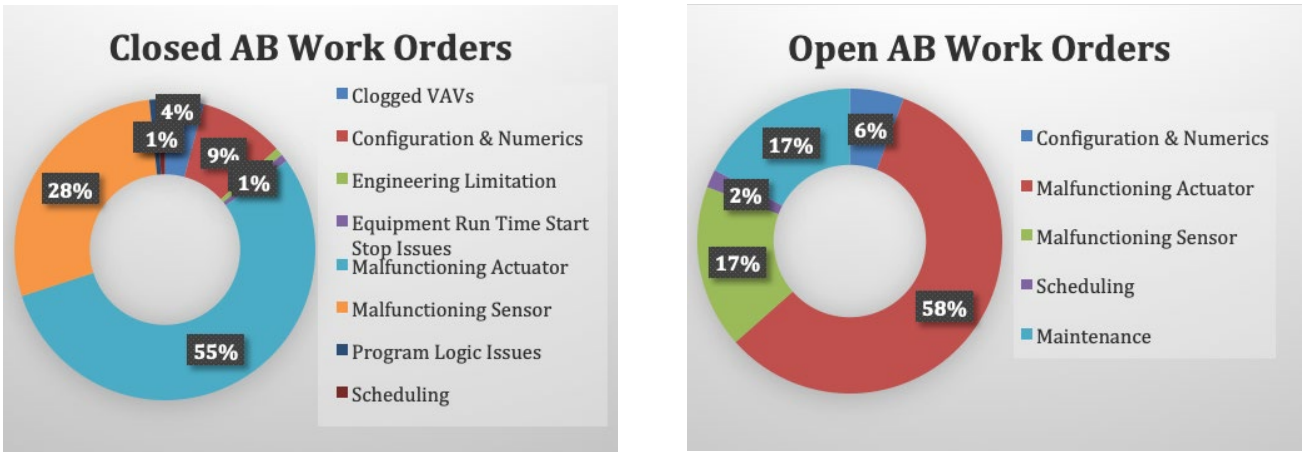
The ACCO-BEMS platform was used to guide the commissioning and energy improvement efforts of the project's optimization period. The guidance was done through:

- Exploratory data analysis using the ACCO-BEMS dashboards
- Detection of faulty sensors through the sensor anomaly dashboard
- Detection of faulty logic using ACCO-BEMS' equipment anomaly dashboard and the built-in automated commissioning reports.

The Pomona team initiated a series of work orders based on the findings of the ACCO-BEMS platform. Only fixes and replacements of physical systems were channeled through work orders. Any fixes to sequence of operations and upgrades to the controller programs, required to accommodate cloud control, were undertaken by Pomona's energy manager without any work orders.

A total of almost 260 formal work orders have been issued since the project start. Of these, some 57 work orders remain open as of April 2021, when this report was prepared. COVID shutdowns reduced both the flow of work orders and their completion. Figure 11 is a breakdown by category of all open and closed work orders. Malfunctioning actuators make up the majority (55 percent) of work orders followed by faulty sensors.

Figure 11: Breakdown of Work Orders by Category



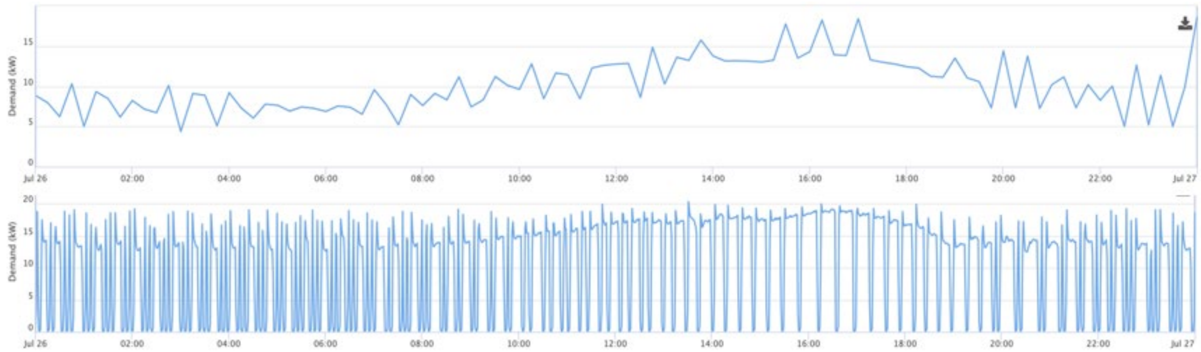
Source: MelRok

The large number of work orders that had to be resolved externally from the project team required physical inspection and resolution of the problems for each piece of equipment and component. The need for facility staff to respond on these issues created a bottleneck for the progress of the commissioning efforts, resulting in only six of the buildings being commissioned ahead of activating ACCO-BEMS cloud control. While many of the detected failures were relatively conventional, some of the unexpected findings were reported in this paper because many of them had a significant impact on energy efficiency.

Short Cycling of a 120-Ton Chiller

ACCO-BEMS highlighted the importance of high temporally resolved (specifically higher-frequency sampling) data in discovering issues with equipment and sequence of operations that are otherwise not detectable with 15-minute data (the standard sampling interval for logged data in the BMS). One such problem was the behavior of a new 120-ton chiller at the JC Cowart IT Building, shown in Figure 12. The top chart is the 15-minute interval demand profile, and the bottom chart is the 1-minute demand profile. The charts emphasize the importance of 1-minute data in highlighting problems that cannot be detected using 15-min interval data.

Figure 12: Power Profile of a 120-Ton Chiller at JC Cowart IT Building

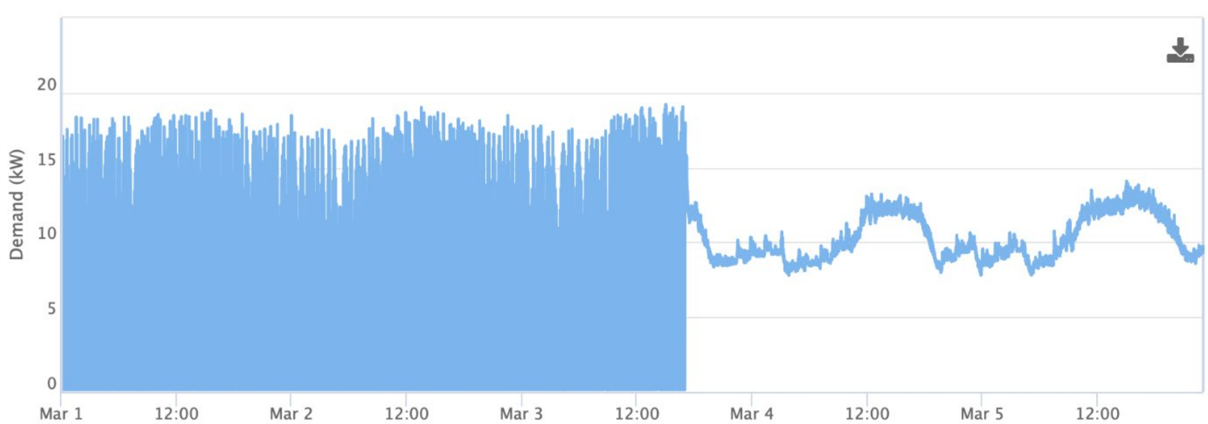


Source: MelRok

ACCO-BEMS flagged the JC Cowart building chiller as excessively short-cycling. Short-cycling dramatically shortens chiller life cycle. Once this anomaly was flagged, it was turned in as a work order via the Pomona College work order system, with the work order finally executed on March 3, 2020. A review of the trends at 1-minute resolution revealed that the chiller had been short-cycling since its installation in fiscal year 2016.

The impact of fixing the chiller short-cycling (monitored at 1-minute intervals) can be seen in Figure 13. Before the fix, the hot gas valves would only function once per cycle. This means that the hot gas valves would only become active when the chiller was in the final unloading sequence. The change in software basically left the hot gas valves open all of the time, thereby allowing the chiller to unload enough to stay online. The root cause of the problem was that the chiller was oversized for the building's cooling load, causing the chiller to short-cycle. The fix allowed the chiller to effectively increase its load by heating the return water. Unfortunately, while this change reduces the mechanical stress on the chiller, associated with continuous rapid power cycling of the chiller, the change had a negative impact on the chiller's energy consumption. A quick comparison of the consumption on the day prior to and after the fix revealed more than doubling of the energy consumption (242 kWh vs. 103 kWh) and a 36 percent decrease in peak demand (13 kW vs. 19 kW.)

Figure 13: Test Change in One-Minute Demand Profile of JC Cowart Chiller After the Fix



Source: MelRok

The costs and risks associated with shortening the life cycle of a chiller far outweighs the increase in energy consumption. In addition to potential maintenance and replacement costs of a chiller failure, any chiller failure presents an additional risk to IT equipment at JC Cowart, Pomona College's data center.

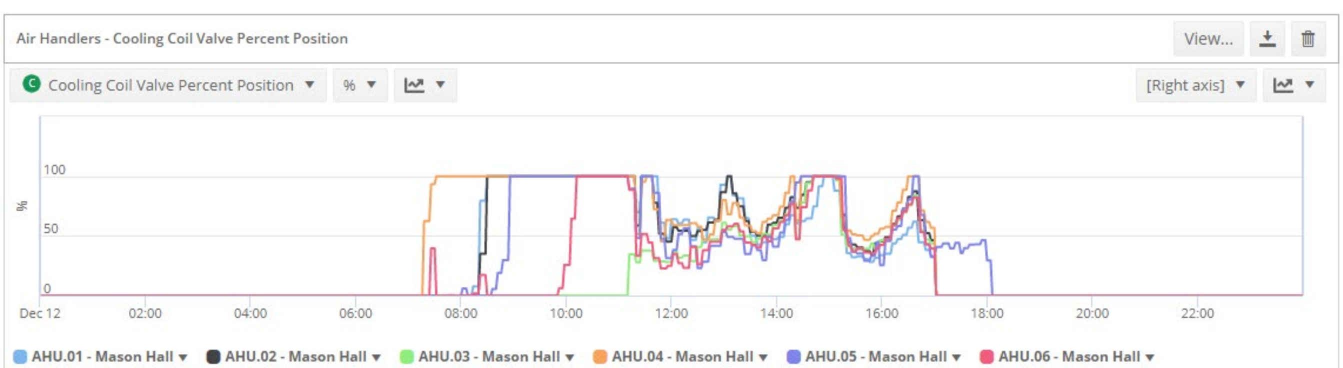
Hahn Hall

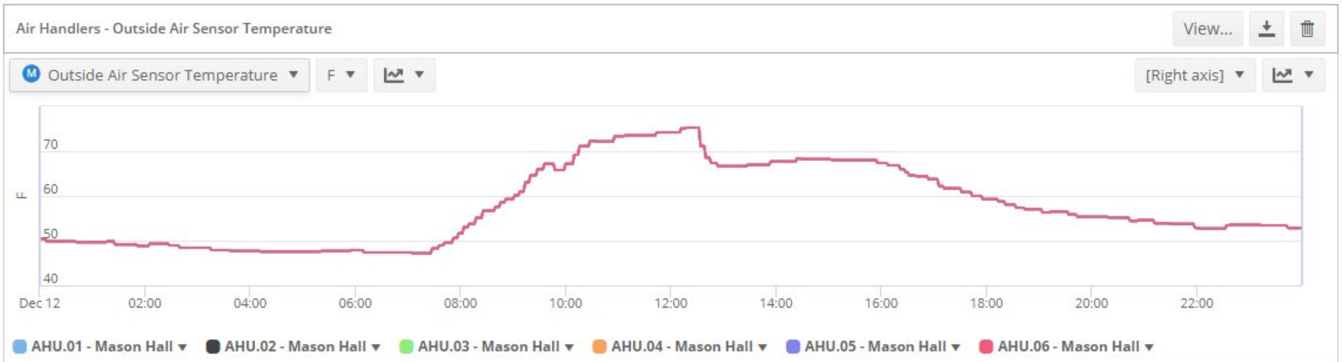
Hahn Hall went through a traditional retro-commissioning process. Part of the execution was a reset strategy for Chiller 1's chilled water. Before the retro-commissioning work, Chiller 1 produced chilled water at a static 45°F (7°C) and depended solely on an outside air lockout as a condition for start/stop.

A new sequence of operation was implemented on Chiller 1 on October 10th 2019. The chiller start/stop was made a function of the outside air lockout and the maximum chilled water valve position of all air handlers in the loop. In addition, a chilled water reset strategy was added, where the chilled water supply temperature would vary between a minimum and a maximum value depending on the maximum chilled water valve position of the air handlers in the chilled water loop.

At the end of November, ACCO-BEMS analysis revealed excessive usage of the chillers during mild ambient weather. Troubleshooting revealed multiple layers of anomalies. The first was that the chilled water valve position of some air handlers served by the chilled water loop was locked at 100 percent. The second was that during the implementation of the new sequence of operation, an error in the program disconnected control of the outside air lockout setpoint. However, after fixing the error and setting the outside air lockout temperature to 65°F (18°C), the chiller was still turning on at ambient conditions as low as 45°F (7°C). The issue was due to poor economizer management by the air handlers, causing their cooling coil valves to open to 100 percent to meet supply air temperature set point. Figure 14 shows a line plot of cooling coil valve positions for some of the air handlers served by Chiller 1 (top panel) compared to the outside air temperature (bottom panel). The air handlers are calling for mechanical cooling when the outside air temperature is below 50°F (10°C). The charts show that the air handlers were calling for mechanical cooling when outside air temperature were low enough to provide the cooling.

Figure 14: Timeline of Air Handler Cooling Coil Valve Position and Outside Air Temperature





Source: MelRok

Furthermore, the supply air temperature set point of at least one air handler was much lower than was intended to be. Troubleshooting this further found that the temperature control program was not executing properly.

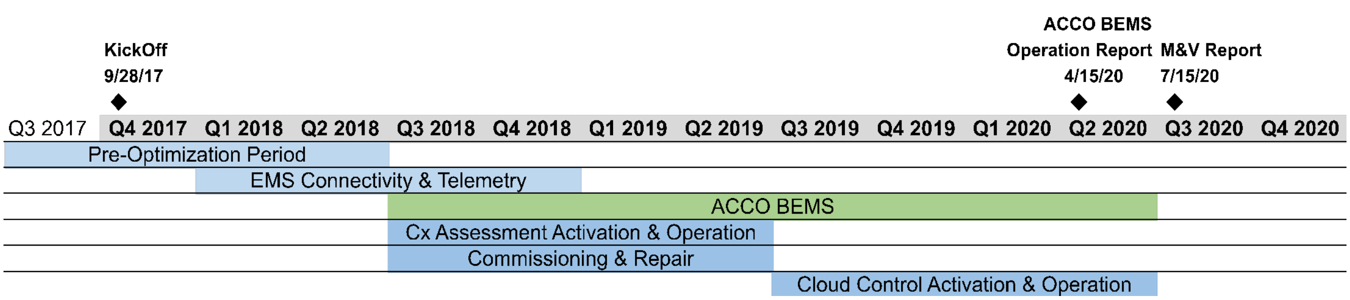
As a result of two failed programs, the economizer program and the temperature control program, Chiller 1 was used excessively even after conventional retro-commissioning efforts.

In summary, had there not been an ACCO-BEMS platform, these anomalies would have persisted until another traditional retro-commissioning was executed. Even worse, typical technicians' response to complaints of hot zones would have been to lower the outside air lockout for the chiller, further amplifying the problem.

Cloud Driven Optimization

The original project schedule, shown in Figure 15, called for starting the launching of ACCO-BEMS in cloud control mode after the commissioning of the buildings. The initial strategy was based on fixing the faults in buildings, especially the physical failures of devices, prior to cloud control. The large number of problems detected during the continuous assessment period preceding cloud control was overwhelming for campus staff. Most of these failures involved defective sensors and actuators and their replacement depended on in-house technicians and outside contractors.

Figure 15: Original ACCO-BEMS Project Schedule



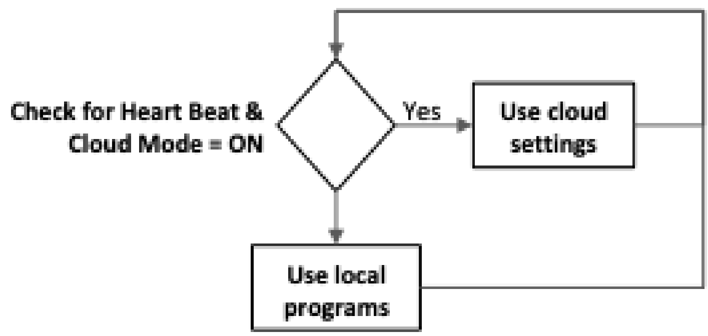
Source: ZNEA

Another key challenge of ACCO-BEMS implementation was that most building BEMS used the legacy Infinet protocol, a serial Master/Slave proprietary and non-published (non-documented) protocols. Even though the ACCO-BEMS platform was successful in sending and receiving messages to the Infinet controller, latency and dependency on intermediate systems decreased the reliability of the overall system.

Prior to enabling cloud control, two tasks needed to be accomplished for every controller:

- Identify the control parameters that will be controlled from the cloud.
- Add code to the controller to accommodate cloud control and to allow the controller to automatically revert back to its own local programs should connectivity to the cloud be lost, see Figure 16.

Figure 16: Algorithm for Reverting to Local Controls in Case of Loss of Connectivity



As a result of delays in commissioning and ensuing repairs to buildings, and to safely proceed with cloud control of Infinet controllers, the project team implemented cloud control sequentially. The following approach was used:

- Deploy and test one system at a time in first set of buildings
- Deploy to other buildings after each system test
- Start next set of tests in first set of buildings

As cloud control was used, it was first tested in a subset of the buildings before deployment across other buildings. The test buildings at various times were Hahn, Pearsons, Mudd Science Library, and Smith Campus Center.

Deployment of cloud control initially ran into some issues, mainly with accommodating stalled/ frozen controllers, and with wiring problems at some buildings. Whenever a problem was encountered, and in abundance of caution, cloud control was paused until the problem was properly diagnosed and repaired.

One of the findings observed from the deployment of code to enable cloud control on legacy controllers, was that cloud control was less taxing on legacy resource-limited controllers than the legacy control code. The memory requirement for adding two lines of code to accommodate cloud control were smaller than the memory required to replicate the dynamic strategies deployed in the cloud. With many of these controllers having memory measured in kilobytes, the reduced memory was an impediment toward implementing more sophisticated control strategies on legacy controllers.

Cloud control proceeded with dynamic optimization of air handlers, specifically outside air damper position, supply air temperature, and supply air static pressure. Air handler optimization considered the input from the air handler and from all terminal units being served by the air handler. Data from the terminal units included continuous tracking of the required heating and cooling loads, determined by the difference between space temperature and space temperature set points for each zone.

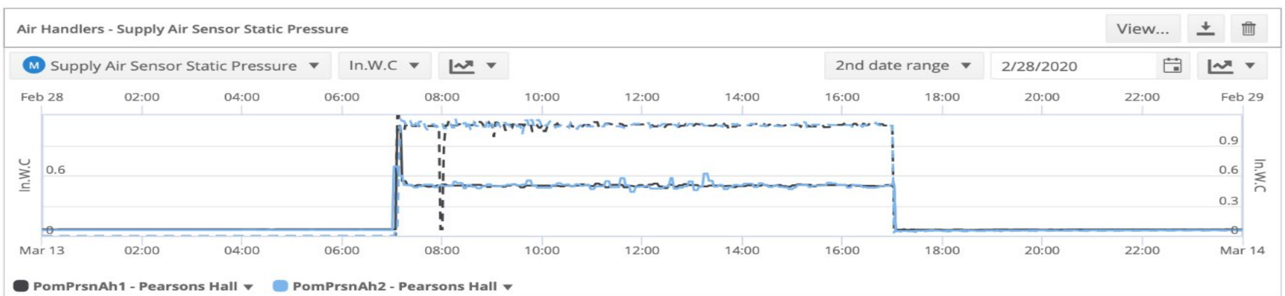
Impact of Cloud Control

The impact of cloud control was apparent almost instantaneously upon activation. A few examples are given below.

Pearsons

Figure 17 displays the line plots for supply air static pressure before (dotted blue and black lines) and after (solid blue and black lines) ACCO-BEMS cloud control activation on March 13, 2020, at Pearsons air handlers (Ah1 and Ah2). The drop of about 0.5 inch water column (inWC) in supply air static pressure was accompanied by a decrease in supply air fan current from about 6 Amps (dotted lines) to 4 Amps (solid lines), or 30 percent, as shown in Figure 18.

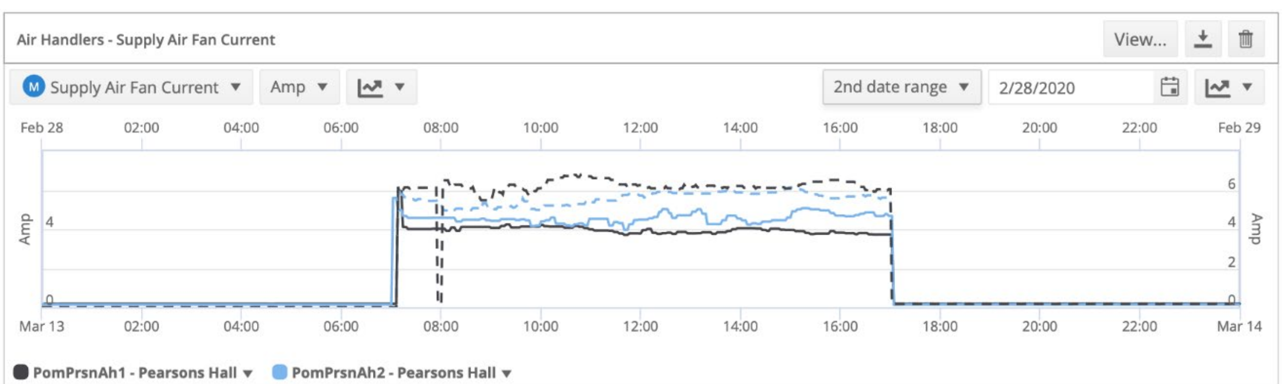
Figure 17: Drop in Supply Air Static Pressure as a Result of Cloud Control at Pearsons Hall



Solid line represents post-cloud control activation (left axis), dashed line represents pre-cloud control activation (right axis)

Source: MelRok

Figure 18: Drop in Supply Air Fan Current as a Result of Cloud Control at Pearsons Hall

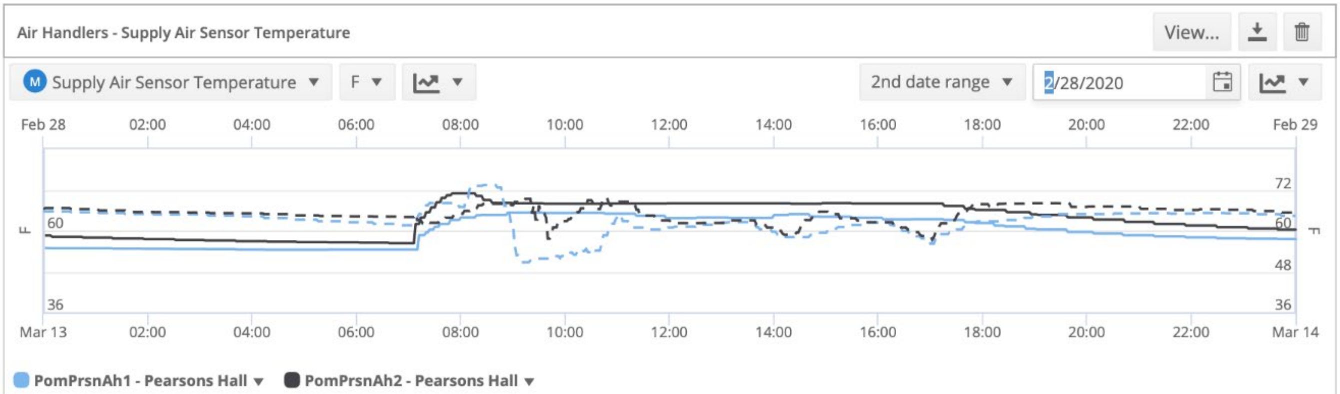


The solid line represents post-cloud control activation (left axis), while the dashed line represents pre-cloud control activation (right axis).

Source: MelRok

Similarly, the supply air temperature was on average higher during operation hours post-activation of ACCO-BEMS cloud controls, as shown in Figure 19, while all zones were still within their desired space temperature set points.

Figure 19: Increase in Supply Air Temperature as a Result of Cloud Control at Pearsons Hall

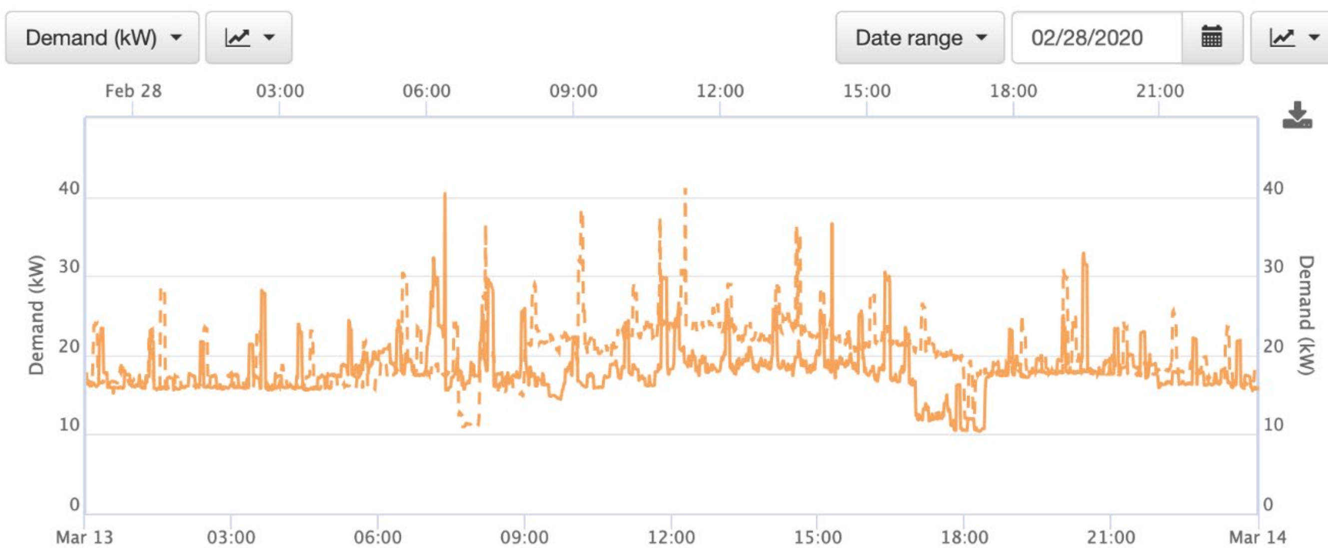


The solid line represents post-cloud control activation (left axis), while the dashed line represents pre-cloud control activation (right axis).

Source: MelRok

While air handler sub-metering data is not available, the main meter data comparing similar days pre- and post-cloud control shows a drop of approximately 4 kW (~ 16 percent) during occupied hours, see Figure 20. While these findings were preliminary, they demonstrate the immediate impact of cloud control on air handler operations and potential for energy savings.

Figure 20: Pearsons Hall Total Demand Profile for Two Similar Days Pre- and Post-Cloud Control



The solid line represents post-cloud control activation (left axis), while the dashed line represents pre-cloud control activation (right axis).

Source: MelRok

Smith Campus Center

ACCO-BEMS cloud controls commenced on March 13, 2020, at Smith Campus Center air handler, Ah2. Similar to Pearsons, the drop in the supply static pressure (50 percent) was immediate and noticeable, in tandem with the decrease in supply air fan current and an increase in supply air temperature (from a static 55°F [13°C] up to 68°F [20°C] at times).

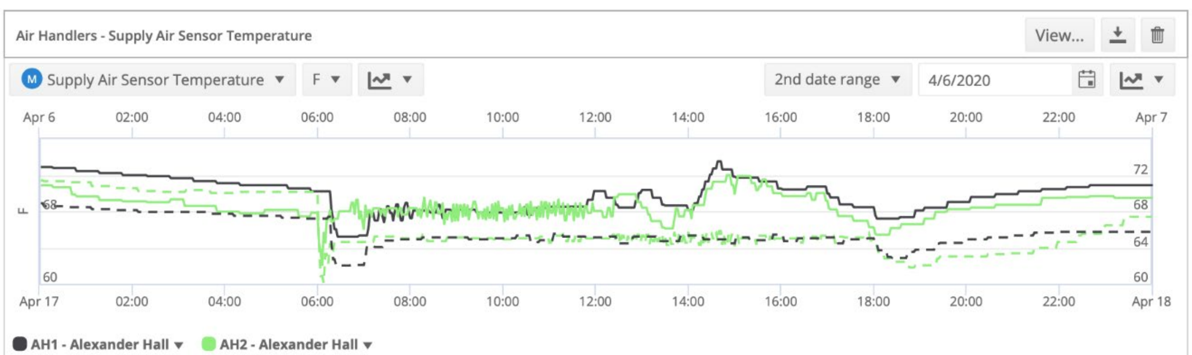
Hahn

ACCO-BEMS cloud controls commenced on March 12, 2020, for Ah1 at Hahn. In alignment with the results at Pearsons and the Smith Campus Center, there was a drop in the supply air static pressure by more than half, and an increase in supply air temperature from 60°F (16°C) to 68°F (20°C). While no sub-metered energy data exists for the air handlers, the impact of cloud control was reflected in the ~ 17 percent decrease in supply air fan speed.

Alexander

Deployment of cloud control of ACCO-BEMS at Alexander was only possible after BEMS wiring issues were fixed, and communication restored on March 23, 2020. ACCO-BEMS cloud controls were activated on April 11, 2020, after a two-week period to confirm proper operation of the BEMS communication. Pre- and post-supply air temperature profiles for similar days are shown in Figure 21 (dotted lines are pre-implementation temperatures, continuous lines are post-implementation values), highlighting the effect of a dynamic supply air strategy. The air handler current consumption was observed to decrease by up to 50 percent for one of the air handlers post-cloud control. Similar results were observed in other buildings.

Figure 21: Profile of Alexander Hall Air Handler Supply Air Temperature for Days Pre- and Post-Cloud Control



Graph highlights the reduction in cooling effected at the air handler post-cloud control

Source: MelRok

Occupancy Analysis and Results

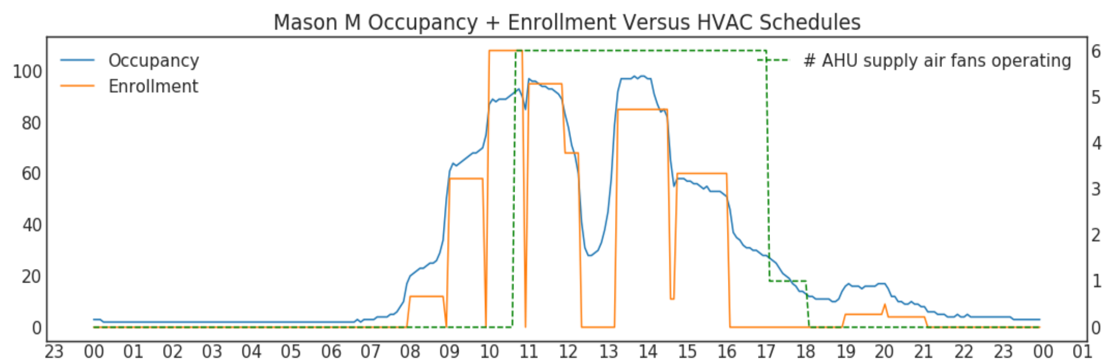
Applications

Analysis of the occupancy count data gathered through the COUNT software identifies where occupancy information could save energy. LBNL designed applications to address these areas, including occupancy-driven HVAC schedules, occupancy-aware ventilation rates, and power forecast models.

Occupancy-Driven HVAC Schedules

Similar to other universities or campuses, Pomona facilities set their HVAC schedules to operate during generic weekday business hours and to turn off for weekends and some predetermined holidays. The research team determined that using the same hours of operation for every building, day of the week, and season would waste energy. Figure 22 shows a misalignment between building occupancy and air handler operation. Figure 23 shows the occupancy and enrollment data compared to the static HVAC schedule at Mason Hall in Fall 2019. The air handling unit were starting too late, thereby compromising comfort, and shutting off too late, wasting energy. This suggests the need for dynamic schedules based on occupancy trends.

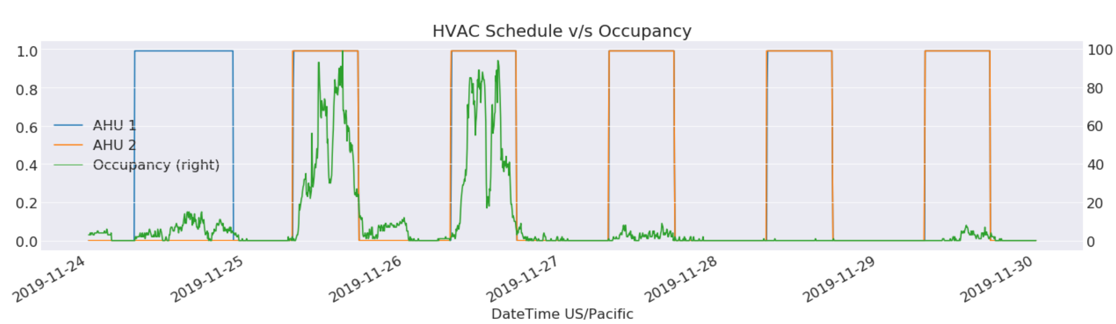
Figure 22: Occupancy vs. HVAC Schedule vs Enrollment Schedule for a Building



Source: MelRok

The current system has certain holidays programmed in, but it is not explicitly based on each year's academic calendar. As a result, there are events when the buildings are empty, and the HVAC system is operating at normal levels. Figure 23 shows Thanksgiving Break where the occupancy is close to zero for Wednesday through Friday of the break, but the building is operating as usual. On the other hand, there are events where a meeting is not programmed into the HVAC schedule and the change in occupancy over normal levels needs to be flagged so that the HVAC system responds. Identifying and responding to both types of events are important to keep the building functioning optimally, and through dynamic event-identification, the system flags events that are below, or above, the expected occupancy levels and responds accordingly.

Figure 23: Occupancy and HVAC Schedules at Pearsons Building



Before (Sunday to Tuesday) and during the Thanksgiving break (Wednesday to Friday).

Source: MelRok

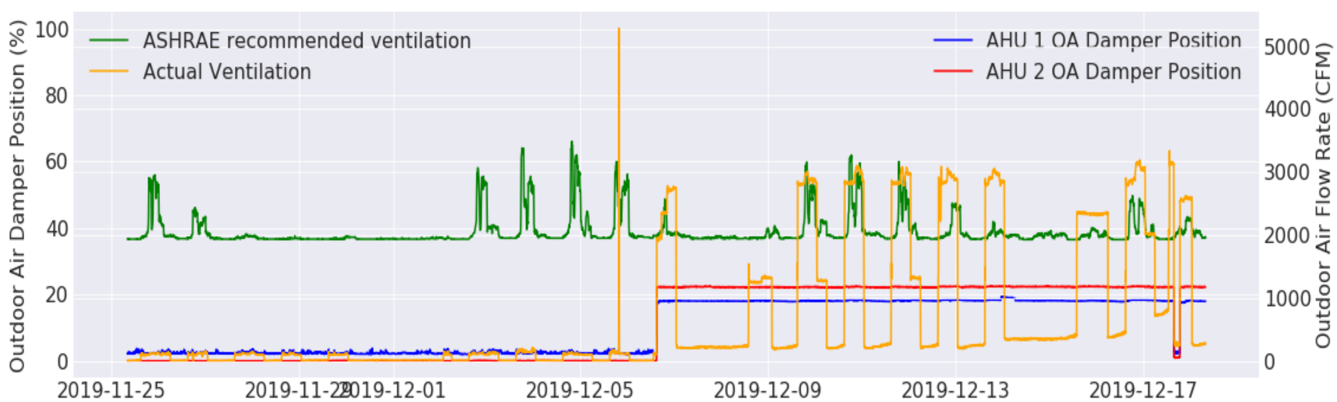
The occupancy-aware HVAC schedules and dynamic event identification create a robust application. The static schedules are based on occupancy trends, and event identification allows deviations from the general trends to be addressed appropriately. Additionally, acknowledging the events in real time enables the anomalies to be addressed without having to program them into the schedule, avoiding the perpetuation of a one-time event for months (examples of this were seen throughout the data analysis).

Occupancy-Aware Ventilation Rates

According to ASHRAE 90.1, building ventilation should be based on both the size of the building and the number of occupants. However, most buildings do not have occupancy data so the ventilation rates are usually determined with occupancy-based design parameters, or by rule of thumb, which will usually overestimate occupancy most of the time. With the Wi-Fi-based occupancy information, the project team was able to calculate a continuously responsive ventilation rate, as shown by the green line in Figure 24.

To evaluate the discrepancy between the implemented ventilation rates and the recommended ventilation rates, the project team calculated the actual ventilation from the supply air rates at the variable air volume level and outdoor air damper position in an air handle unit and compared these values to the code-compliant ventilation rate. Figure 24 shows that Hahn building was found to be under-ventilated due to outdoor air dampers in two air handling units being closed almost all the time (until December 5, 2019). This problem was corrected after the issue was reported. The new behavior of the damper is illustrated in Figure 24 (after December 12, 2019) and the corresponding change in ventilation is shown. The correction to this problem led to an improvement in air quality.

Figure 24: Outdoor Damper Positions of Several Air Handle Units in Hahn



Before and after correction and the continuously varying recommended and actual ventilation rates.

Source: MelRok

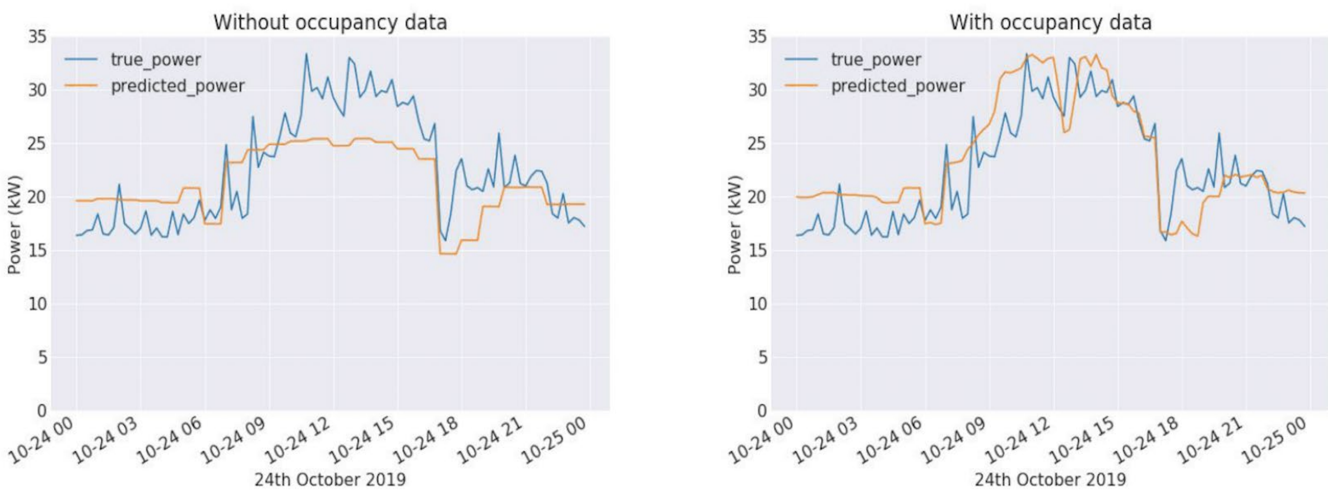
Currently, the occupancy-driven ventilation rates are used as a reference, but the data has promising applications for setting the ventilation rates based on occupancy and/or comparing the recommended and actual ventilation to trigger a static reset.

Power Forecast Models

Most utilities include demand charges and time-of-use prices in their tariffs for commercial buildings. Thus, forecasting building load is useful for implementing strategies (such as precooling) that minimize customer bills and, at the same time, minimize stress on the grid. There are multiple ways to forecast peak demand (Yunsun et al., 2019; Chirag et al., 2017; Grant et al., 2014), many of these methods make use of only power and weather data. Given the availability of occupancy data, we tested whether the forecast of peak demand would improve by adding this new variable to existing models.

We ran a linear regression model[2] with about five months of data (spanning two semesters and summer break) to forecast peak demand for the next 24 hours on a building in Pomona College. First, the model was run with just one independent variable (weather) and other time-dependent variables such as time-of-day and day-of-week. Then, Wi-Fi occupancy was added as another independent variable to see if there were any improvements. Data was sampled at 15 min intervals. For the sake of testing the algorithm, occupancy, and weather prediction data for the next 24 hours were assumed to be correct, and these were used to make predictions of the power through the two models.

Figure 25: Actual (blue line) Power Consumption vs. Forecasted (orange line) Power Consumption (kW) Without and With Occupancy data in Pomona's Student Center



Source: MelRok

Figure 25 shows the results on a single day (October 24, 2019) of this test. As demonstrated by the figure, occupancy data allows a better prediction of the peaks and troughs. Improving the peak demand prediction will enhance the development of strategies to minimize energy cost, as well as relieve stress on the grid.

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[2] Linear Regression: A method used for finding relationship between target and one or more predictors.

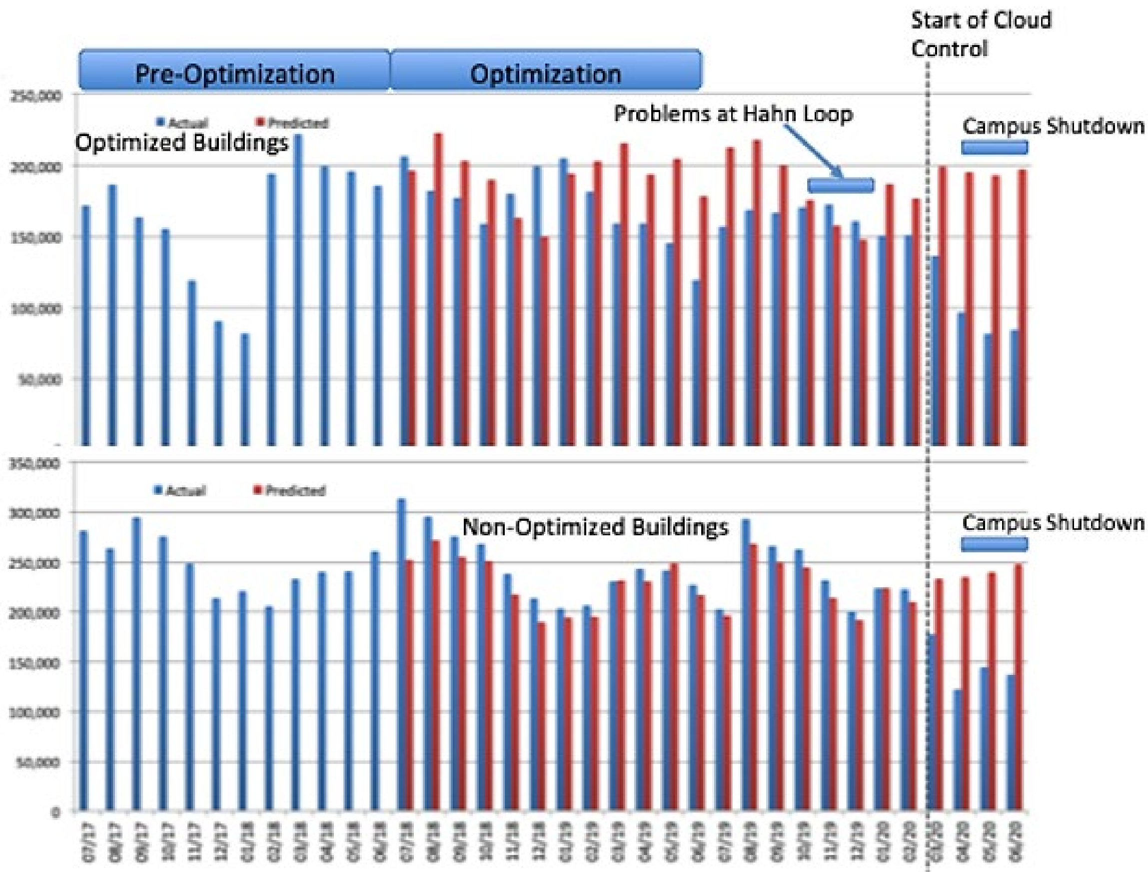
COVID Repercussions

The COVID pandemic severely impacted the ACCO-BEMS project on multiple fronts: 1) the lockdown practically stopped the resolution of open work orders, 2) the pre-optimization baseline became almost irrelevant given the severe decrease in building occupancy, and 3) the cloud control logic had to be paused until a clear direction was given as to what logic should be implemented to safeguard buildings post-pandemic. In July, Pomona College announced that classes would not resume in the fall of 2020, and that the campus would remain largely closed through the summer of 2021. The project team then developed a new measurement and verification protocol to best accommodate the circumstances. The strategy is described in the Measurement and Verification the following section.

Preliminary Energy Savings Findings

The campus shutdown associated with COVID came within a couple of weeks of the launch of cloud control. Even then, only the air handlers were being managed from the cloud and cloud control of chillers and terminal units had not been deployed. Although the preliminary results described previously are positive, accurate evaluation of the impact of cloud control required a creative M&V strategy to account for the COVID occupancy patterns and anomalies. Figure 26 shows the predicted (in red, using a weather-normalized empirical model) and actual (in blue) monthly energy usage for the two sets of buildings: the top chart represents the buildings where retro-commissioning efforts were undertaken guided by the ACCO-BEMS platform. The bottom chart is the predicted vs. actual energy for the buildings that were not retro-commissioned during the optimization period (because facility staff and contractors could not handle all the work orders that had been generated).

Figure 26: Actual vs Predicted Energy Use for Two Sets of Buildings



The top chart represents the buildings that were retro-commissioned; whereas, the bottom chart represents buildings where no retro-commissioning was done.

Source: MelRok

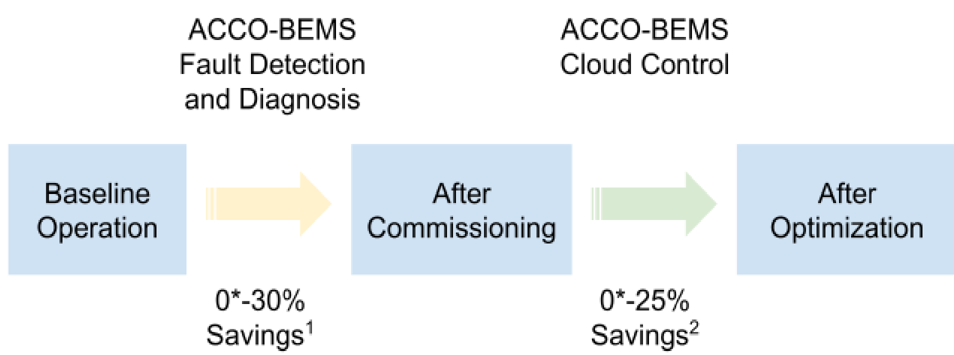
Another impact of COVID was the inability to deploy the software applications in the Pomona campus that had been developed by LBNL, because under COVID conditions: 1) schedules and ventilation rates were strictly controlled by campus for health; and 2) occupancy, used to better estimate power, dropped to almost zero.

CHAPTER 4: Measurement and Verification

While an M&V plan was developed early in the project (ACCO-BEMS Pre-optimization Analysis Report), delays in commissioning and changes in building operation and occupancy, due to COVID-19, forced the project team to re-evaluate the proposed approach. In fact, the baseline building energy use, collected before the start of the project, was not directly comparable with the energy use in the post-implementation period. For most facilities in the Pomona campus, the occupancy and schedules were substantially altered under COVID lockdown since instruction was moved online (Figure 27). To follow best practice in M&V, a fair evaluation of ACCO-BEMS performance would require 9 to 12 months of data after the buildings are back to full occupancy, which is not compatible with the timeline and budget of the project.

To mitigate this issue, the team consulted M&V experts at LBNL and developed three methods to evaluate savings. Individually, each method is limited, but taken together they provide reasonable estimates for energy savings generated by ACCO-BEMS. Table 6 shows ranges of savings estimated using the suggested methods. ACCO-BEMS enabled savings in two ways: 1) by providing information about faulty and underperforming equipment to the campus commissioning team (0* to 30 percent); and 2) by directly controlling and optimizing the HVAC operation (0* to 25 percent).

Figure 27: Representation of General Findings of the M&V Analysis and Proposed Evaluation Methods



Source: E3

Detailed information about savings per building, using the three M&V methods are illustrated in Table 6. The cells highlighted in yellow represent savings due to the fault detection and diagnosis features of ACCO-BEMS and the cells highlighted in green correspond to the savings due to cloud control. Savings for COUNT are estimated at the end of this section, since the developed applications could not be tested in the field as described in Chapter 4.

Table 6: Summary of Estimated Change in Energy During Operation for Different Time Periods

Assessment	Baseline Period	Performance Period	Method	Savings (%) (negative value means saved energy)									
				Hahn	Mason	Pearsons	Carnegie	Crook-shank	Thatcher	JC	Mudd	Alexander	SCC
Commissioning	7/17-6/18	7/18-6/19	M1	-9	2	4	-1	-8	-32	-14	10	3	15
Pre-Covid	7/17-6/18	7/19-3/20	M1	-8	10	1	-4	-1	-30	-17	1	15	16
Post-Covid	7/17-6/18	3/20-7/20	M1	-78	-28	-26	-56	-41	-38	-17	-25	-40	-60
Post-Covid	7/17-6/18	8/20-12/20	M1	-41	9	-7	-21	-9	-15	-21	-20	-24	-40
Post-Covid	AHU ON CC OFF hours (3/20-7/20)	AHU ON CC ON hours (3/20-7/20)	M2	NA	NA	NA	NA	NA	NA	NA	13	-17	-17
Post-Covid	AHU ON CC OFF hours (8/20-12/20)	AHU ON CC ON hours (8/20-12/20)	M2	1	-19	-7	NA	NA	NA	NA	-25	11	-12
Post-Covid	CC OFF hours (8/20-12/20)	CC ON hours (8/20-12/20)	M3	-20 (OAT<85F)	-25	-13					-20 (Aug), ~0 (Nov)	-15~20 (low load)	-10 (OAT<90F)

Includes the commissioning phase (yellow row) and the performance period. The performance period is subdivided into three periods: Pre-COVID (red row), Post-COVID (white rows), and Post-COVID (green rows).

AHU = air handling unit; CC = cloud control; OAT = outside air temperature
Source: E3

For each row, the savings are calculated as the difference between a baseline period and a performance period, using a specific methodology. Three different methods are used, identified in the table as M1, M2 and M3. M1 consists of using an empirical method to model the energy profile of the building during a baseline period, while M2 and M3 consist of comparing the energy between select periods and/or hours with cloud control ON vs. periods/hours with cloud control OFF. The most relevant numbers in the table are the last two rows, as they represent savings estimate during the post-COVID period with a certain degree of building activity and occupancy levels. From March through July 2020, only a few buildings had some level of activity comparable to pre-COVID, namely JC Cowart, Alexander, Thatcher, and Mudd Halls (Science Library) for part of the period. The other buildings only resumed some level of activity comparable to pre-COVID in August 2020; hence, the segregation of post-COVID period as pre and post August 2020.

In addition to the analysis, the research team examined the potential energy savings in using COUNT for Wi-Fi-based occupancy building controls for HVAC systems, in particular through delaying HVAC start times. As stated previously, due to the limiting in-person factors of the COVID-19 pandemic, in a hypothetical context, the team estimated the approximate savings for Pomona College buildings in past semesters, Spring 2019, Summer 2019, Fall 2019 and Spring 2020. They generated optimized HVAC schedules, specifically targeting delayed HVAC start times, and its corresponding potential building energy savings using time series analysis of building sensor data and machine learning methods for Wi-Fi-based occupancy detection.

The team defined moments in which the building was either occupied or unoccupied using change point detection and K-Means clustering and classification. Separately, the building's daily conditioning time (the time taken for the building to heat/cool and reach the required conditions) was estimated in order to properly evaluate potential regions of savings. This information was combined to generate ideal HVAC schedules and estimate the potential HVAC savings of the building.

The research team found that, in a subset of seven out of ten Pomona buildings that are relevant to this project, the HVAC systems turned on earlier than needed. The different types and uses of the individual buildings also produced a wide range of savings potential. It was estimated that delaying HVAC start times using Wi-Fi occupancy-based controls can potentially save an average of 2.3 percent (31,753 kWh) of total building energy usage during Spring 2019, Summer 2019, Fall 2019, and Spring 2020 semesters. Detailed savings are found in Table 7.

Table 7 contains the potential savings estimates for seven Pomona College buildings, listed in rows 1 to 7, Building column, for the Spring 2019 (2019-04-25 to 2019-05-12)[3], Summer 2019 (2019-05-29 to 2019-08-01), Fall 2019 (2019-09-18 to 2019-12-13) and Spring 2020 (2020-01-21 to 2020-03-15)[4].

The individual building's savings, the semester savings, the semester energy use and their corresponding annual totals are in kWh. Partially observed buildings contain "N/A" in table building savings for semesters unobserved, due to data access limitations.

The semester savings percent is the semester savings over the semester energy use. The average savings percent is the total annual energy saved over the total annual energy use.

Table 7: Estimated Savings for COUNT Scheduling Application

Building	Spring '19	Summer '19	Fall '19	Spring '20	Total Annual (kWh)	Average Savings (percent)
Alexander	641	4,046	1,038	30.9		
Carnegie	N/A	N/A	N/A	58.5		
Crookshank	N/A	N/A	527	45.3		
Hahn	640	691	675	26.2		
Mason	365	1,860	1,193	267		
Pearsons	N/A	N/A	26.9	16.6		
SCC	1046.5	5,575	7,686	5,326		
Semester Savings (kWh)	2,666	12,172	11,146	5,770	**31,754**	
Semester Energy Use (kWh)	133,285	450,822	464,400	33,9412	**1,387,919**	
Semester Savings (percent)	2.0 percent	2.7 percent	2.4 percent	1.7 percent		**2.3 percent**

Source: E3

[3] Does not include full semester, network data access started 2019-4-25

[4] Does not include full semester, campus closed on 2020-03-18 due to the COVID pandemic

Lessons Learned

Continuous Assessment is Critical

The retro-commissioning of buildings served by the Hahn chiller loop demonstrated the complexities and interdependencies of certain systems that span multiple buildings. Unexpected adverse effects resulted from the commissioning of the chiller plant, which could only be detected and diagnosed with continuous detailed monitoring and assessment of the BEMS.

Vulnerability to Device Failures

Cloud control relies on a chain of information for proper operation. Should any link break, cloud control can be jeopardized. To prevent system failure, the research team developed a fallback mechanism that gave back control to local controllers whenever the information chain between the cloud and the devices was severed, and whenever faulty sensors were detected. This safety mechanism was an issue at Alexander Hall, when frequent failure of communication led to sensor data being frozen. As a result, cloud control was disabled, and control reverted to local programs. In the future, intelligence should be embedded in the cloud control to extrapolate faulty or missing values and continue cloud-based controls in spite of the missing information. This is probably a better alternative than relying on local controls, where the response to missing data may be non-deterministic.

Jumpstart Cloud Control

The retro-commissioning efforts resulted in a deluge of work orders, which delayed the commissioning of almost half the buildings. As a result, the project team proceeded to cloud control before all buildings were retro-commissioned, as initially planned. However, the impact of cloud control on non-retro-commissioned buildings was obvious from the first day. Dynamic reset strategies for supply temperatures and static pressures resulted in noticeable reductions in energy use. A lesson learned for future implementations is to proceed with cloud control at the earliest opportunity. As cloud control proceeds, faulty equipment and devices can be detected and fixed.

Potential for Application Integration

The extensive data analysis performed in this project identified many opportunities for the use of occupancy-informed applications and demonstrated value in integrating Wi-Fi data with ACCO-BEMS controls. The benefits of implementations as discussed above, include reducing energy waste, optimizing ventilation, and improving user comfort. There are numerous ways to use the data for a wide range of applications. The next steps to implement these applications require integrating real-time processed occupancy data into the ACCO-BEMS system.

Occupancy Sensing Granularity and Accuracy Tradeoffs

Establishing the relationship between access point locations and HVAC zones is important to implement occupancy-based applications at the zone-level. A significant effort was made to map the access points in each building to the closest HVAC zone. This process involved several sources of information, and the updating of outdated equipment maps to enable an accurate mapping. Additionally, relating the access point to the "closest" variable air volume involves assumptions on whether closeness is determined solely by distance, or if walls and other physical obstacles are taken into account. There are several factors that determine the access point to which a device connects, including proximity, number of devices already connected to the access point, and the physical barriers in between the access point and device. Because of these factors it is difficult to create a mapping where all devices connected to an access point are consistently in a certain HVAC zone. This process illustrates the tradeoff between granularity of data (building-level versus zone-level) and accuracy, highlighting the need for an established process and set of assumptions to standardize this mapping.

CHAPTER 5: Benefits to Ratepayers

Economic Evaluation with Avoided Costs Framework

In addition to the cost benefits of substantially and sustainably reducing energy use, there are other ancillary economic benefits to the ACCO-BEMS project. This section evaluates those ancillary benefits following the avoided cost framework adopted by the CPUC for evaluating demand side cost effectiveness. The California Public Utilities Commission (CPUC) Distributed Energy Resources Avoided Cost Calculator calculates the hourly cost of delivered electricity that is 'avoided' by distributed energy resources (CPUC, 2020). The avoided cost framework has been developed over the last 20 years and is the standard approach employed by the CPUC and CEC to evaluate distributed energy resources, including energy efficiency and demand response. The avoided cost approach assumes that distributed energy resources reduce system costs on the margin, but that the resource portfolio and underlying grid operations remain unchanged.

In the avoided cost framework, the ability to reduce load during peak hours with the ACCO-BEMS project provides benefits to the grid. From an energy perspective, this means reducing consumption in hours with highest wholesale energy costs. From a power/peak capacity perspective this means reducing consumption during hours that are setting the peak capacity of the grid – thus easing strain on the electric system and deferring upgrades to the transmission and distribution systems. From an emissions perspective, this means reducing load during hours with highest emissions. Project benefits from the avoided cost framework are on the wholesale market side and could be realized by wholesale market participants, but typically would not be directly realized by a retail customer. Emissions benefits represent a societal benefit and would not be directly realized by wholesale market participants.

The grid benefits of ACCO-BEMS were calculated by comparing the hourly energy savings during the optimization year and the post-optimization year to the baseline year energy consumption.

This analysis estimates that if ACCO-BEMS were deployed in all the non-residential buildings in California by 2030, California could see over $2 billion in grid benefits. Additionally, using COUNT to implement Wi-Fi occupancy-based controls to delay HVAC start times could potentially save an average of 2.3 percent of total building energy use. If COUNT dynamic HVAC scheduling were used in non-residential buildings, California could save an additional $200 million.

Avoided Cost Framework

For the Avoided Cost Calculator approach, hourly energy consumption profiles of the Pomona College buildings are used in conjunction with several benefit streams to determine total benefits for these categories (explanations provided below):

- Avoided Wholesale Energy Costs
- Avoided Losses

- Generation Capacity Value
- Transmission Capacity Deferral Value
- Distribution Capacity Deferral Value
- Avoided Emissions Value

Hourly Load Profiles

To set the foundation for the avoided cost analysis, an aggregate hourly load profile was calculated for the 11 Pomona College buildings participating in the project.

For ACCO-BEMS, the baseline year was July 1, 2017 through June 30, 2018. The optimization period, also known as the commissioning/tuning phases, was July 1, 2018 through June 30, 2019. The post-optimization period where the performance of the ACCO-BEMS was assessed was July 1, 2019 through February 1, 2020. Due to COVID-19, data after February 2020 is not comparable to the baseline. However, the peak summer months with the greatest avoided cost benefits are still included in this post-optimization time.

To estimate the potential savings from the use of COUNT, LBNL used building energy data from April 2019, through March 2020. LBNL estimated how long HVAC start times could be delayed each day until building occupancy reached a 20 percent threshold. The estimated energy savings from delayed HVAC start times were used to calculate grid benefits.

Wholesale Energy Benefits

Wholesale energy benefits (also referred to as avoided wholesale energy costs) are the cost savings associated with either purchasing wholesale electricity in time periods with lower prices or purchasing less wholesale electricity compared to baseline operations. Avoided wholesale energy is calculated by taking the difference in energy consumption in each hour of the optimization or post-optimization period and the same hour in the baseline. The change in energy consumption for each hour is then multiplied by the month-hour average of the projected wholesale energy price for climate zone 9 for every year in the analysis.

System Loss Benefits

System loss benefits are defined in this analysis as the avoided costs for energy lost due to the inefficiencies in the transmission and distribution systems. During peak hours, when the system is more constrained, losses are typically higher because of higher levels of energy flowing through the transmission and delivery system. When losses are higher, more electricity generation is required to serve the same amount of load on the grid, thus driving up the costs to serve load.

This benefit stream is calculated by taking the change in energy consumption with and without the ACCO-BEMS platform and multiplying it by the system losses cost stream. The system losses cost stream is calculated by multiplying hourly wholesale energy prices by the loss factor from the respective time-of-use (TOU) period. Loss Factors, seen in Table 8, are defined by the Avoided Cost Calculator for each investor-owned utility, in each TOU period. The loss factors from SCE (Climate Zone 9) were used for this analysis.

Table 8: Electricity System Loss Factors by Investor-Owned Utility from the 2020 CPUC Avoided Cost Calculator

TOU Period	Description	PG&E	SCE	SDG&E
1	Summer Peak	1.109	1.084	1.081
2	Summer Shoulder	1.083	1.054	1.071
3	Summer Off-Peak	1.048	1.022	1.043
4	Winter Peak	1.083	1.054	1.071
5	Winter Shoulder	1.048	1.022	1.043
6	Winter Off-Peak	1.109	1.084	1.081

Source: MelRok

Generation Capacity Benefits

The value of generation capacity benefits is determined by the project's ability to reduce power use from the grid in peak hours. This reduction in power use decreases the power that needs to be procured to meet that peak demand period. The economic value of this benefit is determined to be the cost of contracting this power in the open market, in $/kW yr.

The amount of peak load reduced is calculated as the average reduction in load during peak hours at the Pomona College buildings during the optimization and post-optimization years. Peak hours are defined as the five peak evening hours, typically corresponding with the time between 4 p.m. and 9 p.m. July, August, September, and October are the peak load months. Figure 28 shows the actual weighting of peak capacity hours in Climate Zone 9 used for this analysis. Reducing load during peak hours in September would have the greatest impact on avoided capacity.

Figure 28: Month-Hour Weighting for Capacity Value from CPUC Avoided Cost Calculator

Month-Hour Average Capacity Allocators				
	July	August	Sept	October
16	0%	0%	0%	0%
17	0%	0%	6%	0%
18	0%	0%	10%	0%
19	0%	0%	11%	0%
20	0%	0%	32%	1%
21	0%	1%	27%	0%
22	0%	0%	10%	0%
23	0%	0%	1%	0%

To determine total annual capacity value.

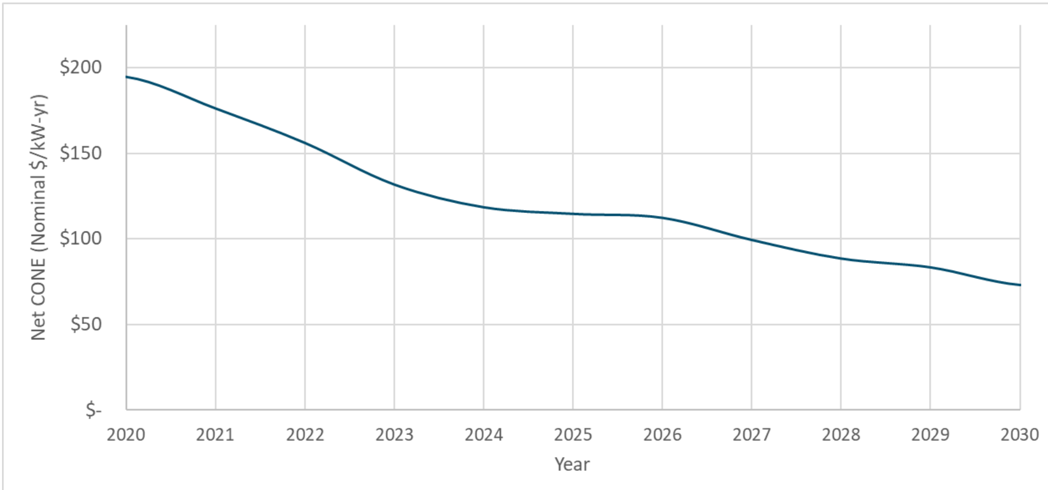
Source: E3

Historically, the capacity value is based on the cost of constructing a new gas-fired peaking power plant in California, based on the net Cost of New Entry, or Net CONE. In 2020, the

CPUC Avoided Cost Calculator methodology switched to using the Net CONE of a new utility scale battery as the bases for capacity value.

Figure 29 shows the declining Net CONE of capacity over time. By 2030, the net cost of new entry is about $73 per kW-year.

Figure 29: Input Capacity Costs From the 2020 CPUC Avoided Cost Calculator



Source: E3

Transmission & Distribution Deferral Benefits

The transmission and distribution deferral benefits include the value of reducing the need for new infrastructure and equipment for transmission and distribution capacity expansion. Because upgrades are often installed in large increments, upgrades can be deferred for multiple years, or avoided altogether. Deferring an upgrade for multiple years generates value, based on the time-value of money, while indefinite upgrade deferrals generate value at the total cost of the avoided upgrade. While the other avoided cost benefit streams are broadly applicable to a large region, for transmission and distribution deferral, both the value and hourly allocation are location specific. Transmission and distribution costs are specific to utility; this analysis uses costs for SCE from the CPUC Avoided Costs Calculator. Figure 30 and Figure 31 show the allocation of transmission and distribution deferral benefits used in this analysis. The benefits of avoided transmission will be seen if load is reduced during peak hours in July, August, September, or October. Distribution benefits would be seen in any month of the year, but the largest benefit is seen in June during peak hours.

Figure 30: Month-Hour Transmission Allocations Factors

Month-Hour Average Transmission Allocators				
Hour	July	August	Sept	October
12	0.0%	0.0%	2.2%	2.2%
13	0.0%	2.2%	4.5%	4.5%
14	6.6%	6.6%	4.6%	6.8%
15	8.8%	6.6%	4.6%	6.8%
16	8.7%	6.5%	4.4%	4.6%
17	2.1%	0.0%	0.0%	4.4%
18	0.0%	0.0%	0.0%	2.2%

Source: E3

Figure 31: Month-Hour Distribution Allocation Factors

Month-Hour Average Distribution Allocators												
	July	August	Sept	October	Nov	Dec	January	February	March	April	May	June
0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
1	0.0%	0.0%	0.0%	0.0%	0.0%	0.6%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.1%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
10	0.1%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
11	0.4%	0.6%	0.1%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.2%
12	0.1%	0.5%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%
13	0.5%	0.5%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.1%	0.6%
14	0.7%	2.1%	0.4%	0.1%	0.0%	0.1%	0.0%	0.0%	0.0%	0.1%	0.4%	2.1%
15	1.8%	3.4%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0.2%	0.0%	0.1%	3.8%
16	1.6%	2.6%	0.0%	0.1%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	9.7%
17	2.8%	1.6%	0.5%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	20.7%
18	2.2%	1.6%	0.2%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	13.0%
19	2.0%	0.4%	0.2%	0.1%	0.0%	0.1%	0.4%	0.1%	0.1%	0.0%	0.1%	7.1%
20	0.0%	0.0%	0.1%	0.0%	0.0%	0.4%	0.1%	0.1%	0.0%	0.2%	0.0%	1.5%
21	0.1%	0.2%	0.0%	0.0%	0.0%	0.1%	0.0%	0.2%	0.1%	0.0%	0.0%	2.5%
22	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%	0.0%	1.6%
23	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.4%

Source: E3

Avoided Emissions Benefit

The avoided emissions benefit is the value of short-run marginal emissions reductions. Short-run marginal emissions are the emissions associated with increasing or decreasing load for the marginal generator on the grid. For a given point in time, it is assumed that there is a power plant that would be responding to any marginal change in load on the grid; that power plant would be the marginal generator. If load increases, the marginal generator will come online or increase its output, and if load decreases, the marginal generator will turn down its output.

Each power plant has an associated heat rate (plant efficiency) depending on physical characteristics, and where it is operating in respect to its load curve. Based on that heat rate, and the carbon intensity of the power plant's fuel, the marginal change in emissions can be calculated. Short-run marginal emissions assume that the installed generation resource mix on the grid will not change based on a change in load. As a counterexample, a long-run emissions factor, in a Renewable Portfolio Standard-driven procurement scheme, would factor in increased renewables purchases offsetting a portion of any additional load.

To calculate short-run marginal emissions, hourly electricity prices from the production simulation model are used along with forecasted natural gas prices to assume a corresponding hourly marginal heat rate.[5] Based on the assumed marginal heat rate, and carbon intensity of methane gas, the marginal emissions rate is calculated for each hour. The marginal emissions rate is reported in tons of CO2-equivalent per megawatt-hour (tCO2-e/MWh). Figure 32 shows the average calculated emissions rate for each month and hour in 2030. It is observed that during midday hours when solar is on the margin, emissions rates are typically zero. Emissions rates are highest in the summer evening peak period. To calculate avoided emissions, the marginal emissions rate is multiplied by the change in electricity consumption in the optimization and post-optimization years.

Figure 32: Heat Map of the Marginal Emissions Rate (tCO2-e/MWh)

	July	August	Sept	October	Nov	Dec	Jan	February	March	April	May	June
0	0.320	0.373	0.382	0.359	0.361	0.380	0.355	0.355	0.338	0.319	0.315	0.319
1	0.319	0.364	0.374	0.357	0.355	0.377	0.353	0.353	0.325	0.323	0.316	0.317
2	0.319	0.365	0.372	0.356	0.355	0.374	0.352	0.353	0.336	0.325	0.312	0.315
3	0.318	0.371	0.373	0.355	0.354	0.375	0.350	0.349	0.337	0.329	0.309	0.315
4	0.319	0.374	0.378	0.360	0.355	0.376	0.354	0.350	0.347	0.326	0.312	0.316
5	0.323	0.379	0.389	0.373	0.364	0.383	0.365	0.364	0.370	0.345	0.317	0.320
6	0.322	0.375	0.389	0.383	0.374	0.393	0.380	0.391	0.382	0.352	0.312	0.318
7	0.321	0.369	0.372	0.369	0.372	0.402	0.393	0.394	0.362	0.328	0.313	0.321
8	0.322	0.371	0.369	0.350	0.358	0.390	0.385	0.361	0.341	0.327	0.325	0.321
9	0.324	0.373	0.369	0.350	0.355	0.383	0.374	0.341	0.334	0.330	0.333	0.326
10	0.333	0.376	0.370	0.358	0.353	0.371	0.357	0.270	0.298	0.309	0.322	0.329
11	0.326	0.384	0.375	0.359	0.349	0.376	0.361	0.295	0.316	0.285	0.321	0.334
12	0.347	0.396	0.381	0.364	0.351	0.374	0.346	0.281	0.319	0.290	0.314	0.339
13	0.330	0.408	0.389	0.370	0.354	0.375	0.357	0.305	0.320	0.256	0.294	0.338
14	0.359	0.441	0.416	0.386	0.360	0.376	0.356	0.317	0.320	0.267	0.277	0.353
15	0.419	0.502	0.457	0.419	0.387	0.385	0.365	0.338	0.329	0.313	0.332	0.383
16	0.469	0.558	0.511	0.458	0.429	0.418	0.395	0.372	0.374	0.388	0.398	0.410
17	0.647	0.646	0.623	0.498	0.479	0.444	0.430	0.421	0.424	0.406	0.410	0.451
18	0.644	0.653	0.638	0.501	0.482	0.453	0.462	0.463	0.468	0.447	0.451	0.482
19	0.652	0.662	0.640	0.473	0.449	0.441	0.448	0.440	0.463	0.475	0.467	0.507
20	0.636	0.640	0.605	0.446	0.424	0.438	0.425	0.419	0.450	0.443	0.455	0.481
21	0.584	0.606	0.602	0.419	0.421	0.440	0.431	0.409	0.405	0.386	0.402	0.403
22	0.363	0.437	0.439	0.384	0.391	0.401	0.396	0.389	0.396	0.358	0.364	0.360
23	0.328	0.389	0.404	0.371	0.378	0.390	0.369	0.379	0.372	0.343	0.339	0.334

Averaged by month and hour, for 2030 from the 2020 CPUC Avoided Cost Calculator

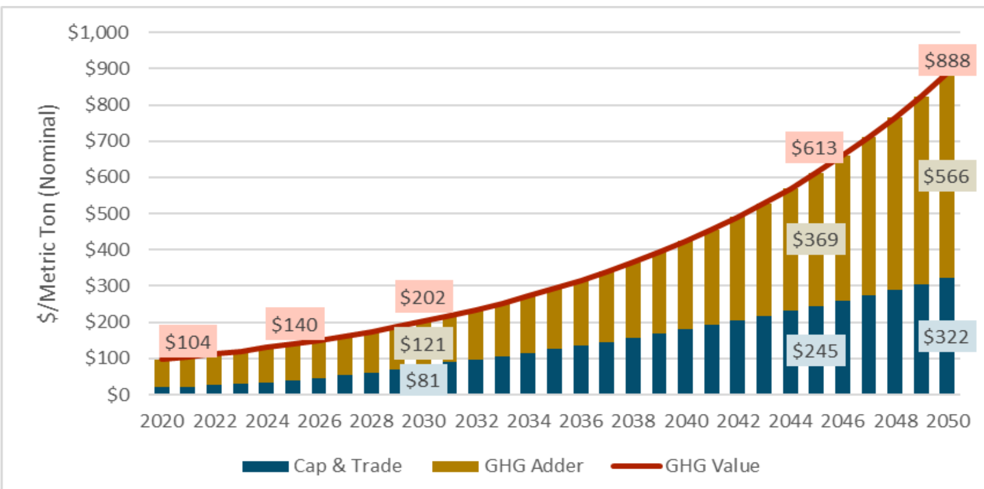
Source: E3

[5] 2020 ACC Documentation, page 20: https://files.cpuc.ca.gov/gopher-data/energy_division/energyefficiency/cost effectiveness/2020%20ACC%20Documentation%20v1a.pdf

To assign value, calculated avoided emissions are multiplied by the value of emissions reductions in a given year. In 2018, in light of findings in the Integrated Resource Procurement proceedings, the CPUC published a value of greenhouse gas (GHG) emissions for the purposes of evaluating distributed energy resources.[6] This value, referred to as the CPUC GHG Value, assigns value to emissions reductions from distributed energy resources based on the shadow price of incremental emissions reductions from supply resources (e.g., solar + storage). If statewide energy procurement targets are driven by GHG emissions targets, and a given distributed energy resource reduces emissions that will, in turn, reduce the amount of renewable energy that is needed to be procured by investor-owned utilities and other load serving entities. In effect, this represents the benefit of additional renewable energy integration within the avoided cost framework to achieve the annual emissions intensity target.[7]

The electric sector GHG value (from Integrated Resource Plan modeling) is divided into two components, the Cap-and-Trade Value, and the GHG Adder. The GHG Adder represents the additional cost of meeting GHG emission targets in the electric sector based in Integrated Resource Plan modeling. The total GHG value is shown in Figure 33. The GHG value is expected to increase each year and will be nearly double its current value by 2030.

Figure 33: GHG Value From the 2020 CPUC Avoided Cost Calculator



Source: E3

Economic and Greenhouse Gas Reduction Benefits - Avoided Cost Framework

The economic value from an avoided cost perspective is broken out into the categories described below. The avoided cost perspective reflects the cost savings for a load serving entity (such as investor-owned utilities) to serve load to its customers, based on wholesale market and utility cost streams. The benefits are based on the load reduction and cost-benefit tables discussed in the Economic Evaluation with Avoided Costs Framework section. Benefits

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[6] CPUC 2018, Page 106: http://docs.cpuc.ca.gov/PublishedDocs/Published/G000/M209/K771/209771632.PDF

[7] 2020 ACC Documentation, page 24: https://files.cpuc.ca.gov/gopher-data/energy_division/energyefficiency/costeffectiveness/2020%20ACC%20Documentation%20v1a.pdf

are calculated based on changes in operation at Pomona College during the optimization and post-optimization years. The ACCO-BEMS and COUNT optimized load profiles were applied to benefit streams, such as peak capacity and emissions. Results are summarized.

ACCO-BEMS

The ACCO-BEMS project is divided into three main phases:

1. Baseline Year:
   - July 2017 to June 2018
   - Pre-Optimization Phase
   - 12-month monitoring and installation phase during which the unaltered behavior of all systems is recorded while the Touch Gateway and sensors are being installed.
2. Optimization Year
   - July 2018 to June 2019
   - Continuous Assessment and Commissioning
   - During which commissioning efforts are implemented based on the ACCO-BEMS findings and ACCO-BEMS control is sequentially activated.
3. Post-Optimization Year
   - July 2019 to February 2020
   - Cloud Control Activation & Operation
   - 8-month (due to COVID-19) post-implementation monitoring phase where the performance of the ACCO-BEMS is assessed.

The grid benefits of ACCO-BEMS were calculated by comparing the hourly energy savings during the optimization year and the post-optimization year to the baseline year energy consumption.

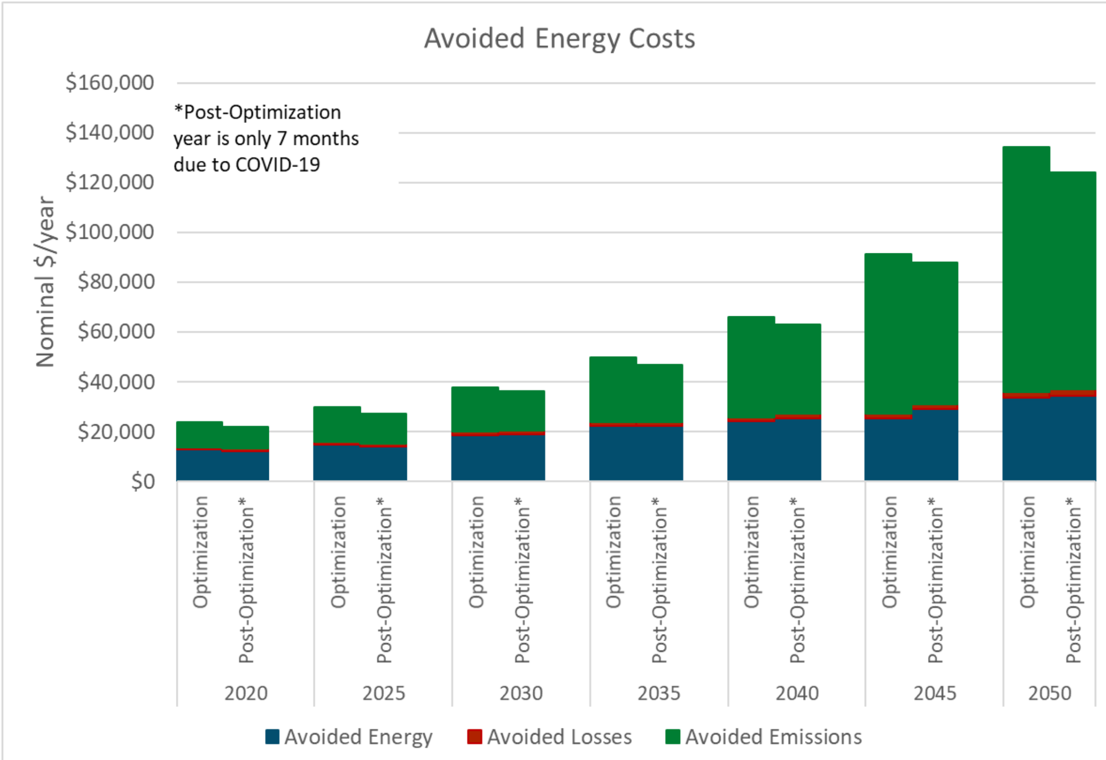
Wholesale Energy Benefits

Wholesale Energy Benefits (also referred to as Avoided Wholesale Energy Costs) are the cost savings from purchasing wholesale electricity during time periods with lower prices. These benefits are estimated for each forecasted energy price year between 2020 and 2050. It is noted that Avoided Losses are roughly proportional to avoided energy costs.

As seen in Figure 34, the load reduction results in increasing value to the load-serving entity over time. Although the post-optimization year only had 7 months' worth of energy savings, the avoided cost value is just as much or more than the optimization year. This suggests that the savings could be even greater in a typical operation year.

Avoided emissions benefit makes up some amount of the total benefit, but it is noted that this is an electric sector planning value outside of existing carbon markets such as the Cap-and-Trade market; it is not as readily monetizable as the other value streams.

Figure 34: ACCO BEMS Avoided Wholesale Energy Costs



Source: E3

Peak Load Reductions

The month-hour average demand reductions for the optimization year and post-optimization year are shown in Figure 35 and Figure 36. Negative values seen in July, December, and January indicate there was an average demand increase during that month-hour relative to the baseline year. The largest demand reductions were seen in June during the optimization year, and July during the post-optimization year.

Figure 35: Optimization Year Average Month-Hour Demand Reduction

Optimization Year Month-Hour Average Demand Reduction (kW)												
Month	July	August	Sept	Oct	Nov	Dec	January	February	March	April	May	Jun
0	7	137	179	184	54	23	36	111	155	173	184	216
1	-57	96	90	89	136	69	91	145	132	61	80	142
2	-73	72	66	67	46	10	26	57	96	26	45	109
3	-42	112	77	55	27	-4	9	35	76	20	35	74
4	-38	86	74	50	19	-6	0	29	70	16	35	62
5	-83	41	57	18	7	-13	-8	20	73	18	28	55
6	-73	32	51	13	5	-19	-22	8	70	18	30	56
7	-63	26	68	17	0	-18	-26	5	76	35	40	47
8	-63	29	61	13	0	-16	-29	4	76	37	43	45
9	-56	24	65	13	1	-19	-31	1	76	40	43	52
10	-42	23	61	11	1	-17	-30	3	71	36	41	56
11	-46	22	59	10	-1	-17	-30	3	65	34	42	51
12	-128	-108	46	9	-7	-21	-38	-4	46	27	34	38
13	-36	8	112	59	-3	-23	-41	-15	45	31	43	42
14	3	71	125	65	5	-32	-49	-7	75	62	65	140
15	8	80	56	75	29	-12	-13	19	94	68	73	201
16	9	98	90	91	33	-11	-4	41	93	67	97	202
17	8	89	101	83	20	-3	13	60	99	48	95	167
18	6	101	104	84	21	12	15	89	106	43	83	148
19	17	95	103	84	34	18	34	87	97	52	80	155
20	15	91	84	96	39	11	35	108	96	69	83	146
21	8	86	61	85	48	16	15	115	109	83	90	148
22	4	88	72	80	49	16	23	117	104	90	98	153
23	9	93	73	91	49	15	42	113	99	85	108	161

Source: E3

Figure 36: Post Optimization Year Month-Hour Demand Reduction

Post Optimization Year Month-Hour Average Demand Reduction (kW)								
Month	July	August	Sept	Oct	Nov	Dec	January	February
0	319	240	168	174	115	126	122	101
1	179	86	22	35	148	141	148	156
2	127	43	1	19	31	66	76	90
3	126	48	21	10	4	49	58	78
4	134	24	21	14	-2	47	49	75
5	93	40	69	3	-12	41	41	72
6	84	51	89	-2	9	40	46	76
7	79	49	97	11	6	41	45	81
8	75	48	91	-1	8	37	47	83
9	80	42	103	-6	3	32	45	82
10	91	42	104	-20	0	30	38	77
11	77	34	99	-23	-5	22	23	61
12	12	-30	37	-34	12	47	43	81
13	168	112	104	34	17	46	45	81
14	224	147	142	46	42	50	46	92
15	199	142	131	39	38	46	52	81
16	199	133	143	86	29	45	59	88
17	200	116	123	107	40	61	74	92
18	212	104	116	115	68	91	91	103
19	210	91	112	114	77	96	103	100
20	214	91	104	118	100	105	97	102
21	211	102	98	107	106	115	96	107
22	211	91	88	107	119	126	102	99
23	209	93	87	116	122	123	120	92

Source: E3

The load reduced during peak capacity, transmission, and distribution hours were calculated using the allocation factors from previous figures. Peak load reductions are estimated in Table 9. Distribution value capacity reduction is only calculated for July through February of each year to allow for direct comparison. All three categories have a larger peak load reduction in the post-optimization year, with transmission and distribution value more than doubling.

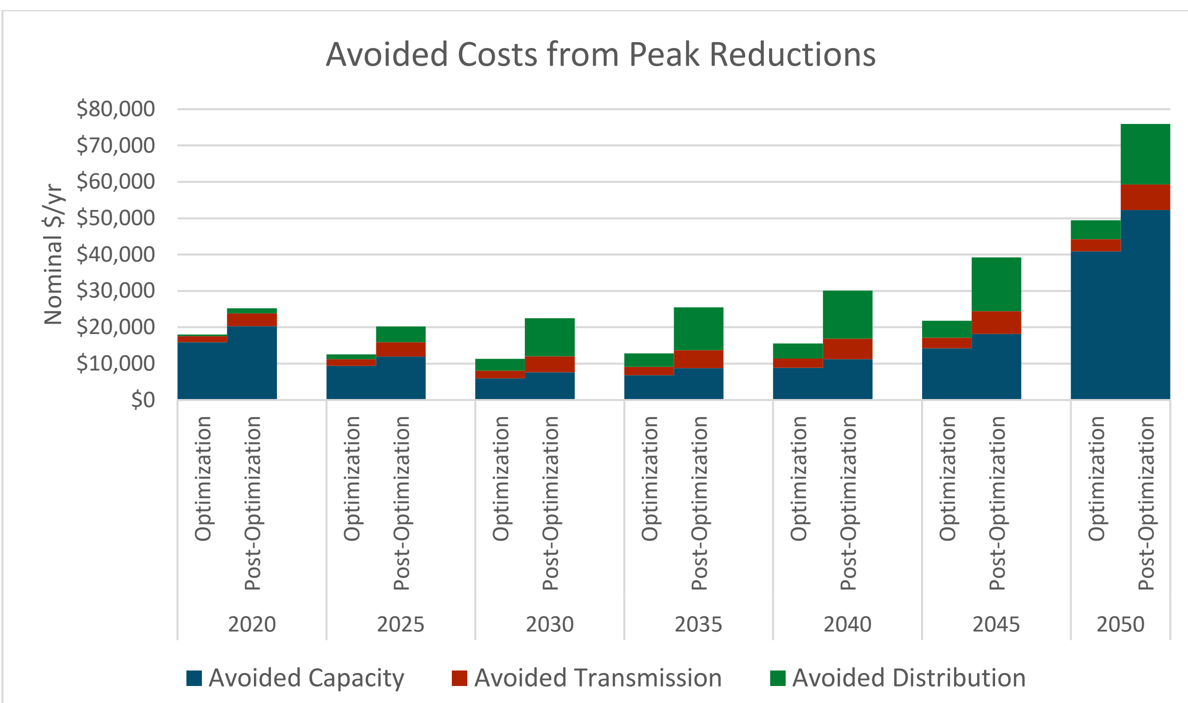
Table 9: Calculated Average Peak Load Reductions

Calculated Peak Load Reduction (kW)	Optimization Year	Post-Optimization Year
Generation Capacity	82	104
Transmission Capacity	59	126
Distribution Capacity	15	47

Source: E3

Figure 37 shows the weighted peak capacity reductions in the optimization and post-optimization years. It is noted that many of the distribution peak hours are in months not included in the post-optimization year, so this value would likely be higher in a typical operation year. Capacity and transmission avoided costs are greater during the post-optimization year because the demand reductions are greater during the peak hours. Avoided capacity makes up the largest proportion of benefits for the optimization year results. The post-optimization year results show avoided distribution with the largest proportion of benefits in 2030 to 2045.

Figure 37: Avoided Costs from Peak Reductions



Source: E3

Statewide Benefit

This section provides a discussion of estimating the potential statewide benefit to deploying this technology in all non-residential buildings by 2030. The total square footage of the Pomona College buildings participating in this study is 279,838 square feet. Table 10 shows the estimated avoided costs in 2030 per square foot. This table shows that the greatest value of ACCO BEMS to the grid is the reduction in energy generation and emissions.

Table 10: 2030 Avoided Costs per Square Foot of Pomona College Buildings

Avoided Costs per Square Foot in 2030	Optimization Year	Post-Optimization Year
Avoided Energy	$0.03	$0.07
Avoided Losses	$0.00	$0.00
Avoided Capacity	$0.02	$0.03
Avoided Transmission	$0.01	$0.02
Avoided Distribution	$0.01	$0.04
Avoided Emissions	$0.03	$0.06
Total	$0.10	$0.22

Source: E3

Pomona College is located in Climate Zone 9. To estimate statewide benefits, the avoided cost impact per square foot was adjusted for each climate zone using the heating and cooling load (HDD and CDD) relative to the Climate Zone 9, as seen in Table 11.[8] Finally, the adjusted avoided cost factors were calculated by the expected square footage of non-residential buildings in each climate zone in California by 2030.

[8] https://www.pge.com/includes/docs/pdfs/about/edusafety/training/pec/toolbox/arch/climate/california_climate_zones_01-16.pdf

Table 11: Square Footage and Load Adjustment Factor by Climate Zone in 2030

Climate Zone	Million square feet of Non-Residential Buildings	Heating and cooling load adjustment
1	259	1.38
2	52	1.25
3	1,171	1.12
4	377	1.10
5	635	1.07
6	238	0.73
7	206	0.81
8	300	0.88
9	590	1.00
10	1,143	1.13
11	614	1.54
12	594	1.32
13	663	1.39
14	193	1.88
15	155	2.04
16	1,259	1.94

Climate Zone 3, 10, and 16 have the largest potential for use of ACCO BEMS in non-residential buildings. These climate zones also have a higher heating/cooling load than Climate Zone 9 where Pomona College is located. ACCO BEMS would result in even greater grid and ratepayer benefits in these climate zones.

Table 12 shows that if ACCO-BEMS were deployed in all the non-residential buildings in California by 2030 and performed as it did in the post-optimization year, California could see over two billion dollars in grid benefits. Most of those benefits come from avoided energy and emissions. Additionally, the reduction in energy consumption during peak hours leads to significant savings in avoided capacity and distribution.

Table 12: Potential 2030 Statewide Avoided Costs

Statewide Avoided Costs 2030 [nominal $]	Optimization Year	Post-Optimization Year
Avoided Energy	$364,762,000	$757,856,000
Avoided Losses	$26,263,000	$54,532,000
Avoided Capacity	$236,853,000	$302,378,000
Avoided Transmission	$81,682,000	$175,494,000
Avoided Distribution	$130,216,000	$423,479,000
Avoided Emissions	$319,036,000	$677,129,630
Total	$1,159,813,000	$2,390,397,000

Source: E3

COUNT HVAC Scheduling

This section describes the potential grid benefits of implementing the COUNT dynamic HVAC scheduling technology. Implementing Wi-Fi occupancy-based controls to delay HVAC start times could potentially save an average of 2.3 percent whole building energy use.

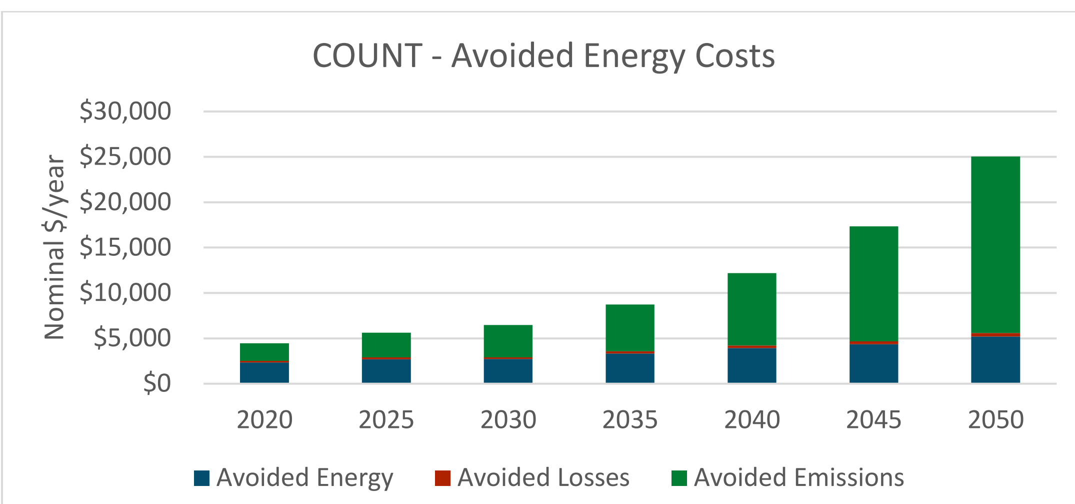
1. Baseline Year:
   - April 2019 to March 2020
   - Actual building demand
2. Savings Potential:
   - April 2019 to March 2020
   - Implementation of Wi-Fi occupancy-based controls to delay HVAC start times until 20 percent occupancy threshold.

Wholesale Energy Benefits

Wholesale energy benefits (also referred to as avoided wholesale energy costs) are the cost savings from purchasing wholesale electricity during time periods with lower prices. These benefits are estimated for each forecasted energy price year between 2020 and 2050. It is noted that avoided losses are roughly proportional to avoided energy costs.

As seen in Figure 38, the avoided energy benefits of COUNT are roughly a quarter of the benefits of the ACCO-BEMS technology. Nonetheless, the implementation of COUNT would result in a significant reduction of energy generation each year. By 2030 and beyond, the primary benefit of this load reduction is avoided emissions. It is noted that this is an electric sector planning value outside of existing carbon markets such as the Cap-and-Trade market; it is not as readily monetizable as the other value streams.

Figure 38: COUNT Avoided Energy Costs



Source: E3

Peak Load Reductions

COUNT provides very little benefit from peak load reduction. The load reduction from HVAC scheduling typically occurs in the morning through delayed HVAC start times. As a result, the load reduction does not align well with peak hours (Figure 39).

Figure 39: COUNT Demand Reduction

Month-Hour Average Demand Reduction (kW)												
Month	July	August	Sept	October	Nov	Dec	January	February	March	April	May	June
0	0	0	0	0	0	3	0	0	0	1	0	0
1	0	0	0	0	0	3	0	0	0	1	0	0
2	0	0	0	0	0	3	19	2	0	1	0	4
3	0	0	0	0	0	3	42	15	2	10	23	15
4	2	5	3	4	0	3	49	28	6	22	51	21
5	5	8	8	18	1	9	62	30	6	22	51	21
6	19	37	52	79	3	41	90	34	6	22	51	23
7	21	41	64	87	4	67	129	47	11	30	65	27
8	17	34	35	34	1	57	109	78	23	40	78	25
9	11	14	14	12	0	37	61	70	23	24	58	17
10	7	11	15	8	0	21	28	39	8	9	17	6
11	7	4	14	5	0	7	13	22	3	6	8	4
12	4	1	9	0	0	4	8	9	1	4	3	4
13	1	0	6	0	0	0	0	6	1	0	0	2
14	2	2	6	0	0	0	0	1	1	0	0	3
15	0	2	6	0	0	0	0	1	1	0	0	2
16	0	0	3	0	0	0	0	1	0	0	0	0
17	0	0	0	0	0	0	0	1	0	0	0	0
18	0	2	0	0	0	0	3	2	0	0	0	0
19	0	2	0	0	0	0	2	2	0	0	0	0
20	0	1	0	0	0	0	1	2	0	0	0	0
21	0	0	0	0	0	0	1	1	0	0	0	0
22	0	0	0	0	0	0	0	1	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0

Source: E3

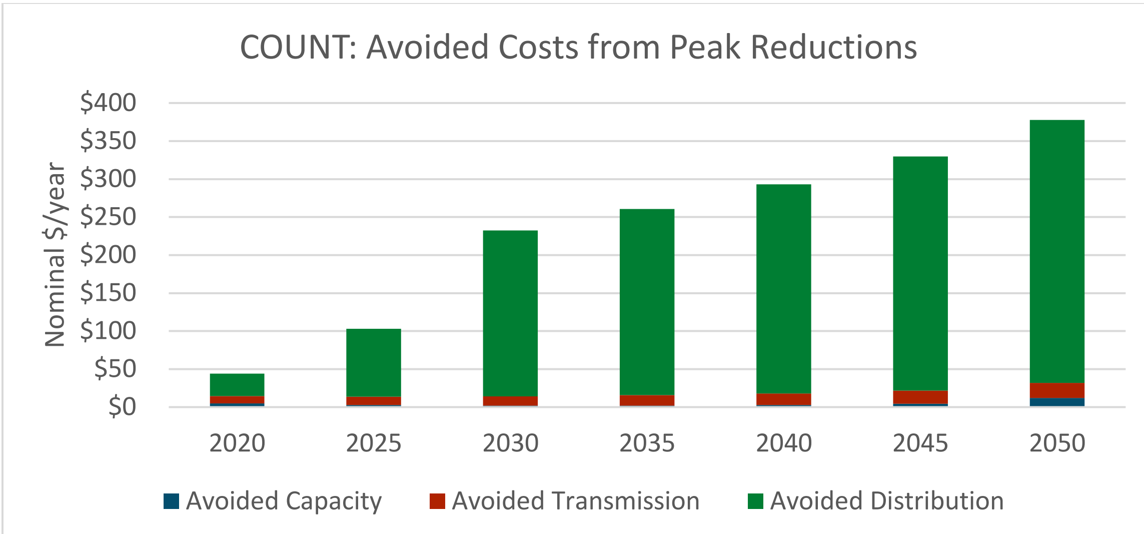
Additionally, the magnitude of the reduction is much less compared with ACCO-BEMS. Table 13 shows that the annual peak load reductions are 1.2 kW or less. The largest benefit comes from distribution capacity avoided costs.

Table 13: COUNT Peak Load Reduction

Calculated Peak Load Reduction (kW)	Potential Savings
Generation Capacity	0.02
Transmission Capacity	0.35
Distribution Capacity	1.19

Overall, the avoided costs from peak reductions are less than $50 in 2021, and only increase to a $400 annual benefit by 2050 (Figure 40).

Figure 40: COUNT Avoided Costs from Peak Reductions



Statewide Benefit

This section provides a discussion of estimating the potential statewide benefit to deploying COUNT in all non-residential buildings by 2030. The total square footage of the Pomona College buildings participating in this study is 279,838 square feet. Table 14 shows the estimated avoided costs in 2030 per square foot.

Table 14: 2030 Avoided Costs per Square Foot of Pomona College Buildings

Avoided Costs per Square Foot in 2030	Potential Savings
Avoided Energy	$0.010
Avoided Losses	$0.001
Avoided Capacity	$0.000
Avoided Transmission	$0.000
Avoided Distribution	$0.001
Avoided Emissions	$0.013
Total	$0.024

This table shows that the greatest value of COUNT to the grid is the reduction in energy generation and emissions.

Pomona College is located in Climate Zone 9. To estimate statewide benefits, the avoided cost impact per square foot was adjusted for each climate zone using the heating and cooling load relative to the Climate Zone 9. Finally, the adjusted avoided cost factors were calculated by the expected square footage of non-residential buildings in each climate zone in California by

2030. Table 15 shows the potential statewide benefits of the COUNT dynamic HVAC scheduling.

Table 15: Potential 2030 Statewide Avoided Costs

Statewide Avoided Costs 2030 [nominal $]	Potential Savings
Avoided Energy	$82,090,982
Avoided Losses	$5,910,551
Avoided Capacity	$53,884
Avoided Transmission	$369,468
Avoided Distribution	$6,591,289
Avoided Emissions	$107,083,829
Total	$202,100,003

If COUNT were deployed in all the non-residential buildings in California by 2030, California could see over $200 million in grid benefits. Most of those benefits come from avoided energy and emissions.

CHAPTER 6: Knowledge Transfer

Introduction

As part of the ACCO-BEMS Project, the project team (including the Zero Net Energy Alliance, MelRok, Lawrence Berkeley National Lab, and Pomona College) jointly conducted knowledge transfer activities to share lessons learned and best practices in automated building energy management with key stakeholders, including facility managers in higher education, commercial real estate, and technology providers. The knowledge transfer team collaborated on multiple events, including two joint Technical Advisory Committee meetings, published several academic research papers, and developed the Aliso Canyon Partners' Network to disseminate information on the ACCO-BEMS software solution in the context of other high impact energy savings measures. Key stakeholders were engaged to learn more about the potential of ACCO-BEMS and related energy conservation measures that can help property owners and managers reduce their energy costs, usage, and related emissions.

Target Audience and Outreach

The project team successfully engaged many organizations and individuals, conveying not just the goals and methods but also the unique challenges involved in automated building energy management. Key audiences for knowledge transfer target audiences included:

- Major Higher Education Campuses
- Commercial and Industrial building managers
- Retail Chains
- Academic institutions and Subject Matter Experts

Presentations on ACCO-BEMS included presentations at the EPIC symposiums held throughout the grant period, and at the annual ACEEE conference and Summer Study in Asilomar, California. Presentations at these events included the following papers on Wi-Fi occupancy sensing:

- Clark C., Prakash A, Pritoni M., Kloss M., Gupta P., Nordman B., Piette M.A. Kamel M., Eisele A., Hage D., Flannery P. 2020. "Harvesting the low-hanging fruit of high energy savings – Virtual Occupancy using Wi-Fi Data." ACEEE Summer Study on Energy Efficiency in Buildings. https://escholarship.org/uc/item/45s9h8v0
- "COUNT: An open-source library to extract and analyze occupancy data from existing building Wi-Fi infrastructure " Journal Paper, in preparation
- Occupancy counting with Wi-Fi data using ACCO-BEMS. Demand Response & Distributed Energy Resources World Forum 2020, October 12-14

In addition to these papers, LBNL has made available an open source licensing framework for the Wi-Fi occupancy sensing code generated by this project:

- Open-source COUNT software with a LBNL IP Office issued modified BSD license. Download available at: https://github.com/LBNL-ETA/count

Technical Advisory Committee Meetings

The project team used the Technical Advisory Committee's (TAC) domain experts to disseminate information from the project, provide input into final deliverables, and encourage industry-wide information sharing. The TAC included representation from subject matter experts including college campus facility management professionals, data management professionals, energy consultants, policy advocates, and non-profit organizations. The TAC met twice during the grant engagement and a full list of participants can be found in the appendix of the Knowledge Transfer report.

Aliso Canyon Partners Network

The Aliso Canyon Partners Network was developed to enable a select group of large commercial properties and campuses in the Aliso Canyon impact area to pursue energy and cost savings of 20 percent+. Higher education campuses were targeted because of the large numbers of buildings and square footage under unified management, and the robust decarbonization and cost reduction goals in place at many institutions. Core members of the network included: Pomona College, Harvey Mudd College, California State University (CSU) Los Angeles, CSU Northridge, and CSU Fullerton. With the resources provided by the California Energy Commission, these major institutional property managers were provided with a no-cost *Energy Business Case* fully customized to their building portfolio to identify efficiency projects with immediate positive return on investment. To serve the Aliso Canyon Network, the project team brought together four leaders in strategic energy management – MelRok, Correlate, Helios, and Ecoshift Consulting. These firms worked together to ensure that each participant was provided with these key services and benefits to inform and accelerate their progress in energy efficiency and decarbonization:

- **Customized Energy Business Case:** Each partner received an Energy Business Case that identified energy savings opportunities in the range of 20 percent+. These savings were identified through bill data analysis by MelRok combined with building performance and Energy Efficiency Measure modelling developed by Helios and deployed in partnership with Correlate.
- **Innovative Project Finance:** Participants were provided access to project finance options to fund efficiency projects largely through bill savings. Often, identified energy solutions were cash flow positive.
- **Self-Driving Buildings Energy Management Service:** To lock in efficiency gains, participants were introduced to the MelRok ACCO-BEMS *Self-Driving Buildings* software, which works with existing building systems to sustain efficiency savings.

Modeled Potential Savings Results

Based on available data and the inputs provided by MelRok to the Helios Exchange team, significant savings from the ACCO-BEMS platform were identified for the Aliso Canyon participants. In total across the 263 buildings and more than 17 million square feet of floor area electricity savings of more than 14 GWh per year were identified representing 7,394 KW of peak demand savings. Further, fuel savings of more than 16 billion Btu per year were identified. Collectively these savings represent emission reductions of 67,184 MtCO2e per year and annual cost savings of more than $2.5 million. Table 16 summarizes individual savings potential of the ACCO-BEMs technology by campus (based on inputs provided by MelRok IoT to Helios exchange.

Table 16: ACCO BEMS Savings Potential by Campus

	Campus					
Unit	**Pomona**	**H. Mudd**	**CSULA**	**CSUN**	**CSUF**	**TOTAL**
Number of buildings	10	22	36	81	114	263
Building Floor Area (ft^2)	279,818	671,452	4,173,621	6,408,206	5,701,940	17,235,037
Electricity Savings (kWh) per yr	409,120	1,442,886	2,948,470	4,405,668	5,002,883	14,209,027
Peak Demand Savings (KW)	214	826	1,722	2,027	2,605	7,394
Other Fuel Savings (kBtu) per yr	1,070,480	828,676	1,269,451	9,772,453	3,737,742	16,678,802
GHG emissions (MtCO2e) per yr	2,086	5,123	15,850	22,712	21,413	67,184
Energy Use Reduction (percent)	9.2 percent	9.6 percent	6.2 percent	8.9 percent	8.1 percent	
GHG Reduction (percent)	8.6 percent	9.3 percent	6.0 percent	8.1 percent	7.9 percent	
Measure Costs ($)	$52,474	$122,729	$675,399	$998,091	$838,643	$2,687,336
Incentive ($)	$15,743	$36,820	$200,935	$297,630	$250,311	$801,439
Annual Savings ($/yr)	$77,702	$248,110	$503,271	$821,304	$867,873	$2,518,260
Payback (yrs)	0.5 yrs	0.3 yrs	0.9 yrs	0.9 yrs	0.7 yrs	
IRR (percent)	211 percent	289 percent	103 percent	115 percent	146 percent	

Campus Energy Strategy Themes Identified by ACEPN

Several key themes were identified by the project team as a result of engagement with the Accounting Continuing Professional Education Network (ACEPN) members. These include:

Widespread Interest in Solar Thermal

While most locations had solar electric project implementations, industrial solar thermal was identified as a campus-wide opportunity that could yield significant natural gas reductions. Many campuses operate a central plant and cycle warm water through the campus to maintain building set points. This presents an opportunity for the California Energy Commission to fund additional efforts to study and develop solar thermal projects to augment the campus central plants, as this would be a novel implementation of a technology that has significant potential to mitigate carbon-based fuel use.

Need for Strategic Energy Planning and Capital Budgeting Strategies

Several ACEPN members expressed difficulty in fully implementing an Energy Management System and meeting ISO 15001 standards. This was a result of: 1) insufficient internal staffing capacity, or 2) limited capital budgets to implement energy and emissions projects with high return on investment.

Lack of Benchmarking Resources

ACEPN participants expressed a sentiment that they did not have the resources to effectively implement a benchmarking program and were relieved that the deadline to comply has been extended. Human capital to effectively implement a program and data availability/data quality issues were cited as primary reasons for not fully meeting campus-wide benchmarking requirements.

Strategic Energy Management Capacity Building

The project team identified that the following strategic energy management strategies were of common interest across many institutions, including: Streamlining of Benchmarking, Data Analysis, Project Development identification, finance, and implementation, and ongoing M&V activities. Most facilities in California are being phased into the Statewide Benchmarking program, including all ACEPN participants. In addition, Campuses in the CSU system have an obligation to report regular energy and utility consumption data to the statewide CSU administration. However, none of the participants currently use the Energy Star Portfolio Manager benchmarking tool. There was universal acknowledgement among participants that with additional resources and resources, tools like Energy Simulation Performance Metrics and Building Energy Modeling could be used effectively to implement energy saving projects. There is an immediate opportunity to provide additional resources to support implementation and compliance with the California Benchmarking and energy analysis program.

Lack of Data Gathering and Automation

All the campuses engaged in this project had some level of energy and utility sub-metering. Many of the participants had non-functional or outdated data capture systems, such as Btu meters. The data systems are not fully automated, so the process to obtain recent or real time energy consumption at the building level requires significant human effort from energy team members. Some of the campuses were in the process of implementing energy data management systems, such as Energy Cap or SkySpark. Other campuses had existing software platforms provided by ESCOs (like Johnson Controls / Siemens), that had various levels of submetering and data reporting systems. Few of the campuses engaged had traditional Utility Bill Management and auditing software, which may be an opportunity to streamline and automate the bill audit and energy accounting functions within the organizations.

Power Procurement Options and Formation of Higher Education Community Choice Aggregation

The project team also identified the potential for the formation of a Community Choice Aggregation (CCA) agency that serves California's higher education institutions. CCAs are a mechanism that allow local governments and agencies such as Joint Powers Authorities to procure power on behalf of their residents, businesses, institutions, and municipal accounts from an alternative supplier while still receiving transmission and distribution service from their existing utility provider. CCAs are an attractive option for communities that want more local control over their electricity sources, more renewable and/or carbon-free power than is offered by the default utility, and/or lower electricity prices. By aggregating demand, communities gain leverage to negotiate better rates with competitive suppliers and choose cleaner sources of electricity supply.

There has been an extended effort, led by the CSU system and Chancellor's office, to evaluate the feasibility of forming a higher education CCA that extends these benefits to California's universities and community colleges. This effort has been motivated by the collective commitments of California's higher education institutions to climate protection, sustainability, and social equity goals, and continually escalating costs in the electricity sector. A CCA that is focused on serving the needs of the higher education industry in California has the potential to support the achievement of those goals and commitments.

Many existing CCAs in California offer robust local energy programs that the independently-owned utilities do not offer. These include programs that offer valuable financial and technical assistance to customers who implement energy efficiency, renewable energy, and resiliency projects. These programs add additional layers of value to the programs and incentives that are currently available, which can be leveraged by customers to make beneficial projects feasible. The opportunities for higher education institutions, including those who have participated in the ACEPN project, to implement cost-effective energy conservation and renewable energy projects throughout their portfolios of buildings and assets can be enhanced by the formation of a higher education-focused CCA. The project team recommends that all members of the ACEPN consider supporting the ongoing efforts to develop and implement a plan for creating a CCA that can serve all higher education institutions in California to unlock the potential benefits that can support the implementation of the measures identified through the ACEPN analyses.

CHAPTER 7: Conclusions/Recommendations

Key Conclusions and Results from Wi-Fi Occupancy Sensing

In this project, the research team deployed an open-source software library to estimate occupancy using Wi-Fi data. The software collected over a year of anonymized Wi-Fi data from 10 buildings at Pomona College campus; and researchers integrated the software library with the native building automation systems. The data were gathered into distinct academic periods, including fall and spring semester, academic breaks, and summer sessions. LBNL developed the data collection system and the automatic data cleaning process and created three applications: two used real-time occupancy data to inform optimal HVAC schedules and ventilation rates to identify and reduce energy waste; a third application demonstrated that peak demand forecasts can be improved by incorporating occupancy data.

This project leveraged existing data in Wi-Fi networks to estimate building occupancy in real-time, relatively accurately, and with minimal additional expense. Wi-Fi occupancy sensing can result in significant benefits, saving energy, and thereby reducing carbon emissions as well as energy costs.

Recommendations and Next Steps

Over the course of this project, the research team identified a number of recommended next steps:

1. Field test the integration of the developed applications with an energy management system, such as ACCO-BEMS (planned demonstration was not possible due to COVID-19).
2. Develop guidelines and tools to ensure cybersecurity and protect data privacy.
3. Develop methodologies to streamline coordination and cooperation for integrating Wi-Fi occupancy sensing among facilities, energy management, IT, and the deployment team.
4. Identify methods to simplify and standardize the process of integrating Wi-Fi occupancy sensing with building automation systems (to include BACnet, Fault Detection and Diagnostic tools, emerging advanced supervisory control software, and other energy management tools).
5. Increase the granularity of Wi-Fi occupancy sensing to the floor or zone level.
6. Isolate and quantify the energy savings realized from Wi-Fi occupancy under common scenarios. HVAC may represent the biggest savings opportunity. Identify and explore other ways in which Wi-Fi data might enhance buildings controls.

7. Engage network equipment manufacturers in emerging applications for Wi-Fi data in building systems. Collaborate on ways to simplify and standardize use of inferential data and make these capabilities widely available to customers.
8. Develop relevant codes and standards for adoption.
9. Undertake additional field work to demonstrate the energy savings potential of this new sensing technology at scale.
10. Set up a repository to pool information on Wi-Fi occupancy:
    - Develop a knowledge database
    - Identify issues and post solutions
    - Collect case studies
    - Gather data
    - Compare energy results

While significant progress has been made by the research community in demonstrating the potential of Wi-Fi-based occupancy detection, further work needs to be done to facilitate its deployment at scale in the field, as identified.

Key Conclusions and Results from ACCO-BEMS Deployment

The project successfully deployed an automated BEMS platform that consists of a cloud component and a physical component installed on-site, at 10 buildings at Pomona College. MelRok was successful in establishing real time connectivity to energy meters and BEMS controllers in each building, with data from these devices being logged every minute in a cloud database. MelRok was also successful in implementing real time cloud-based controls of select parameters on the BEMS, namely setpoints used by the BEMS logic to manage the HVAC equipment in the buildings. The platform was used to guide commissioning efforts prior to activating cloud control of HVAC components in the buildings. The COVID pandemic and ensuing lockdown resulted in limiting cloud control to control of air handling units and impacted the M&V of the performance of cloud control. Appropriate changes in the M&V methods were developed to compare performance of ACCO-BEMS within like periods of low-occupancy during the COVID lockdown period. Unfortunately, this likely understated the full benefit of ACCO-BEMS by inhibiting pre/post comparative analysis of the impact of cloud controls under normal operational conditions with full student and staff occupancy.

Key Results

- MelRok was successful in integrating with BACnet and legacy BEMS controllers.
- Meter and BEMS data was logged in real time at 1-minute intervals for the duration of the project.
- 1-minute interval data was instrumental in showing cyclical behavior with periods of less than 5 minutes, which are otherwise un-detectable with 15-minute resolution data. Such behavior included dampers and valves “hunting,” specifically opening and closing at a rate of once every few minutes and in a continuous manner.

- Conventional re-commissioning proceeded slower than expected and delayed the start of the cloud control phase of the project.
- Cloud-guided commissioning – in which 1-minute data from all HVAC devices is automatically analyzed – speeds up the re-commissioning process and makes it more accurate and complete.
- The COVID pandemic and ensuing lockdown caused a halt in the deployment of cloud control beyond air handlers, and obstructed implementation of the M&V process as originally designed.
- Two new M&V methods were used to evaluate the impact of cloud control without referring to the pre-COVID baseline. The methods compared the energy of hours with cloud control to hours without cloud control in the same post-COVID period.
- Cloud control of air handler units' supply air temperature and static pressure setpoints was effective in reducing the energy consumption of buildings, compared to hours with no cloud control.
- Simple control measures are effective in improving the energy performance of buildings.
- The average change in energy per building in the August to December period, between hours with cloud control and hours with no cloud control was –9 percent and –16 percent for methods 2 and 3 respectively; specific efficiency gains were +9 percent to +16 percent. The cost and energy savings realized by the College would have been equal or greater under full occupancy due to overall consumption levels being larger, with correspondingly greater gains achieved due to ACCO-BEMS implementation.

Recommendations and Next Steps

The project team suggests the following recommendations related to the deployment and use of cloud-based platforms for optimization of building energy:

1. Cyberphyiscal platforms, specifically platforms with a cloud component and a physical component on-site, are necessary for robust and secure communication to existing devices in buildings. Deployment of a local gateway allows for the integration of non-IP based devices and for local backup of acquired data in case of loss of internet communication and for a more secure form of data transmission to the cloud.
2. Fast sampling of BEMS data, at a resolution of at least once a minute, is key in more accurate fault detection and diagnostics.
3. Integration of BACnet compatible BEMS can be fully automated and allows for the deployment and full configuration of cloud faut detection and cloud control within hours.
4. Commercial scalability of the cloud optimized and controlled buildings should not require a change in the local BEMS programs for a successful and secure implementation. This translates to requiring a local gateway to ensure a safe fallback logic in case communication to the cloud is interrupted.

5. Real time data-driven and automated analytics processes should be required in the commissioning of buildings to enable ongoing and periodic commissioning. Standards for automated "soft" commissioning of buildings can be established based on ASHRAE guideline 36 and other commissioning processes.
6. Cloud-based analytics and control is effective in reducing energy consumption, in reducing maintenance costs, and in standardizing sequence of operations across a portfolio of buildings.
7. Cloud-based control can be effective in the rapid implementation of changes to sequence of operations across a portfolio of buildings, such as in response to the COVID pandemic.
8. Standard processes need to be defined for the calculation of whole-building energy savings, for commercial and utility-incentive performance-based contracts, post March 2020. Two methods have been proposed for measuring impact of cloud control, these methods may be applicable to energy improvement measures that can be enabled and disabled in sequence.
9. Standards can be established for cloud-based automated functional testing of equipment as part of future commissioning processes (first time commissioning, recommissioning, and ongoing commissioning)
10. Standards can be established for cloud control measures as a function of building type, such as the control logic to manage air handle unit setpoints and schedules, that will allow these measures to be "deemed" and thus offer incentives on a \$/ft^2, \$/cubic feet per minute capacity, or \$/kWh basis.

GLOSSARY AND LIST OF ACRONYMS

Term	Definition
ACC	Avoided Cost Calculator
ACEPN	Aliso Canyon Energy Partner’s Network
AI	Artificial intelligence
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BEMS	Building energy management systems
CCA	Community Choice Aggregation
CPUC	California Public Utilities Commission
CSU	California State University
EPIC	Electric Program Investment Charge
EUI	Energy Use Intensity
FY	Fiscal Year
GHG	Greenhouse gas
HVAC	Heating, ventilation, and air conditioning
IoT	internet of things
IP	Internet protocol
IT	Information Technology
KPI	key performance indicator
kW	kilowatt
LBNL	Lawrence Berkeley National Laboratory
PaaS	platform as a service
TAC	Technical Advisory Committee
TOU	Time-of-use
ZNE	Zero Net Energy

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CALIFORNIA ENERGY COMMISSION

CALIFORNIA NATURAL RESOURCES AGENCY

ENERGY RESEARCH AND DEVELOPMENT DIVISION

Appendix A: TAC Participants

May 2024| CEC-500-2024-042

APPENDIX A: TAC Participants

Name	Organization
Amir Ehyai	CEC
Anne Eisele	Pomona College
Dotty Hage	Pomona College
Eric Eberhardt	University of California Office of the President
Callie Clark	LBNL
Mary Ann Piette	LBNL
Gari Kloss	LBNL
Bruce Nordman	LBNL
Marco Pritoni	LBNL
Anand Prakash	LBNL
Kecia Davison	ABM
Michael Sontag	E3
Michel Kamel	Melrok
Paul Erhlich	Building Intelligence Group
Ram Narayanamurthy	EPRI
Richard Schorske	ZNE Alliance
Sam Irvine	ZNE Alliance

ENERGY RESEARCH AND DEVELOPMENT DIVISION

Appendix B: COUNT Evaluation

May 2024 | CEC-500-2024-042

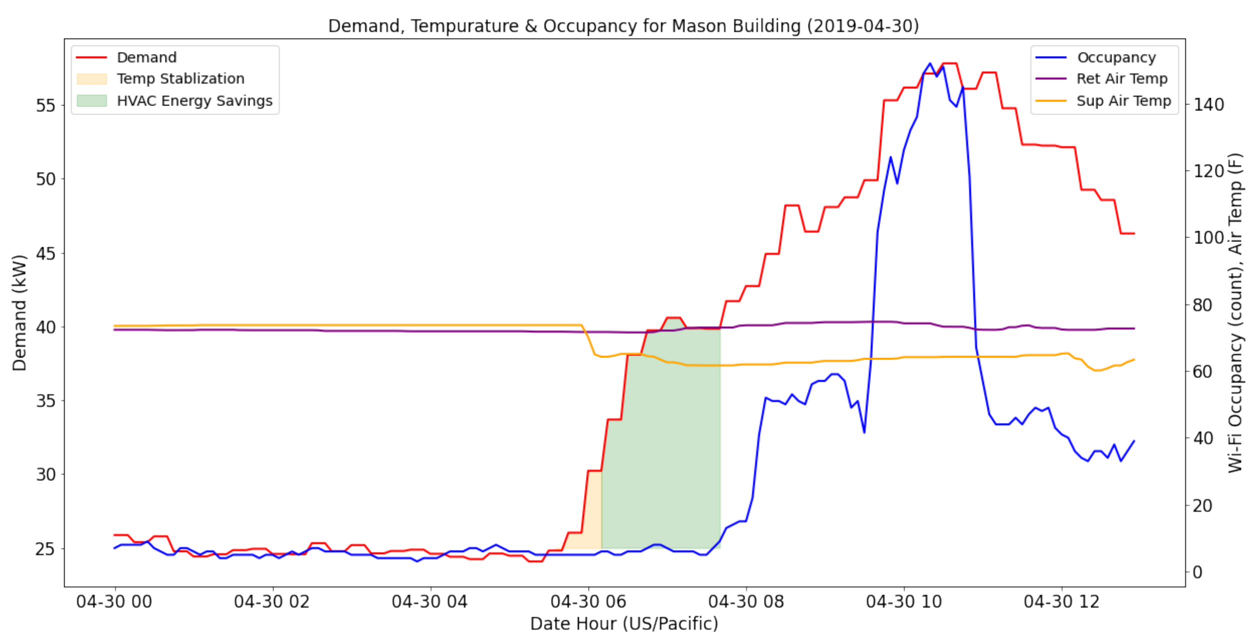
APPENDIX B: COUNT Evaluation

This section describes LBNL's data collection and analysis to estimate the potential savings from the use of COUNT for dynamic HVAC scheduling, in particular through delaying HVAC start times. The team found that the HVAC systems turned on earlier than needed in 7 out of 10 Pomona College buildings that are relevant to this project. The different types and uses of the individual buildings also produced a wide range of savings potential. The team found that if they implemented Wi-Fi occupancy-based controls to delay HVAC start times in these seven buildings, an average of 2.3 percent (31,753.5 kwh) of total building energy use could have been potentially saved during Spring 2019, Summer 2019, Fall 2019 and Spring 2020 semesters.

B1. Introduction

This report seeks to approximate potential HVAC energy savings of Pomona College campus buildings by applying Wi-Fi occupancy-based analysis. Currently, the buildings in Pomona College operate on fixed schedules, irrespective of the occupancy count. Using the number of devices connected to the Wi-Fi network as a proxy for occupancy, we are proposing an occupancy-aware start time for the HVAC systems in buildings. The analysis specifically focuses on delayed HVAC start times, defined as instances in which the HVAC was turned on prior to the Wi-Fi based occupancy reaching a machine learning classified occupied state. Figure B-1 illustrates an example of premature HVAC start time. These repeated instances accumulate to potentially thousands of kWh of energy savings.

Figure B-1: Demand, Temperature and Occupancy for Mason Building



On this date the HVAC started around 5:45 am, which corresponds to the increase in building demand (red line). The yellow region is the conditioning time and the green region corresponds to the area of potential energy savings, which stops at 7:50 am when the building Wi-Fi based occupancy spikes.

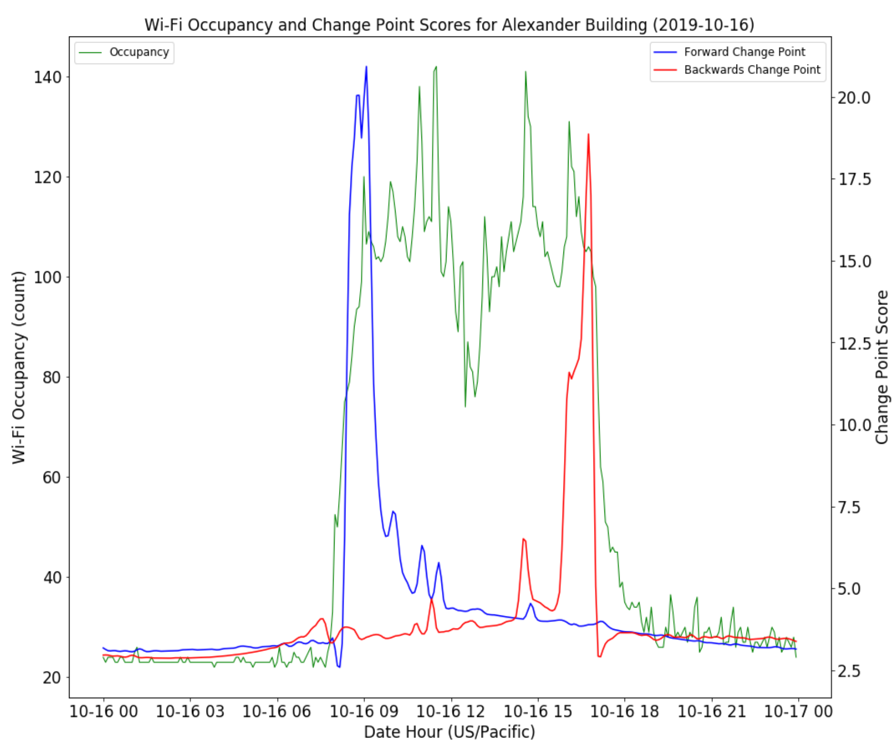
B2. Methods

In this analysis each building was separated by semester. Each semester contained the buildings: 1) network occupancy count, 2) HVAC on/off status, 3) supply air temperature, 4) return air temperature, and 5) building demand. Within the methods pipeline, the team first defined moments in which the building was occupied/unoccupied using change point detection and K-Means clustering and classification. Separately, the team estimated the building's daily conditioning time to properly evaluate potential regions of savings. The aforementioned building information was combined to estimate the potential HVAC savings of the building.

B2.1 Occupancy Classification

To use COUNT as an effective means of describing occupancy, "occupied" versus "unoccupied" must be defined. In the cases of premature HVAC start times, the interest was in detecting moments in which there were distinct and definite spikes in Wi-Fi occupancy counts as well as large drops. The team captured those moments of influxes and outflows of "people" using change point analysis. Change point detection can broadly be defined as a time series analysis method that indicates an abrupt and significant change in the data generating process. (Garcia et al., 2020) Moments of abrupt change are distinguished with a high change point score, as seen in Figure B-2.

Figure B-2: Wi-Fi Occupancy and Change Point Scores for Alexander Building

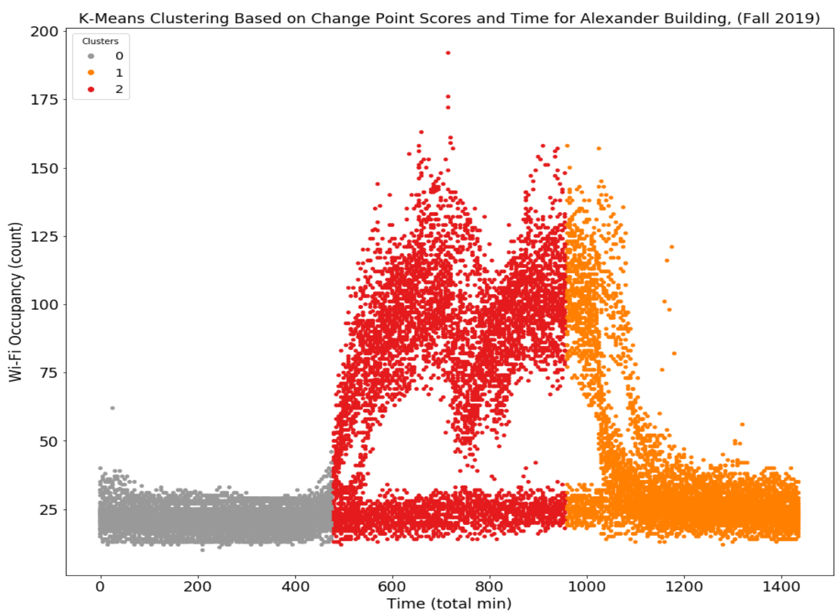


This figure illustrates the Wi-Fi occupancy count and its corresponding change point scores (for both forward and backwards analysis) for Alexander Building over the course of a day (October 16, 2019). The distinct increase in the forward change point score (blue line) relates to the sharp increase in Wi-Fi occupancy count number. The distinct increase in the backward change point score (red line) relates to the sharp decrease in Wi-Fi occupancy count number.

The team implemented an unsupervised machine learning algorithm, K-Means clustering, in order to classify instances of occupancy, in which the objective is to group similar data points together and discover underlying patterns (Li et al 2012). To achieve this objective, K-means looks for a fixed number (k) of clusters in a dataset. The change point scores, both forward and backward, as well as the time of day (in minutes) were used as inputs. We selected k=3 clusters, and an example output is illustrated in Figure B-3.

The occupancy data was optimally defined by three clusters: 1) Unoccupied (AM), 2) Occupied (AM/PM), and 3) Mixed Occupancy (PM). Our savings analysis focused on the Unoccupied (AM) and Occupied (AM/PM) clusters. However, exploring optimal HVAC scheduling for evening shutoff times with the Mixed Occupancy (PM) cluster would be a future extension to this analysis.

Figure B-3: K-Means Algorithm Clustered Alexander Building's Fall 2019 Semester Dataset

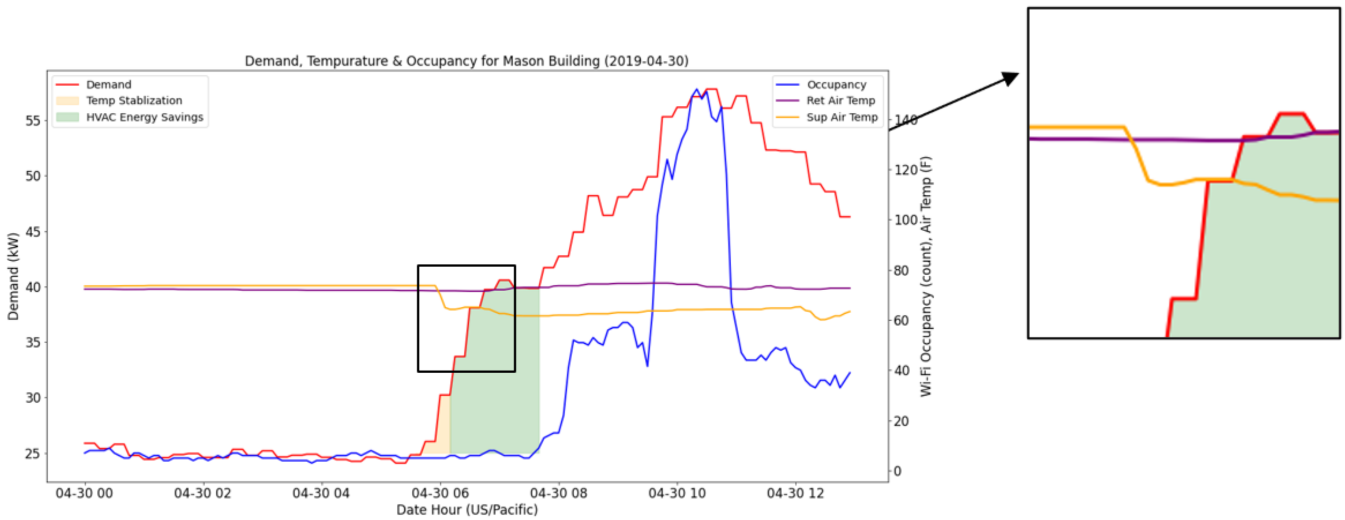


The graph is the relation to time of day (elapsed minutes) and Wi-Fi occupancy count. Cluster 0 (grey) can be interpreted as Unoccupied (AM) instances. Cluster 2 (red) can be interpreted as Occupied (AM/PM) instances. Lastly, Cluster 1 (orange) can be interpreted as Mixed Occupancy (PM) instances.

B2.2 Conditioning Time Approximation

To properly estimate the potential HVAC savings of a building, the HVAC energy usage of each building during a time period of savings was estimated. To do so, the team determined the times in which the HVAC turned on and off, as well as the duration of time it took for the supply air temperature and return air temperature to stabilize. Stabilization was determined when the supply and return air temperature measure met and retained tangential point lines after the HVAC was turned on. This accounted for an instance-based approximation of sufficient conditioning time (heated or cooled). This is further illustrated in Figure B-4.

Figure B-4: The Temperature Stabilization Time for Mason Building



This figure is an extrapolation of Figure B-1. The temperature stabilization time period (yellow region) begins at 5:45 am and ends at 6:10 am. This end time is determined by the return air (purple line) and supply air (yellow line) stabilizing, specifically both obtaining a tangent line of approximately 0, as you can more closely observe in the sub figure.

These conditioning/stabilization times were noted as the start of a savings period. Dates with anomaly behavior such as dates in which stabilization was never met (infrequent) or the HVAC was never on (frequent on weekends), were noted and marked as outliers. Thus, not included in this analysis.

B2.3 Potential HVAC Energy Savings Estimation

Moments of potential savings were assessed by HVAC-On times that existed within the Unoccupied (AM) cluster (Cluster 0) after the temperature stabilization period, t_{stable}. The end of a savings period was determined by a the time in which data points transition from Unoccupied (AM) to the Occupied (AM/PM) (Cluster 2), $t_{start\ of\ occupancy}$.

Hence, the ideal start time t_{ideal} of the HVAC system can be defined as $t_{start\ of\ occupancy} - t_{stable}$. All instances in which the $t_{stable} > t_{start\ of\ occupancy}$ were noted and not included in potential savings. Therefore, potential HVAC energy savings can be estimated as follows:

$$t_{hvac\ start} = time\ in\ which\ HVAC\ turns\ on,$$

$$savings\ (kWh) = \sum_{t=t_a}^{t_b} demand(t) - \sum_{t=t_a}^{t_b} baseline(t)$$

Where,

$t_a = t_{ideal}$, $t_b = t_{start\ of\ occupancy}$, $baseline(t)$ = *demand before* $t_{hvac\ start}$ *(fixed number)*

$$savings\ (percent) = \frac{savings\ (kWh) * 100}{total\ building\ energy\ consumption\ (daily, kWh)}$$

B3 Results

Using the previous methods, the team calculated savings in 7 of 10 Pomona College buildings. Thatcher, IT Building, and Seely G Mudd were excluded from this study. Thatcher did not have return and supply air temperature available for the 2019 to early 2020 year, therefore we could not approximate its HVAC conditioning time. The IT Building was excluded due to the fact that the building's HVAC system was always on, which is likely due to the data center within the building that needs constant cooling. Contrastingly, Seely G Mudd, which houses only temporary offices/classrooms, was excluded due to the HVAC system always being off.

Buildings that were observed for only certain semesters included Carnegie, Crookshank, and Pearsons. For Spring 2019, Summer 2019 and Fall 2019, Carnegie's HVAC system was consistently off. During Spring 2020, we observed Carnegie building retain a normal HVAC schedule, therefore included it in the Spring 2020 savings estimates. The Wi-Fi-based occupancy data was not available for Pearsons and Crookshank till July 2019, therefore, it was only included in the Fall 2019 and Spring 2020 savings estimates. These partially observed buildings contain "N/A" in the results table (Table B-1) for semesters un-observed. The results of our potential HVAC savings estimations are further illustrated in Figure B-5.

Table B-1: Potential Savings Estimates for Seven Pomona College Buildings

Building	Spring '19	Summer '19	Fall '19	Spring '20	Total Annual (kWh)	Average Savings (%)
Alexander	641.2	4046.3	1037.8	30.9		
Carnegie	N/A	N/A	N/A	58.5		
Crookshank	N/A	N/A	527.1	45.3		
Hahn	640.0	691.3	675.2	26.2		
Mason	365.0	1859.9	1192.7	266.8		
Pearsons	N/A	N/A	26.9	16.6		
SCC	1046.5	5574.7	7685.9	5325.8		
Semester Savings (kWh)	2665.7	12172.2	11145.6	5770.0	**31753.5**	
Semester Energy Use (kWh)	133285.0	450822.2	464400.0	339411.8	**1387919.0**	
Semester Savings (%)	2.0%	2.7%	2.4%	1.7%		**2.3%**

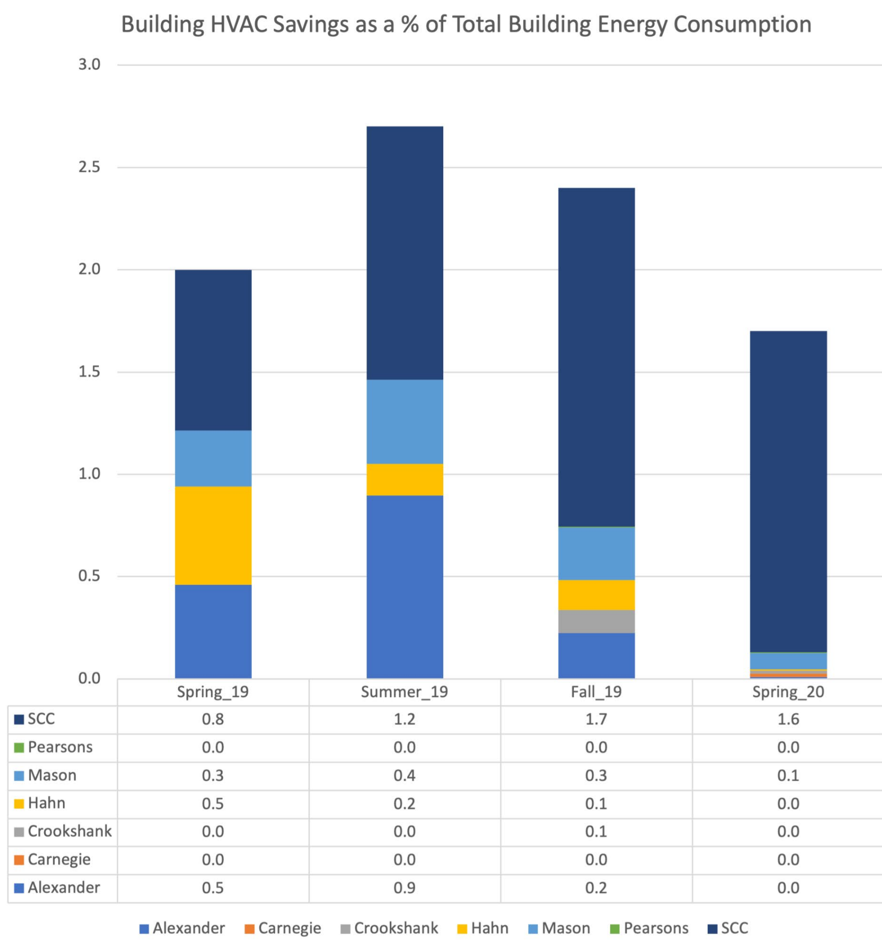
Building column, for the Spring 2019 (2019-04-25 to 2019-05-12)[9], Summer 2019 (2019-05-29 to 2019-08-01), Fall 2019 (2019-09-18 to 2019-12-13) and Spring 2020 (2020-01-21 to 2020-03-15)[10].

[9] Does not include full semester, network data access started 4-25

[10] Does not include full semester. Campus closed on 2020-03-18 due to COVID pandemic

The individual building's savings, the semester savings, the semester energy use, and their corresponding annual totals are in the kWh unit (Figure B-5). The semester savings percent is the semester savings over the semester energy use. The average savings percent is the total annual energy saved over the total annual energy use.

Figure B-5: Savings as a Percent of the Buildings' Total Energy Consumption for the Semester



	Spring_19	Summer_19	Fall_19	Spring_20
SCC	0.8	1.2	1.7	1.6
Pearsons	0.0	0.0	0.0	0.0
Mason	0.3	0.4	0.3	0.1
Hahn	0.5	0.2	0.1	0.0
Crookshank	0.0	0.0	0.1	0.0
Carnegie	0.0	0.0	0.0	0.0
Alexander	0.5	0.9	0.2	0.0

This illustrates the savings as a percent of the buildings' total energy consumption for the semester, further segmented by each individual building allocated percent. For example, column 1/bar 1 can be interpreted as approximately 2 percent of the Spring 2019's observed buildings energy consumption could have been saved with Wi-Fi-based occupancy controls, .8 percent of that being SCC's savings.

B.4 Future Work

Future work includes exploring more comprehensive COUNT methods that intuitively incorporate building type/use, capacity/sq. ft., building conditioning time, and worker schedules as additional parameters for savings estimations. These changes would generate more accurate HVAC estimated savings. Moreover, in future work, we plan to explore potential savings and optimized HVAC scheduling involving occupancy-based HVAC shut-off time as well.