

Evaluating the Performance of HVAC Optimal Control Based on Real-time Floor-by-Floor Occupancy Data

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ABSTRACT

Meeting aggressive decarbonization goals requires radical advancements that reduce existing buildings' carbon footprint. New smart building technologies that offer continuous dynamic optimization of commercial Heating, Ventilation, and Air Conditioning (HVAC) control hold promise to advance building operations for decarbonization, efficiency, and flexible control. Typical HVAC control sequences are designed to condition spaces over a fixed schedule to meet space temperature setpoints. By incorporating occupancy information into HVAC control, space conditioning can be delivered more efficiently and adjust to changes in occupancy. This paper illustrates the results from a field evaluation of a cloud-based building operation platform that was installed in an office building. In the study, 22 occupancy counters were installed (two at each floor) as a part of the platform to measure floor-by-floor building occupancy in real-time. The platform used these occupancy data along with thermal modeling, and machine learning algorithms to implement optimal start-up, shut down, and intra-day fan speed adjustment to the air handling units (AHUs) for each floor in the pandemic. This paper presents how the technology is implemented, the energy savings performance, and how occupancy information can be used to support executing dynamic operation during COVID-19 time period. The technology reduced weekday AHU run times by over three hours and reduced fan speed by more than ten percent during lunchtime in the Pandemic period. The simulated savings results are presented and compared with another similar study. The assessment results provide valuable insights to help end-users and industry partners understand real-world performance of occupancy based control technologies and reduce technical risks.

Introduction

The federal government has set aggressive economy-wide goals to reduce greenhouse gas emissions, reaching net-zero by 2050. Meeting decarbonization goals requires radical advancements that reduce existing buildings' carbon footprint. New smart building technologies that offer continuous dynamic optimization of commercial Heating, Ventilation, and Air Conditioning (HVAC) control present a promising solution for increasing the operational efficiency of building HVAC systems. These techniques use a dynamic system model and disturbance forecast to predict system performance with a given control law, thereby allowing the control law to be optimized for a given objective and taking into consideration future events. They combine the model with the real-time data read from building automation system (BAS) to determine the optimal schedule or control setpoints (e.g. static pressure setpoint, chilled water leaving temperature setpoint, and zone air temperature setpoint), and write analytically based optimal schedule or setpoints back to the BAS (Lin et al. 2020). Two-way communication (read

and write) with BAS during the HVAC operation process is the distinguishing feature of this type of optimal control technologies.

A snapshot of the literature shows that optimal control solutions have been developed and tested for cooling plants (Ma and Wang 2011), air handler units and variable air volume terminals (Liang et al., 2015), and packaged systems (Putta et al. 2013). To test and evaluate these optimized control solutions, researchers commonly conduct simulation-based assessments (Ma and Wang 2011, Wang et al. 2013, Liang et al. 2015) and field evaluations (West et al. 2014, Benga et al. 2015). This paper presents the results from a field evaluation of a cloud-based building operation platform that was installed in an office building. The platform integrates diverse building data streams and provides analytics and optimal control using real-time floor-by-floor occupancy data. Ease of installation and commissioning process, capability to enable energy efficiency, as well as energy and cost savings are evaluated in this study.

Technology and Site Description

The technology evaluated in this study is a cloud-based building energy information and management system which integrates disparate building data streams and provides analytics and optimal control. The platform uses AI and Machine Learning technologies to build a memory of building rhythm to predict, prescribe, and influence building performance. The technology provides a single integrated operating platform connecting all building functions and has the following unique features:

- **Data Integration and Visualization:** Integrate and visualize the data from the various sources, including but not limited to BAS, utility meters (e.g. electricity, gas, and water), occupancy counters, IoT (Internet of Things) sensors, isolated HVAC units, and localized weather. It provides a “single pane of glass” interface to monitor multiple real-time data streams.
- **Occupancy-based Automated System Optimization:** Traditional optimal control algorithms don’t consider real-time building occupancy as it is not monitored in BAS. This technology installs occupancy counting sensors at the building entrance and exit or at each floor to track real-time building occupancy. The technology has advanced the BAS into an AI-based Human-Out-of-The-Loop (HITL) system by providing precooling and preheating recommended startup to minimize total energy consumption and peak demand while satisfying estimated human thermal comfort. It utilizes day-ahead prediction of interior space conditions, occupancy profiles, and outdoor conditions developed using ML methodologies. The occupancy information is also utilized to determine the optimal ramp-down and ramp-up, and end-of-day operation adjustment of the building HVAC system. This technology is taking advantage of adaptive ML-based algorithms where the fidelity and performance of the application are improved with time (when more data is available). It should be noted that the user can choose to manually adjust HVAC systems, automatically adjust HVAC systems, or a combination of the two.
- **Predictive & Prescriptive Analytics:** Machine learning to correlate, trend disparate data streams, and learn thus providing predictive and prescriptive insights. Benchmarks consider similar operating and weather days from the past, calculating the optimal amount of energy to use throughout the current day. It provides an operational guide for optimal demand and consumption performance on a daily basis.

- Reporting & Data Export: Portfolio level, strategic insights that allow operators to understand how, where, and when energy is being consumed and which systems, processes, and facilities are driving consumption.

The demonstration site where the technology was installed for evaluation is a commercial office building located in downtown Washington, DC. Information for the building site is summarized in Table 1.

Table 1. Characteristics of the demonstration site

Floor Area	299,000 square ft
Vintage	1965
# Floors	12 floors above ground and 4 floors of parking below ground; each floor above ground has 2 wings; the ground level is retail.
HVAC system	A central chiller/boiler plant consists of two chillers (500 and 350 ton), two primary chilled water (CHW) pumps (one for backup), two cooling towers with variable speed fans, two secondary CHW pumps (one for air handling units[AHUs], the other for fan coil units[FCUs]), four boilers, and three hot water pumps (one for AHUs, one for FCUs, and the other for backup). 22 AHUs serve 2nd to 12th floors, with each AHU serving a wing on each floor. All AHU's have variable speed supply fans with all but six AHU's also having variable speed return fans. Four unitary heat pumps serve the ground floor. Cooling or heating is provided to space by a large number of variable-air-volume terminal units and FCUs .
HVAC Control	HVAC operations are controlled by a Tridium JCI Niagara AX BAS. HVAC units are set to turn on and off based on a programmed operating schedule (M-F 6:00am-18:00pm). There are no optimal start/stop controls. The AHU controls to maintain the supply air temperature setpoint which is reset by the return air temperature. Supply/return fans modulate to maintain the supply air static pressure setpoint.
Meter Data Management System	Mach Energy
% Occupancy	100% before pandemic, 5% in summer 2020
Occupied Time	M-F 8:00-18:00

As a part of this demonstration study, a 3rd party occupancy sensing technology (22 occupancy counters) were installed (two at each floor) to track the occupancy on a floor-by-floor basis. The occupancy sensors are 3-D vision counters that were installed at egress and ingress points on each wing at each floor. Each of the counters was calibrated to ensure accurate counting before it was integrated into the platform. The platform uses these occupancy data along with thermal modeling and physics-informed machine learning algorithms to optimize the start and stop as well as the static pressure setpoints of AHUs (Figure 1) to reduce the fan speed as required. The adjustment was done automatically by the platform.

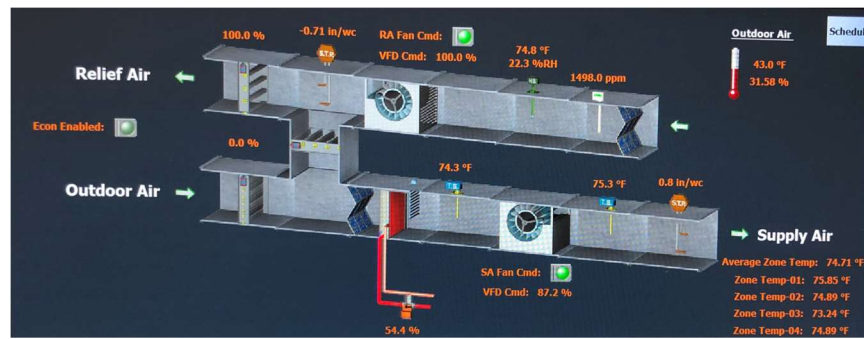


Figure 1 Building automation system graphic for AHU at the site

Evaluation Methodology

This section details the methodology that was used to validate the technology performance at the demonstration site. It covers ease of installation and commissioning process, capability to enable energy efficiency, as well as energy and cost savings.

Ease of Installation and commissioning process

The assessment of the installation and commissioning process was accomplished based on interviews with site operation staff and activity tracking throughout the course of the evaluation. The following items were documented during the installation and commissioning process:

- Detailed account of activities during the process and the lead time for completing the activities respectively.
- Type of support needed from on-site engineers and other staff, and estimated labor hours.

Capability to enable energy efficiency

The main energy savings of the platform can be attributed to the following energy conservation measures (ECMs):

- Optimal start – The platform utilizes proprietary AI and Machine Learning algorithms to recommend and automate the startup of AHUs based on occupancy data, the next day's weather, the building thermal capacity and the predicted interior space temperatures within the building just prior to start-up. The recommended start time is designed to reduce peak demand, consume the least amount of energy while ensuring the space reaches its desired temperature by 8am as required in the lease.
- Early shut down – The platform determines the shut down times of AHUs based on the real-time occupancy: if the occupancy count in a particular floor reads as 0 after a specific time pre-determined by the building operator, the unit waits 15 minutes before shutting down the AHU for the rest of the day. This measure is only applicable during pandemic time as only a few tenants come to the building on weekdays and they typically do not stay in the building for the whole day. The facility staff suggested that this measure would not continue when the building goes back to the full occupancy operation mode in future because at that time many more tenants will work in the building until 6pm.
- Midday ramp down/up - During the lunch hours, the platform implements HVAC ramp down sequences (tentatively reduce AHU static pressure setpoint (or fan speed) prior to

heating or cooling loads decreasing or increasing at each floor based on variation of occupancy. The enabled and disabled times are determined by proprietary machine-learning algorithms using occupancy data. The reduction of fan speed decreases fan electricity use and may increase the chilled water energy use as supply air temperature setpoint might be reset to lower values. The simulation approach adopted in this evaluation takes into account this interaction effect and presents the net energy savings.

- End-of-day static pressure setpoint (or fan speed) ramp down - The same occupancy-based control also allows for the end-of-day ramp-down to occur as soon as the occupancy level starts to decrease. This measure wasn't executed in the pandemic, but the building operator indicates that it may be implemented instead of the early shut down strategy after the building returns to full occupancy operation mode.

The implementation of the four ECMs above are fully automated in the platform and the BAS. The optimal operation schedule and setpoints are determined in the platform and then written into the BAS. To validate the successful implementation of ECMs, the data trends of the targeted control settings or measurements are plotted in the post-installation periods to validate if the settings change successfully.

In addition to the four ECMs that directly generate energy savings, the platform also provides building operators real-time situational awareness of BAS, occupancy, weather and energy data, which enable them make more informed operational adjustments that contribute to energy savings. Granderson and Lin (2016) indicates that situational awareness for having a platform with real-time monitoring of multiple data sources was a critical component in achieving 17% median site energy savings, and 8% median portfolio savings across 26 organizations.

Energy and cost savings

The technology was installed in July 2020. Due to the COVID 19 pandemic, the building occupancy significantly decreased from 100% in 2019 to 5% in summer 2020. Therefore, the building energy consumption in 2019 can't be used to predict the energy consumption in 2020 and 2021 when the occupancy was much lower than the normal level. The actual building energy consumption in 2020-21 after the platform was installed can't be compared with the building energy consumption in 2019 to conclude the energy savings. Therefore, the IPMVP Option D Calibrated simulation (EVO 2012) was used in this study to simulate the energy savings under fully occupied conditions.

Calibrated simulation uses computer simulation to model energy performance of a whole building and determine building energy consumption in a pre or post installation scenario. EnergyPlus was selected as the simulation tool to access the savings. This simulation model must be calibrated with actually monthly or hourly energy consumption data. Option D is especially useful where a baseline does not exist. Inputs to the model may include building characteristics; performance specifications of new and existing equipment or systems; engineering estimates; spot, short-term, or long-term measurements of energy use of system components; and long-term whole-building utility meter data. After the model has been calibrated, savings are determined by comparing a simulation of the baseline with either a simulation of the post-installation period or actual utility data. If simulation is selected for post-installation energy performance, ECMs would be implemented in the baseline simulation model, and the model is run to estimate the post-installation energy use.

Calibration simulation for an existing building typically follows five general steps:

- (1) Collect data:** The data required for simulating an existing building typically includes
- At least 12 months of utility bill data from the “pre-COVID” period (2019 in this study)
 - Historic weather data
 - Architectural, mechanical, control, and electrical drawings
 - Site survey data for occupancy, building system and equipment.
 - HVAC systems, primary equipment (e.g., chillers and boilers): capacities, number, model and serial numbers, age, condition, operating schedules, etc.
 - HVAC systems, secondary equipment (e.g., air-handling units, terminal boxes): characteristics, fan sizes and types, motor sizes and efficiencies, design-flow rates and static pressures, duct-system types, economizer operation, and type of controls
 - HVAC system controls, including location of zones, temperature set-points, control set-points and schedules, ventilation airflow rates, and any special control sequences
 - Lighting systems: number and types of lamps, with nameplate data for lamps and ballasts, lighting schedules, etc.
 - Plug loads: summarize major and typical plug loads for assigning values per zone
 - Building envelope and thermal mass: dimensions and type of interior and exterior walls, properties of windows, and building orientation and shading from nearby objects. Infiltration rates are important, but are often difficult to determine
 - Building occupants: population counts, occupation schedules in different types of zones (e.g. office, conference room, corridor, and data center)
 - Other major energy-consuming loads: type (industrial process, air compressors, water heaters, elevators), energy consumption, schedules of operation

(2) Input data and test baseline model: Input data into the model, run a few simulations to debug the model, and check the model output files to verify that there are no errors in the program.

(3) Calibrate the baseline model: Model calibration is accomplished by linking simulation inputs to actual operating conditions and comparing simulation results with whole building data. ASHRAE Guideline 14 (ASHRAE 2014) recommends acceptable tolerance for calibration using monthly data are MBE within $\pm 5\%$ and $CV(RMSE) < 15\%$, where MBE is mean bias error and $CV(RMSE)$ is coefficient of variation of the root. In this study, MBE and $CV(RMSE)$ were calculated following the equations (1) and (2) respectively, where y_i is the actual metered value, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the average of the y_i , and n is the total number of data points.

$$MBE = \frac{\sum_i^n (y_i - \hat{y}_i)}{\bar{y}} \times 100 \quad (1)$$

$$CV(RMSE) = \frac{\sqrt{\frac{1}{n} \sum_i^n (y_i - \hat{y}_i)^2}}{\bar{y}} \times 100 \quad (2)$$

A visualization of the testing building energy model is provided in Figure 2. Table 2 shows the key simulation model inputs after calibration.

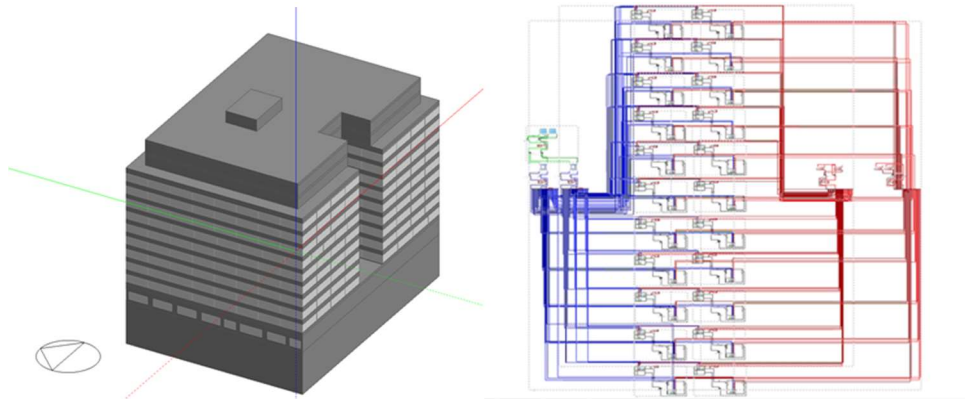


Figure 2 Model view in the DesignBuilder program

Table 2 Inputs for energy model

	Baseline Building Inputs	Source
Envelope	Wall: 4" glazed brick + 4" pierced concrete block, U-Factor=0.29 Btu/h-ft ² -F Window: U-Factor=0.48 Btu/h-ft ² -F, SHGC=0.706, VT=0.637 Window-Wall-Ratio: 0.58 Roof: U-Factor=0.044 Btu/h-ft ² -F	Construction blueprints; IECC 1998
Internal Load	- Lighting: 0.7~1.0 W/sqft, vary between zones - Equipment: vary between zones - Occupancy: vary between zones	DesignBuilder Default Library; IECC 1998 ¹
Occupancy Schedule	Monday to Friday, 8am to 6pm	Building Manager
HVAC - Water Cooling System	2 electric chillers (350 ton and 500 ton) - Monday to Friday, 6am to 6pm - Cut-in at 55F, cut-out at 50F - Chilled water at 45F - Chiller COP 5.5 - Chiller continuous supply pump - Design pump head at 1.38 inH₂O - Design power at 149,140 W - Motor efficiency 0.9 - Variable speed condenser - condenser temperature fixed at 80F - Monday to Friday, 6am to 6pm - Design pump head at 80.3 inH₂O - Design power at 44,742 W - Motor efficiency 0.9	Building Manager; Equipment Nameplates

HVAC - Water Heating System	● 4 natural gas boilers (250 ton each) ○ Monday to Friday, 6am to 6pm, manually turned off from May through September ○ Cut-in at 40F, cut-out at 62F ○ When OAT=10F, HWT=170F; when OAT=50F, HWT=160F ○ Thermal efficiency=0.8 ● Boiler continuous supply pump ○ Design pump head at 80.3 inH₂O ○ Design power at 44,742 W ○ Motor efficiency 0.9	Building Manager; Equipment Nameplates
HVAC - Zone	● AHU without reheat ○ fan efficiency 0.8 ○ economizer fixed dry bulb lockout, minimum temperature 14F, maximum temperature 68F ● Fan coil units ○ Constant fan, variable water flow ○ Cooling coil inlet water temperature at 45F ○ Heating coil inlet water temperature 160F, outlet water temperature 149F ● Zone thermostat setpoints ○ Occupants have manual control, calibrated in models based on locations (perimeter or core zones) and months ○ Perimeter zones ■ Cooling: occupied 75F, unoccupied 75.2F ■ Heating: occupied 62F to 72F, unoccupied 60.8F to 71.6F ○ Core zones ■ Cooling: occupied 73.4F to 74.3F, unoccupied 75F ■ Heating: occupied 62.6F to 73.4F, unoccupied 60.8F to 72F	Building Manager; Calibration

(4) Create and refine the post-installation model: Starting with the calibrated baseline model, the model is updated to include the building's ECMs to create the post-installation period model. Three individual ECMs (optimal start, midday ramp down and up, and end-of-day ramp down) were simulated in this study. The measure of early shut down was not simulated because it will not continue in the full occupancy operation mode. The technology provider of the platform used its internal model to determine the optimal start time of each AHU, the enabled and disabled times of midday ramp down/up, and the enabled time of the end-of-day ramp-down for each weekday of 2019 based on simulated 2019 space temperature data, correlating 2020-2021 actual space temperature and normalized occupancy, and weather data. The AHU start time and static pressure setpoint were changed accordingly in the post-installation EnergyPlus model with Energy Management System codes.

(5) Verify performance and calculate savings: The savings is calculated by subtracting the post-installation model results from the baseline model results using the same input conditions.

Results

Ease of Installation and commissioning process

In this study, two occupancy counters were installed at each elevator bay for floors 2 through 12 in the building. Fifty Monnit wireless temperature, humidity, and CO₂ sensors were also installed in the building to provide increased visibility of the interior environments in various tenant spaces. The platform has successfully integrated ~21,000 data points from the JCI Niagara AX building automation system (all associated AHUs, fan coil units, VAVs, chilled/condenser water systems and associated pumps/sensors/valves/chillers/cooling towers, and all equipment associated with hot water system such as boilers, heat exchangers, etc.), existing and new Monnit wireless sensors, electric and natural gas meters, and occupancy counters (Figure 3). A graphic user interface dashboard was created inside the BAS to allow building operators to enable or disable the new schedule/setpoint sent by the platform.

The standard process to implement the platform consists of a period of installation and configuration (including data integration), followed by a machine learning period and a commissioning period. During the machine learning period, the algorithms in the platform were tuned to fit to the specific site, using measured operational, energy use, and occupancy data. During the commissioning period, the technology provider worked with the site to test if the optimize start/stop signal or new control setpoint signal can be delivered to the BAS and successfully override the existing settings. Table 3 summarizes the activities, the stakeholders involved in, and the time duration for each period. The onboarding and provisioning process was very smooth. The total 4.5-month installation and commissioning time was a marked improvement over the six to twelve months reported in the field evaluation of an HVAC optimization system evaluated in prior work (Granderson et al.2018).

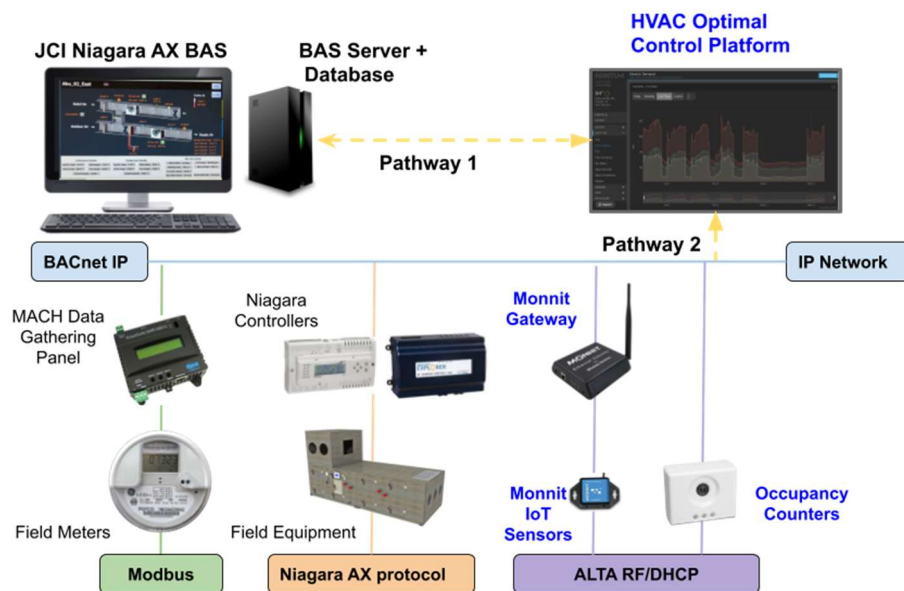


Figure 3 Schematic illustration of the data acquisition process

Table 3. Installation and commissioning activities

Activities Before Initial Testing	Responsibilities	Lead Time
Installation and configuration: connect the platform to BAS, tag all points of interest; install and connect gateways and additional IoT sensors	Tech. provider, site, BAS vendor	~ 1 month
Machine learning: algorithm training; setup, review and configure graphic user interface	Tech. provider	~ 2.5 months
Commissioning: testing of optimal start/stop/control setpoints	Tech. provider, site	~ 1 month

The primary point of contact of the test site estimated about 50 hours' staff time was dedicated to the platform implementation. The most common activities that were required of the on-site engineer or primary organization point of contact during the installation and configuration phase are summarized below:

- Schedule, perform site walk through
- Provide control specs and sequences, meter info, utility bills, and historical energy data
- Involve with IT for network switches and IP configuration for occupancy counters, IoT sensors, and the platform
- Provide full access to JACE controller and BAS controls for data integration
- Help install and commission occupancy counters
- Help test software configurations and connectivity

Capability to enable energy efficiency

Optimal start and early shut down

Originally, AHU fans start at 6:00am and stop at 6:00pm every day during the weekdays. With the platform in place, AHU's new start times are based on multiple factors, including outdoor air temperature, occupancy data, and the calculated time it takes each space to reach its desired temperature by 8am (required by tenant lease) after startup. The new stop times are based on the real-time occupancy - if the occupancy count in a particular floor reads as 0 after a specific time required by the building operator (i.e. 2:00pm), the unit waits 15 minutes before shutting down the AHU for the rest of the day. Figure 4 shows one-day pandemic operation of an AHU serving the 6th floor west wing with optimal start and early shut down implemented by the platform. The building's interior temperature and the weather forecast for the next day allowed for a later start-up time, saving energy and costs compared to a fixed and unchanging start-up schedule. The changes of fan speed (AHU_06_West) indicates that the AHU starts at 7:40am and stops at 14:15pm following the optimized schedule. The platform reduces AHU run time by 5.5 hours on this day. Figure 4 also displays the real-time occupancy on the west wing of the 6th floor. There is another opportunity in future to lower down the fan speed during the entire occupied hours when the occupancy level is low.

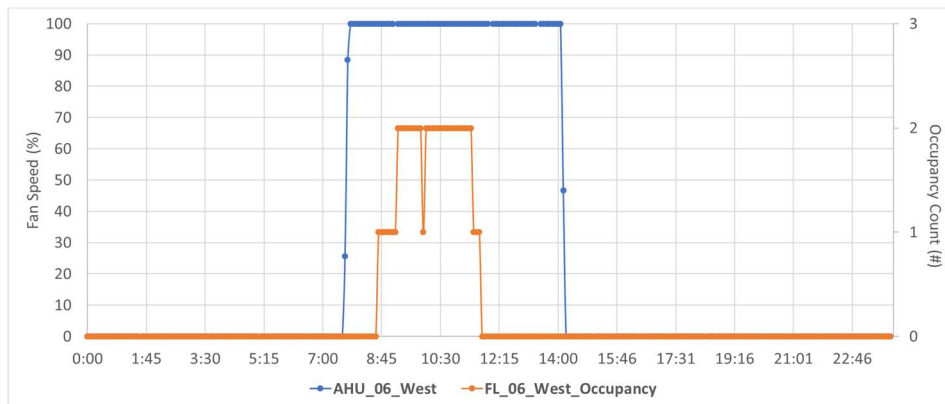


Figure 4 Optimal start and early shut down of AHU_06_West

Midday ramp down, ramp up, end of day ramp down

It was observed that the occupancy would begin to decrease near lunchtime and rise again in early afternoon. This occupancy pattern is an opportunity to reduce energy consumption by adjusting the AHU static pressure setpoints (and associated fan speeds) to match the building profile. When occupancy drops near lunchtime, the platform executes a predetermined ramp-down sequence to the BAS to reduce the energy use, then also to automatically commands the BAS to ramp the AHUs back up as occupancy returns after lunch. Figure 5 shows a one-day example of this midday ramp down and ramp up sequences. The static pressure of AHU_07_West reduces from 1.2 in.w.c. to 1.0 in.w.c. at 11:20 am and goes back to 1.2 in.w.c. at 12:40am. Table 4 summarizes the normal static pressure setpoints and the minimum static pressure setpoint when midday ramp down is deployed for all the AHUs. The AHU static pressure setpoints are dropped by 0.1-0.2 in.w.c. when the ramp-down sequence is executed. Later on in the study, the platform enabled early ramp down, in which the static pressure set points were reduced to the minimum setpoint once a drop in occupancy is detected later in the afternoon.

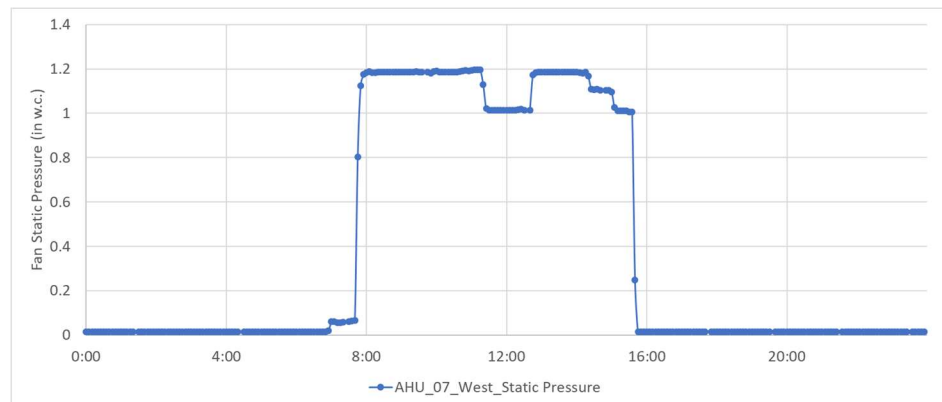


Figure 5 Midday ramp down and ramp up of AHU_07_West

Table 4. Comparison between the AHU normal and minimum static pressure setpoints

Units	Normal Static Pressure Setpoint (in.w.c)	Min Static Pressure Set Point (in.w.c)	Ramp Down Time (approx)	Ramp Up Time (approx)
AHU-2 East	2.00	1.80	11:25 AM	12:48 PM
AHU-2 West	1.40	1.20	11:23 AM	12:47 PM
AHU-3 East	0.40	0.30	11:27 AM	12:43 PM
AHU-3 West	1.40	1.00	11:28 AM	12:49 PM
AHU-4 East	1.10	0.90	11:11 AM	12:47 PM
AHU-4 West	1.00	0.80	11:10 AM	12:53 PM
AHU-5 East	1.00	0.80	11:26 AM	12:39 PM
AHU-5 West	1.00	0.80	11:11 AM	12:37 PM
AHU-6 East	1.00	0.80	11:11 AM	12:49 PM
AHU-6 West	1.00	0.80	11:21 AM	12:30 PM
AHU-7 East	2.00	1.80	11:11 AM	12:38 PM
AHU-7 West	1.20	1.00	11:23 AM	12:44 PM
AHU-8 East	1.50	1.40	11:13 AM	12:39 PM
AHU-8 West	1.50	1.40	11:27 AM	12:33 PM
AHU-9 East	0.40	0.20	11:27 AM	12:49 PM
AHU-9 West	0.30	0.10	11:23 AM	12:40 PM
AHU-10 East	1.00	0.80	11:25 AM	12:44 PM
AHU-10 West	0.80	0.60	11:24 AM	12:42 PM
AHU-11 East	0.80	0.60	11:26 AM	12:36 PM
AHU-11 West	1.40	1.20	11:27 AM	12:42 PM
AHU-12 East	0.60	0.40	11:19 AM	12:45 PM
AHU-12 West	1.10	0.90	11:19 AM	12:32 PM

Energy and Cost Savings

Due to COVID-19, IPMVP Option D Calibrated simulation was selected in this study to simulate the energy savings under fully occupied conditions. The EnergyPlus model of the test site was created and calibrated to match the simulated annual energy consumption with the measured

annual energy consumption in 2019. The model inputs including but not limit to lighting power density, zone thermostat setpoints, and AHU and fan coil control setpoints were revised and refined for the purpose of model calibration. Table 5 presents the indices of calibration results. The indices for both electricity and natural gas are within the acceptable tolerances specified by ASHRAE Guideline 14.

Table 5. Calibration results

Index	Electricity	Natural Gas
MBE	-0.60%	-4.14%
CV(RMSE)	5.17%	12.94%

The annual energy savings were simulated under four scenarios: ECM1-optimal start, ECM2-midday ramp down and up, ECM3-end-of-day ramp down, and ECM4-early shut down. In the midday ramp down and up scenario and the end-of-day ramp down scenario, the minimum AHU static pressure setpoints in Table 4 were implemented in the 2019 calibrated model during the weekday lunch time (approximate 11:30am-12:30am) and later afternoon (approximate 15:00pm-18:00pm), respectively. The start and end time of the lunch hours as well as the start time of end-of-day ramp down were slightly different for each AHU and determined from 2020-2021 data. In the early shut down case, it was conservatively assumed AHUs could shut down at 4pm.

Table 6 shows the whole building energy and cost savings results. In the table, the whole building energy use intensity (EUI) of baseline and three post-installation cases are presented, followed by the energy and cost savings. The final two columns contain the absolute savings of electricity and natural gas. The whole building energy savings is 2.6%, 0.07%, 0.1%, and 2.8% for the optimal start, midday ramp down and up, end-of-day ramp down, and early shut down cases, respectively. Since only one ECM can be implemented in the later afternoon, the total annual whole building energy savings of the three ECMs is 2.8% (\$10,775) if end-of-day ramp down is implemented and is 6.1% (\$23,111) if early shut down is implemented. Figure 6 shows the monthly electricity and natural gas consumption in each case.

There is one other publicly available third-party assessment of this platform to compare these results to. A field evaluation documented in Pachuta et al. (2022) indicated 11% modeled whole building energy savings in a Courthouse and 5.1% modeled whole building energy savings in a Federal Building. Similar calibrated simulation approach was adopted to model the energy savings of ECM1 - optimal start, ECM2 - midday ramp down and up, and ECM3 - end-of-day ramp down. The total modeled savings of ECMs 1, 2, and 3 in this paper is 2.8%, which is less than the savings reported in Pachuta et al. (2022). There are two reasons for that. First, the HVAC units in the testing site of this paper start at 6:00am in the baseline case, which is later than the HVAC units start time in in Pachuta et al. (2022) (3:00am in the Courthouse and 3:00am/4:30am/6:00am in the Federal Building). The later HVAC start time leads to a reduced savings potential. If the HVAC units start at 3:00am instead of 6:00am in the study of this paper, the modeled savings of optimal start would increase to 5.7% which aligns with the savings magnitude in Pachuta et al. (2022). Second, the space cooling is provided by both AHU and fan coils in the demonstration site of this paper. The AHU fan energy use accounts for a less percentage

of the whole building consumption in this paper compared with Pachuta et al. (2022). As a result, the percent energy savings contributed by the reduction in fan energy use due to the midday ramp down/up and end-of-day ramp strategies is smaller.

Table 6. Energy and cost savings results

	EUI (kBtu/sqft)	Whole Building Saving (%)	Whole building savings (\$)	Electricity Savings (kWh)	Natural Savings (Therms)	Gas
Baseline	59.1	-	-	—	—	
ECM1. Optimal Start	57.5	2.6%	\$9,775	54,966	2,777	
ECM2. Midday Ramp Down/Up	59.0	0.07%	\$461	3,831	0.7	
ECM3. End-of-day Ramp Down	59.0	0.10%	\$539	4,936	0.7	
ECM4. Early shut down	57.1	3.4%	\$12,875	74,743	3,411	
Total (ECMs 1, 2, 3)	-	2.8%	\$10,775	47,852	2,671	
Total (ECMs 1, 2, 4)		6.1%	\$23,111	133,540	6,188	

Note: electricity rate: \$0.12 kWh, natural gas rate: \$1.145/therm

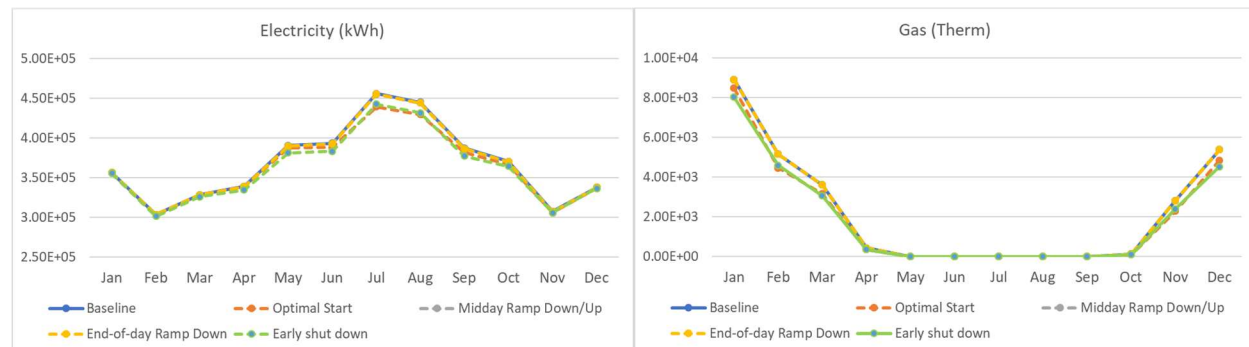


Figure 6 Simulated monthly energy consumption of baseline, optimal start, midday ramp down/up, end-of-day ramp down, and early shut down (Left: electricity, right: natural gas). Since the boilers are turned off from May to September, the gas consumption only displays January to April and October to December.

Conclusions

In this study, a cloud-based building operation platform was implemented in an office building for evaluation. The evaluation was designed to evaluate the technology performance including the ease of installation and commissioning process, capability to enable energy efficiency, as well as energy and cost savings. The platform successfully integrated ~21,000 data points from diverse data streams such as BAS, meters, occupancy counters, and IoT sensors in a month. 22 occupancy counters were installed as a part of the platform to track floor-by-floor

building occupancy in real-time. The platform utilized the floor-level occupancy data together with thermal modeling, and machine learning algorithms to implement optimal start-up, early shut down, and intra-day fan speed adjustment to the AHUs for each floor in the pandemic. The onboarding and provisioning process was very smooth. The technology reduced weekday AHU run time significantly during the 2020-2021 COVID-19 time period. The simulation shows 2.8% annual whole building savings (\$ 10,775 per year) can be achieved if optimal start, midday ramp down and up, and end-of-day ramp down are implemented when the building is fully occupied in the post COVID time period, and 6.1% annual whole building savings (\$23,111 per year) can be achieved if early shut down is applied instead of end-of-day ramp down. These savings results are consistent with the 11% and 5.1% modeled savings documented in Patchuta et al. 2022. Future work is needed to study the various ways that occupancy data can be further used for optimal control, for example, demand controlled ventilation and minimum airflow setpoint of terminal units.

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