The Integration of Wi-Fi Location-Based Services to Optimize Energy Efficient Commercial Building Operations

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Prepared by: Lester S. Shen, Ph.D., Di Sui, P.E., Grant Baumgardner, Anirudh Durbha, and Robert Lysholm, Center for Energy and Environment

Matt Kirk
Design.Garden

Lee Shaver and Ben Bartling, C.E.M., C.M.V.P.
Slipstream

Brad Kult, P.E. and Renae Rich
HGA

Dean Halverson and Terry Schimmel
Leede Research

Christopher Plum

Center for Energy and Environment

Center for Energy and Environment
212 Third Avenue North, Suite 560
Minneapolis, MN, 55101
Phone: 612-335-5858
website: www.mncee.org
Principal Investigator: Lester S. Shen, Ph.D.

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Executive Summary

Location-based services (LBS) use real-time locating systems (RTLS) that identify and track the location of objects and people using wireless technology. In the case of Wi-Fi LBS, access points (APs) receive signals transmitted by Wi-Fi-enabled devices like mobile phones, tablets, and laptops, constantly seeking Wi-Fi networks that are in range. The signal strength of the device received by the Wi-Fi AP can be used as a measure of proximity and, using multiple APs, the location of the device can be determined via trilateration.

This project investigated the use of Wi-Fi LBS in commercial buildings to determine the energy and non-energy benefits of integrating building management systems with occupant location tracking technology. The following were the goals and objectives of this project:

- Develop a non-proprietary, open-source algorithm to perform trilateration to predict the location of Wi-Fi-enabled devices.
- Test and validate the location detection algorithm (LDA) to provide occupancy data.
- Develop and test the communication protocol to deliver occupancy data to an open-source platform for distributed sensing and control such as VOLTTRON.
- Demonstrate the LDA in the field at commercial building settings.
- Determine usability requirements to implement a cost-effective Wi-Fi RTLS in commercial building operations.
- Recommend strategies and programs to promote market acceptance and penetration.

Four field sites were recruited to evaluate the performance of the LDA for occupancy sensing. Three commercial office sites and one hotel agreed to participate in the field demonstrations:

1. The Administration Building located at the Minnesota State Capitol Complex in Saint Paul, Minnesota
2. ConEd's Research and Development (R&D) offices located in their Manhattan headquarters in New York City
3. The second-floor offices of Slipstream in their building located in Madison, Wisconsin
4. The Sinclair, Autograph Collection hotel located in Fort Worth, Texas

This project found that using Wi-Fi data collected from mobile Wi-Fi-enabled devices could provide real-time occupancy data. The open source LDA software application can provide sufficient accuracy of the headcounts to inform a rule-based approach to occupancy-measured HVAC operation including demand-controlled ventilation, as opposed to schedules assuming full occupancy. Monitored occupancy levels rarely exceeded 50% of maximum occupancy of the spaces and typically averaged about 20%. Calculated energy savings using occupancy-based supply fan operation for 25%, 50%, and 75% occupancy levels range from 22% to 8% for electrical energy use and 12% to 4% for heating savings. Negligible cooling savings were found (less than 1%). To estimate the total energy savings for all commercial buildings in the U.S., a weighted average of square footage was used by principal building activity using the electricity consumption rates from CBECS. The median energy savings from ventilation controls was 16.7 TWh (0.06 quads) annually and 6.9 million metric tons of CO_2 emissions avoided. If the mobile device RSSI and MAC address data collected by the wireless network is available for location analytics, no further investment in occupancy sensing equipment is needed. This would then be a software-based retrofit that would be a cost-effective approach to building occupancy sensing and occupancy-monitored HVAC operation.

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List of Acronyms

A/E	Architectural/Engineering
AFMS	Airflow Measuring Station
AHU	Air Handling Unit
ALE	Aruba Analytics and Location Engine
AP	Access Point
API	Application Programming Interface
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
AV	Audio–Visual
BAS	Building Automation System
BLE	Bluetooth Low Energy
BMS	Building Management System
CBECS	Commercial Buildings Energy Consumption Survey
CEE	Center for Energy and Environment
CFM	Cubic Feet per Minute
CMX	Cisco Connected Mobile Experiences
DOE	U.S. Department of Energy
EBI	Honeywell Enterprise Building Integrator
EER	Energy Efficiency Ratio
EIA	U.S. Energy Information Administration
EPA	U.S. Environmental Protection Agency
FPS	Frame per Second
GPU	Graphics Processing Unit
HP	Hewlett–Packard
HTTP	Hypertext Transfer Protocol

HVAC	Heating, Ventilation, and Air-Conditioning
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IR	Infrared
IT	Information Technology
LAN	Local Area Network
LBS	Location-Based Services
LDA	Location Detection Algorithm
M&V	Measurement and Verification
MAC	Media Access Control
MBx	Monitoring-Based Commissioning
OT	Operations Technology
OUI	Organization User Identifier
PNNL	Pacific Northwest National Laboratory
PTI	Parallel Technologies, Inc.
R&D	Research and Development
RCx	Retro-Commissioning
RF	Radio Frequency
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indicator
RTLS	Real-Time Locating Systems
RTU	Rooftop Unit
SBS	Sensible Building Science
UWB	Ultrawide-Band
VAV	Variable Air Volume

Introduction

Location-based services (LBS) have been used successfully in a variety of applications in office, healthcare, retail, and hospitality buildings to track and in some cases interact with individuals. These services include wayfinding, asset tracking, marketing, information, and push notifications. Specific applications include:

- Wayfinding in shopping malls[1] and in the office,[2]
- Asset tracking applications in manufacturing,[3] retail,[4] and healthcare[5]
- Proximity marketing in stores where advertising content such as coupons or offers is provided wirelessly through apps to shoppers when they approach specific items and brands in the aisle[6]
- Information provided in self-guided museum tours[7,8]
- Location-based push notifications[9]

LBSs use real-time locating systems (RTLS) that identify and track the location of objects and people through the use of wireless technology. Within the defined space, fixed reference points, also sometimes called beacons, readers, or access points (APs), receive signals transmitted by the devices or tags that the object or person is carrying. The signal strength of the device/tag to a specific reference point is a measure of proximity and, using multiple beacons, the location of the tag can be determined through trilateration.

There are numerous RTLS technologies that can be used to perform LBS. RTLS technologies include Bluetooth/Bluetooth low energy (BLE) beacons, Wi-Fi, Li-Fi (visible light-based

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[1] Mall of America October 2017. "Mall of America® mobile app integrates live navigation." Mall of America [web site]. https://mallofamerica.com/press/press-releases/OCTOBER-23-2017 (accessed January 7, 2020).

[2] S. Castellanos. January 2020. "Waze for Work? Navigation Apps Come to Mazelike Offices." Wall Street Journal [web site]. https://www.wsj.com/articles/waze-for-work-navigation-apps-come-to-the-office-11578398400, (accessed January 7, 2020).

[3] A. Reddy. April 2015. "The Growing Use of RTLS by Manufacturers." RFID Journal [web site]. https://www.rfidjournal.com/articles/view?12958, (accessed January 7, 2020).

[4] C. Swedberg. 2019. "Concept Store Delivers Product Content via NFC, RFID." RFID Journal [web site]. https://www.rfidjournal.com/articles/view?19118/ (accessed January 7, 2020).

[5] S. Yoo, S. Kim, E. Kim, E. Jung, K.H. Lee, and H. Hwang. 2018. "Real-time location system-based asset tracking in the healthcare field: lessons learned from a feasibility study." BMC Medical Informatics and Decision Making, 18, 80. https://bmcmedinformdecismak.biomedcentral.com/articles/10.1186/s12911-018-0656-0, (accessed January 7, 2020).

[6] S. Mittal. June 2019. "Proximity Marketing Examples: 28 Retail Companies Nailing it with their Campaigns." beaconstac blog [web blog]. https://blog.beaconstac.com/2016/02/25-retailers-nailing-it-with-their-proximity-marketing-campaigns/ (accessed December 9, 2019).

[7] R. Chun. May 2016. "The SFMOMA's New App Will Forever Change How You Enjoy Museums." Wired [website]. https://www.wired.com/2016/05/sfmoma-audio-tour-app/ (accessed December 9, 2019).

[8] S. Pau. April 2017. "Audio That Moves You: Experiments With Location-Aware Storytelling In The SFMOMA App." MW17: Museums and the Web 2017 [website]. https://mw17.mwconf.org/paper/audio-that-moves-you-experiments-with-location-aware-storytelling-in-the-sfmoma-app/, (accessed December 9, 2019).

[9] K. MacFarlane. April 2019. "18 Inspiring Location-based Push Notification Examples & Ideas." Taplytics blog [web blog]. https://taplytics.com/blog/location-based-push-notification-examples-ideas/ (accessed January 16, 2020).

communications), ultrawide-band (UWB), radio frequency (RF), infrared (IR), and electromagnetic position tracking.[10, 11] Each of these technologies has their own strengths and weaknesses and are sometimes paired together to create a complete system. Wi-Fi LBS was the chosen RTLS technology for this project due to its ubiquitous installation in various building types and because most occupants already carry at least one Wi-Fi enabled device, thereby maximizing the potential sample size for this study. The following sections detail the additional benefits of Wi-Fi LBS.

Wi-Fi RTLS

Wi-Fi-enabled devices can serve as a "tag" to provide location since they constantly seek Wi-Fi networks that are in range. Wi-Fi APs that are in range receive the media access control (MAC) address and received signal strength indicator (RSSI) of each device whether that device is logged on to the Wi-Fi network or not (i.e., associated with the network). The MAC address is a hardware identification number that uniquely identifies that specific device on a network. For privacy, some mobile devices transmit randomized MAC addresses over time to anonymize the device. Randomized MAC addresses make it impossible to identify which individual is carrying the device, but for the purposes of this study all data about individuals will be anonymized so randomized MAC addresses will have no impact. The RSSI is a measure of the power level of the signal that is being received by the AP. For the purposes of RTLS, information already gathered by the existing Wi-Fi APs can be used. Once a device is within range of an AP, device presence and identity are immediately sensed, and location can be determined from the RSSI via trilateration. Occupant activity might also be inferred by the space where a Wi-Fi-enabled mobile device is located and/or by the movement of that mobile device around the space.

Wi-Fi RTLS are well suited for occupant sensing in commercial buildings because:

1. Most of the occupants will be carrying a mobile device on them or within their close proximity. For instance, in higher education a factor of 2–3 devices/person could be used to account for a student's cell phone, laptop, and tablet/other devices.[12]
2. Tracking does not require the individual to carry additional hardware (like a badge for RFID beacons) or to have a native app loaded on their device and connected to the network (like Bluetooth beacons).
3. Wi-Fi access points engage all Wi-Fi-enabled smartphone users (iPhone or Android), whether they are logged onto the Wi-Fi network or not.

Minimal additional infrastructure is required for indoor positioning since existing Wi-Fi hotspots (installed for the communications needs of mobile devices and computer users) provide the coverage that can be used for the location tracking. Increased resolution may be possible by

[10] Zhang, et al. 2017. "Indoor positioning tracking with magnetic field and improved particle filter." *International Journal of Distributed Sensor Networks*. 13(11). doi:10.1177/1550147717741835. https://journals.sagepub.com/doi/full/10.1177/1550147717741835

[11] Trinh, et al. 2022. "Two-Dimensional Position Tracking Using Gradient Magnetic Fields." *Sensors* (Basel). 22(14):5459. doi: 10.3390/s22145459. PMID: 35891131; PMCID: PMC9321341. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9321341/

[12] B. Kult, personal communication, 2019.

increasing the density of Wi-Fi access points, but a usable tracking resolution can be achieved using the access points already installed in an existing space.

Wi-Fi RTLS provides the following capabilities that make it a good candidate for occupant sensing.

1. There is virtually no latency between the time when a new device has entered the room and when an updated occupancy count is calculated (as opposed to CO_2 sensors). The frequency of the count is based on the time interval chosen to rescan the AP data.
2. Failure rates that occur with motion sensing are avoided when the device is at rest.
3. Wi-Fi LBS can map mobile devices across rooms and other areas of interest and trigger customized operating conditions. If individuals choose to opt in, Wi-Fi LBS can identify them and further customize their experience.

Wi-Fi RTLS has a limited resolution for sensing the occupant's position. Scholarly research generally agrees that a resolution of ±10 feet is achievable indoors. This resolution is acceptable when occupants reside well within a single area of interest, but presents a challenge when occupants reside near the edge of two or more areas, as the Wi-Fi RTLS cannot confidently resolve the appropriate area of the occupant. Nonetheless, this level of resolution is well matched to the area (500 to 3,000 square feet) typically served by a single zone in a building HVAC system.

Wi-Fi Location Analytics and Occupancy Sensing

There are commercially available Wi-Fi platforms that provide proprietary Wi-Fi location analytics. The two main manufacturers are Cisco with their Meraki Location Analytics[13] and Connected Mobile Experiences (Cisco CMX) Analytics[14] and HP with their Aruba Analytics and Location Engine (ALE).[15] The Cisco and HP platforms allow their location data to be shared with third-parties through application programming interfaces (APIs). This data can then be analyzed and made available for use by building automation systems (BASs) to adjust occupancy-based temperature and ventilation based on the predicted locations of mobile devices detected by the wireless platform.

The Canadian company Sensible Building Science (SBS)[16] employs Wi-Fi LBS using the Cisco CMX wireless platform. This system includes applications of the latest RTLS methods to provide energy efficient building operation. The SBS Bridge software receives real-time Wi-Fi data using the location analytics provided by the Cisco CMX network platform. The collected Wi-Fi data from the CMX-provided APIs are:

- The timestamp of the recording
- The connected device's MAC address

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[13] Cisco Meraki, "Location Analytics" webpage. https://meraki.cisco.com/solutions/location-analytics

[14] Cisco Meraki, Cisco CMX Configuration Guide, Release 10.6.0 and Later, Chapter: The Cisco CMX Analytics Service. January 31, 2019. https://www.cisco.com/c/en/us/td/docs/wireless/mse/10-6/cmx_config/b_cg_cmx106/the_cisco_cmx_analytics_service.html

[15] HPE Aruba Networking, "Location Analytics" webpage. https://www.arubanetworks.com/products/location-services/analytics/ale/

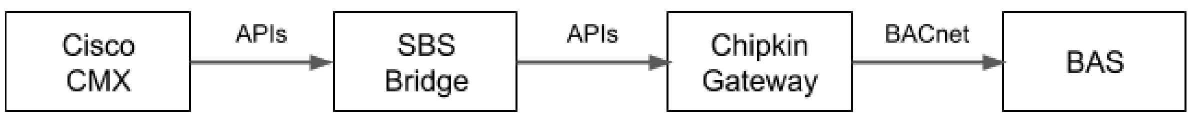
[16] Sensible Building Science homepage. https://sensiblebuildingscience.com/

- The RSSI of the signal from the connected device
- The MAC address of the Wi-Fi AP connected to the device

To ensure privacy, all occupancy information is anonymized. Ideally the APs are located within the space to optimize location while still providing good Wi-Fi coverage.

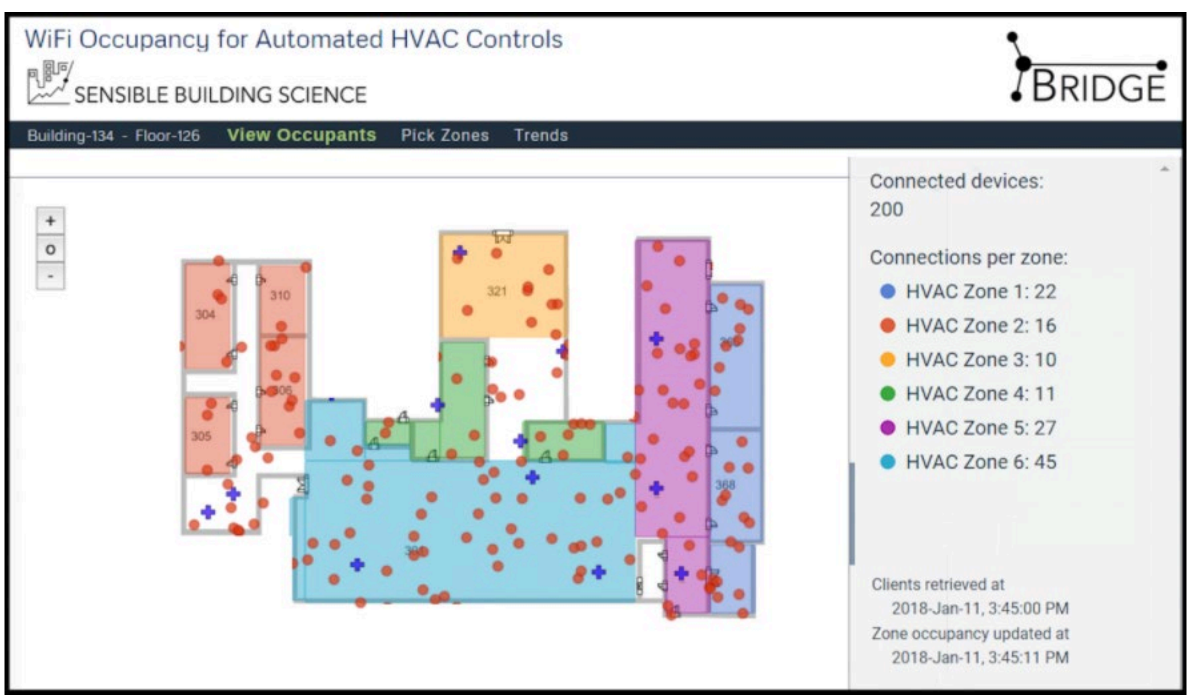
The only information needed for the BAS is occupant count in a defined space or zone. The Bridge software then sends the zone occupancy data to a gateway (produced by Chipkin Automation Systems) that communicates to the BAS via BACnet to control HVAC and lighting. This approach has been integrated in buildings with Johnson Controls, Siemens, and Delta Controls systems. Figure 1 shows how the data flows from the Wi-Fi APs to the BAS controls.

Figure 1. SBS's location analytics data flow from Wi-Fi detection to BAS.



Device location and count are updated every five minutes to provide occupant presence, count, and location information within the building and defined HVAC zones. Figure 2 shows an example of a dashboard screen that the SBS system provides.

Figure 2. SBS dashboard of Wi-Fi occupancy for automated HVAC controls



Originally tested in buildings on the University of British Columbia campus,[17] SBS is piloting their environmental control systems in buildings in Canada, the United Kingdom, and the United States. As of 2017, SBS has used their approach in over one million square feet of commercial and institutional space, serving over 100,000 occupants in real-time. Preliminary results indicated an average annual savings of 5% in whole-building energy use and have found that buildings with variable occupancy and demand control ventilation (DCV) offer the greatest potential for savings. For example, in lecture halls with periodic classes, SBS were able to reduce fan runtime by 20%–40%. SBS is currently working on bridge solutions for the Cisco Meraki and HP Aruba ALE network platforms.

Scheib et al. (2022) used Cisco's DNA Spaces cloud-based location analytics to create a dashboard to monitor occupancy in individual buildings at New York University. Their wireless-network-based occupancy data portal was used to adjust building schedules and reduce hours of occupied operation.[18] Integrating the system with their BMS was beyond the scope of their project but they noted that issues such as cybersecurity, data validation, and algorithm reliability would need to be addressed.

Project Goals and Objectives

This DOE-funded project sought to investigate, and field validate the use of AP-based Wi-Fi location-based services (LBS) in commercial buildings to determine the energy and non-energy benefits of integrating building management systems with occupant location tracking technology. The following are the goals and objectives of this project:

- Develop a non-proprietary, open-source algorithm to perform trilateration to predict the location of Wi-Fi-enabled devices.
- Test and validate the location detection algorithm (LDA) to provide occupancy data.
- Develop and test the communication protocol to deliver occupancy data to an open source platform for distributed sensing and control such as VOLTTRON.
- Demonstrate the LDA in the field at commercial building settings.
- Determine usability requirements to implement a cost-effective Wi-Fi RTLS in commercial building operations.
- Recommend strategies and programs to promote market acceptance and penetration.

The remaining sections of this report detail the results of the performed tasks.

[17] L. Corpuz-Bosshart. March 2017. "Innovative software converts Wi-Fi data into energy savings," University of British Columbia News. https://news.ubc.ca/2017/03/30/innovative-software-converts-wi-fi-data-into-energy-savings/

[18] C. Scheib, S. Scudere-Weiss, and D. Reagan. 2022. "Existing Wireless Infrastructure Can Be a Low-Cost Path to Occupancy-Based Commercial Building Control." In Proceedings of the 2020 ACEEE Summer Study on Energy Efficiency in Buildings 3:283–297. Washington, DC: ACEEE.

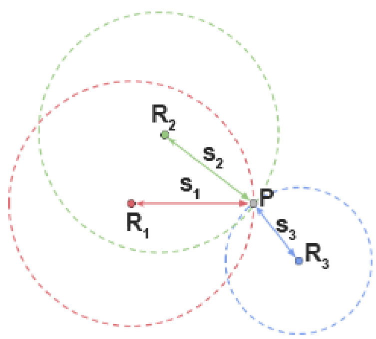
Development of the Wi-Fi Location Detection Algorithm (LDA)

The location detection algorithm (LDA) that was developed for the project makes use of the Wi-Fi trilateration method. This method is able to calculate the distance between a Wi-Fi enabled device and a Wi-Fi access point (AP) based on the strength of the received signal. A more powerful received signal will be closer to the AP and a fainter signal will be further away. The measure of the signal power level is the received signal strength indicator (RSSI) in dBm. When using three or more reference points, the location of the device can be pinpointed by trilateration.

Trilateration

Within the defined space, Wi-Fi enabled devices that the person is carrying transmit signals searching for Wi-Fi networks to join. The RSSI of the Wi-Fi device to a specific wireless AP reference point is a measure of proximity and, using multiple APs, the location of the Wi-Fi device can be determined through trilateration. In Figure 3 below, the three reference points denoted by R_1, R_2, and R_3 each read a signal (s_1, s_2, and s_3, respectively) from the Wi-Fi device. The location of the Wi-Fi device or person P is where the radial signal strengths s_1, s_2, and s_3 intersect.

Figure 3. Determining Location via Trilateration



The distance from each AP is calculated from the RSSI based on the Hato-Okumara model.

Hato-Okumara Model

The Hato-Okumara model is a power signal-based position method defined by the equation:[19]

$$\log d = \frac{1}{10n}\left(P_{TX} - P_{RX} + G_{TX} + G_{RX} - X_a + 20\ \log\lambda - 20\ \log\ (4\lambda)\right) \qquad (1)$$

where:

d is the estimated distance between the transmitter (Wi-Fi router or access point) and the receiver (Wi-Fi-enabled device).

[19] A. Bose and C.H. Foh. 2007. "A practical path loss model for indoor Wi-Fi positioning enhancement." 6th International Conference on Information, Communications and Signal Processing, ICICS. 10.1109/ICICS.2007.4449717.

P_{TX} (dBm) is the transmitted power level. For the OpenMesh APs used in this study, this is 13 dBm.
P_{RX} (dBm) is the power level measured at the receiver or the measured RSSI.
G_{TX} (dBi) is the antenna gain of the transmitter. For the OpenMesh APs, this is 2.5 dBi.
G_{RX} (dBi) is the antenna gain of the receiver (2.5 dBi).
λ (m) denotes wavelength of the signal and can be estimated to be 0.12m for the middle frequency of the 802.11b channel (2442 MHz).
X_a is a normal random variable with a standard deviation of a and is in the range of 3 dB to 20 dB, depending on the building construction and any obstacles that will reflect, diffract, or scatter the signal (standard deviation = ±5 dBm).
n is a measure of the influence of obstacles like partitions, walls, and doors. For an unobstructed line-of-sight (LOS) path between the transmitter and receiver, n = 2 but for obstructed paths, n should be between 4 and 5.

Grouping all the defined constants into one term A, equation (1) becomes:

$$\log d = \frac{1}{10n}(A - P_{RX}) \tag{2}$$

where A can be defined as the reference signal strength received in dBm:

$$A = P_{TX} + G_{TX} + G_{RX} - X_a + 20\ \log\lambda - 20\ \log(4\lambda) \tag{3}$$

The distance d is therefore determined by:

$$d = 10^{\frac{(A - P_{RX})}{10n}} \tag{4}$$

Bose and Foh (2007) suggest that a multi-model approach be used to improve accuracy. From their empirical data, they split the signal propagation model into two parts based on proximity to the access point. At closer ranges (< 5m) they suggest a higher value for the n factor with n = 5, and for distances greater than 5m, n should be set to 4. In the lab environment, this distance corresponds to -49 dBm. So, for RSSI > -49 dBm, n = 5 and for RSSI < -49 dBm, n = 4. They also suggest that a multi-model approach could be used for differences between a LOS and non-LOS environment.

Location Detection Algorithm (LDA)

An application was coded in JavaScript to analyze the measured signal data (RSSI and MAC address) collected from APs to:

1. Identify Wi-Fi-enabled laptops and mobile devices in a space.
2. Determine the location of each device.
3. Correlate the device(s) to an occupant.
4. Assign the occupant’s location to a zone in the space.
5. Determine the headcount for the zone.

The occupancy information from the algorithm (headcount per zone) can be used by building automation systems (BASs) to operate the building’s lighting and mechanical systems. The LDA was developed using OpenMesh Wi-Fi APs.

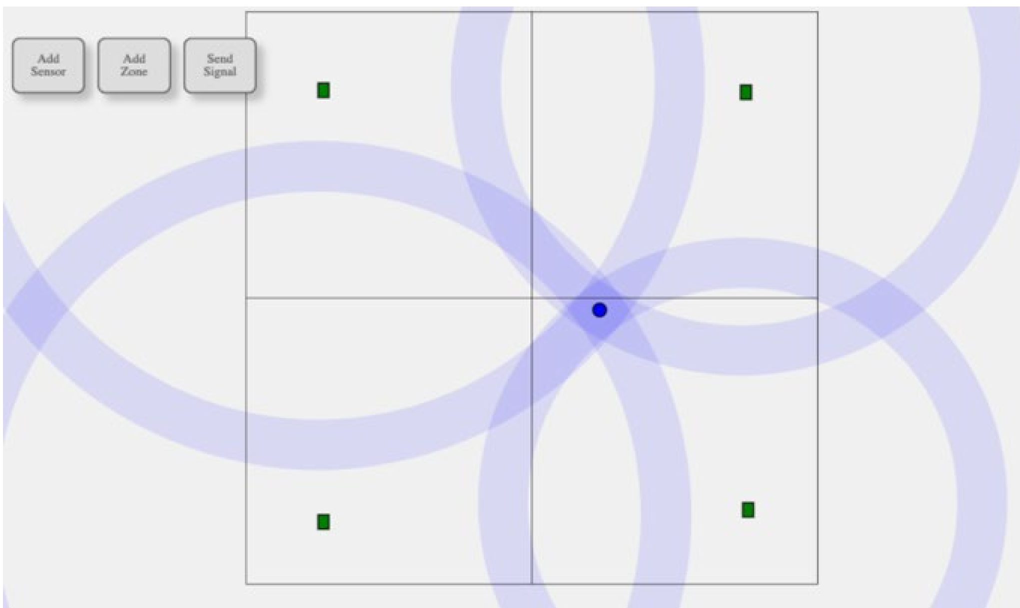
Using the MAC Address to Identify Devices

In addition to the RSSI, the AP receives the MAC address of the Wi-Fi-enabled device sending the signal. The MAC address is a unique device identifier primarily assigned by the device's manufacturer. The MAC address contains an OUI (Organization User Identifier) assigned to the manufacturer by IEEE that can be used to exclude Wi-Fi devices that will not be of value to occupancy sensing such as manufacturers of Wi-Fi enabled office equipment.

Determining Device Location

The application performs trilateration using the RSSI data measured from three or more APs and visually displays the results of the calculations within the floor plan of the space where the APs reside. Figure 4 shows a sample visualization from simulated data in a space with four APs locating one Wi-Fi device.

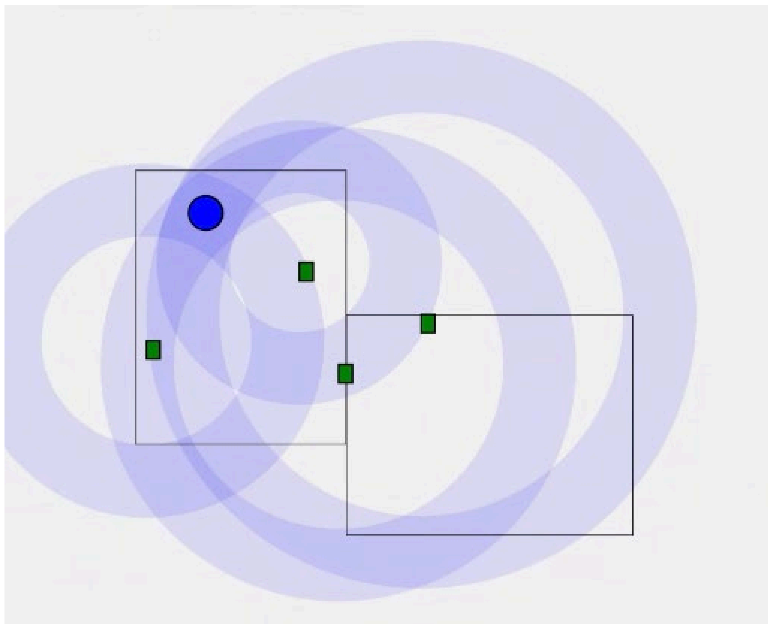
Figure 4. Test visualization of trilateration using four APs



The green squares show the location of the APs and the blue rings around each AP show the calculated radial distance the target device (blue circle) is from the respective AP, the distances calculated from the measured RSSIs. The thickness of the ring shows the probability distribution of the signal's origin, which in this case is the expected measurement error, calculated as ± the standard deviation of RSSI readings over the specified time-period of the measurements (one hour in our tests). With four APs to perform the trilateration, the overlap of the four rings gives the likely locations, and where all the rings intersect is the likeliest location of the target. The value of n was the same for each AP and the space was simulated with unobstructed LOSs for each AP.

The next step in the development was to test the tool using actual measured data from four APs located in an occupied space, in this case, two rooms in the apartment of the lead developer from Design.Garden. The measured data was uploaded from each AP to a remote Design.Garden server and the application accessed this data. To improve the location prediction, the algorithm scaled the value of n for each AP based on signal strength and approximate location based on the location of the reference AP. A minimum of five signals received from the Wi-Fi device was found to provide good accuracy to calculate location. In Figure 5, the intersection of the four rings is shown by the most highly saturated (darkest) blue area and the location of the Wi-Fi device is the blue circle located at the center of that area.

Figure 5. Trilateration visualization with autotuned scaling variable n



In order to calculate the area of overlap, the algorithm uses the visualization tool that displays the trilateration calculations to find the areas of overlap and determine the area of greatest overlap. An array is created that assigns colors to individual pixels to visualize the measured signal strengths to each AP (the blue rings). Pixels where the rings overlap are assigned progressively greater saturation levels as the number of rings intersect for those pixels. From the assigned saturation levels of the pixels, the areas of overlap can be calculated and arrays of overlaps determined. The algorithm finds the array with the largest number of overlaps, then of those arrays, identifies the array with the largest area which is determined to be the location of the Wi-Fi device. This empirical method is basically a computational approach equivalent to visually observing the “darkest” pixels on the screen showing the trilateration results on a two-dimensional plane, as shown in Figure 3. Since one pixel represents about a centimeter in the visual tool, the sensing region will be defined by the expected distance resolution of the location algorithm rather than by pixel. For instance, a region of 64x64 pixels is about 2–3 feet, so filtering by swaths is more efficient and improves the algorithm’s speed.

Filtering Devices

Filtering Distant Devices

The APs receive signals from Wi-Fi devices not only within the space of interest but also outside the space in adjacent rooms or outside of the building. Rules were developed to filter out extraneous signals both within and outside of the space. As described above, the MAC address can be used to identify signals from specific types of devices. Additional filters can be applied based on proximity to the APs. Two rules were created to identify the devices to track within the defined space. The algorithm will only track signals that (1) are received by all the APs in the space and (2) pass a defined signal strength threshold. Testing found that location accuracy increased with the number of signals received from the Wi-Fi device, with a minimum of five readings to provide good accuracy. With these filters, the algorithm could be tested in the field to determine its ability to accurately calculate occupant count within a zone.

Filtering Static Devices

Given that fixed devices remain stationary, one logical approach to identify them is by determining their immobility. In our research, we monitored the test sites continuously. Devices that remained active and immobile throughout the night were deemed to be fixed. This assumes that mobile devices, like smartphones or laptops, would either be turned off, moved, or would exhibit some change in signal strength due to variations in their environmental surroundings (like being kept inside a bag).

Consolidating Randomized MAC Addresses

Traditionally, a device will broadcast its MAC address in probe requests when scanning for Wi-Fi networks; however, to protect user privacy, many modern devices now randomize their MAC addresses. Given the low probability of randomized MAC addresses from two separate devices being equal, we can still use randomized MAC addresses to count devices in the space.

An additional complication is that devices send probe requests at irregular intervals, some more rapidly than others, so device counts must be taken over a window of time. Consequently, a single device that sends multiple probe requests within a window will be counted as multiple devices if each probe request contains a unique, randomized MAC address.

Therefore, it is necessary in this experiment to develop a method to identify and consolidate randomized MAC addresses of a single device. By using the estimated location of devices and a defined consolidation radius, we group together spatially overlapping randomized MAC addresses into a single device to create a 'pseudo person' for analytics and display.

Testing and Validation of the LDA to Provide Occupancy Data

Three sites were used to perform in-situ testing and validation. Because of the pandemic, these sites had limited occupancy, allowing us the flexibility to place known and identifiable devices in the spaces to simulate occupants and target individuals who were present in the spaces. Occupant presence, counts, and location were verified by self-reporting, visual observation, and digital video footage from the temporary deployment of home security cameras.[20] The three sites were the Design.Garden offices, the CEE Lending Center and Admin Office, and the Parallel Technologies' Innovation Lab.

Laboratory Testing

The laboratory testing was performed at the Design.Garden offices where seven APs (OpenMesh OM2P) were installed and multiple Wi-Fi enabled devices were placed in stationary locations: initially three Google Home Smart Speakers and later an additional single Android phone. The LDA was developed to work with any APs that can provide the RSSI and MAC addresses they have received from probe requests of Wi-Fi enabled devices in the space. For development purposes, OpenMesh APs were used because of Design.Garden's familiarity with these devices.

Figure 6 shows the predicted device locations of the Google Home Smart Speakers mapped onto a blueprint of the space and visualized by the LDA. The green squares show the locations of the APs, the small circles show the actual locations of each Wi-Fi device, and the larger circles show the locations of the devices predicted by the algorithm. The lines connecting each set of circles show the distance errors of the calculations. Over five days, we collected data for this experiment as follows: The recurring probe requests of the Wi-Fi devices were received by our seven APs, which forwarded the probe requests to the ingest interface of our software, which extracted and stored the timestamp and RSSI.

Figure 6. Locations of APs and Wi-Fi devices in Design.Garden offices space

[20] Blink for Home homepage. https://blinkforhome.com

Over five days, we collected 256,286 probe requests. These probe requests were not evenly distributed across devices and time; nonetheless, each AP collected at a minimum one probe request per 15 minutes from each device.

Testing the Hato-Okumara Model

Using this data, we first attempted to recreate the experiment outlined in Bose and Foh (2007), using their RSSI-to-Distance transformation adjusted for our equipment and with an arbitrarily chosen X_a of 5 dBM. The transformation operates on individual RSSIs; however, for our experiment we averaged the RSSI over a sampling period to mitigate noise. Using a sampling period of four hours, we produced transformations every 15 minutes over five days, giving us an array of distance guesses per sensor and device through time. Comparing our distance estimates to actual values showed an average error of 7.7 feet. Bose and Foh (2007) report an average error of 7.5 feet, hence we feel we have successfully recreated their experiment.

Table 1. Average error (feet) of distance guesses by sensor and device

Sensor	Device 1	Device 2	Device 3	Device 4	Average
1	17.3	5.1	5.9	7.8	9.0
2	3.4	18.2	16.9	0.8	9.8
3	3.4	12.3	16.2	7.4	9.8
4	11.2	3.2	0.9	5.5	5.2
5	16.2	5.7	3.3	13.8	9.8
6	9.8	5.1	3.3	4.5	5.7
7	4.8	2.8	6.7	3.3	4.4
Average	9.4	7.5	7.6	6.2	7.7

Testing Trilateration

Next, we used our trilateration algorithm to transform the distance guesses into two-dimensional location guesses per device through time. Comparing our location guesses to actual values showed an average error of 10 feet. Table 2 lists the error in feet of our location guess per device per day.

Table 2. Average error (feet) of location guess per device per day of the experiment

Day	Device 1	Device 2	Device 3	Device 4	Average
5	16.3	6.8	10.1	8.2	10.4
4	16.9	6.1	10	6.9	10.0
3	17	6.3	7.9	8.6	10.0
2	16.7	6.8	7.7	8.4	9.9
1	16.4	7.2	7.8	7.1	9.6
Average	16.66	6.64	8.7	7.84	10.0

These initial results confirm the viability of Wi-Fi LBS, and they nearly meet our stated goal of a ten feet maximum error.

Determining the Maximum Error

We based our stated goal of ten feet on results found in the literature regarding the one-dimensional RSSI-to-distance transformation; however, through experimentation we discovered that the error in two-dimensional trilateration varied significantly with placement of devices and sensors. This effect is inherent to trilateration and profound enough that we could conceivably arrange the devices and sensors so that the error would never exceed 10 feet, even if given incorrect RSSI readings.

Therefore, meeting our goal of ten feet is not enough to prove that we have successfully implemented a Wi-Fi LBS. Instead, to prove success we needed to show that we are significantly outperforming a Wi-Fi LBS with the same placement of devices and sensors that fails to correlate RSSI readings to location. We define the resulting error to be the failure threshold of a system given the same device and sensor placement.

Finally, we define the confidence of a Wi-Fi LBS system to be the difference between 1 and the ratio of its location guess to its failure threshold, expressed as a percent. Confidence near 0% represents an inability to perform Wi-Fi LBS, while far less than 0% represents a calibration error.

To calculate our failure threshold, we replaced the RSSI readings for Day 1 with randomly-generated values then we reran our trilateration experiment. This system meets our definition of a failing Wi-Fi LBS — therefore, we can calculate our failure threshold as the difference between its location guesses versus actual values. Comparing our average error for Day 1 to our Failure Threshold gives our Wi-Fi LBS a confidence of 49%, with an improvement of 9.1 feet over the failure threshold.

Table 3. The error, failure threshold, confidence, and error improvement of each device for Day 1

	Device 1	Device 2	Device 3	Device 4	Average
Error (feet)	16.4	7.2	7.8	7.1	9.6
Failure Threshold	19.1	6.4	17.7	31.9	18.8
Confidence	14%	-13%	56%	78%	34%
Error Reduction (feet)	-2.7	0.8	-9.9	-24.7	-9.1

X_a Tuning

Having quantified our confidence in our Wi-Fi LBS, we looked for opportunities to improve our confidence by optimizing our use of the RSSI-to-distance transformation. Notably, the transformation includes a variable, X_a, to account for random path-based attenuation. We assumed X_a would be normally distributed around a non-zero mean per device and sensor pair, and that given the distance we could estimate this mean value over time. This estimated mean could then be substituted for X_a in all future transformations to yield more accurate location guesses.

Unfortunately, this method assumes the path between the sensor and device does not change over time, so it seems unsuitable for Wi-Fi LBS. However, we assumed that if we kept the sensor position static while moving the device throughout all reasonable locations, the resulting estimated mean, X_μ, could then be substituted for X_a regardless of device location. Therefore, we developed an algorithm to estimate X_a per sensor using three of our devices (Devices 1, 3, and 4) as reference points, representing a subset of all reasonable locations, then we reran our trilateration experiment for the fourth device, Device 2. Compared to our previous location guess for Device 2, we improved our error from 7.2 feet to 3.4 feet and improved our confidence from -13% to 47%.

Table 4. The error, failure threshold, confidence, and error improvement of each device after X_a tuning

	Device 1	Device 2	Device 3	Device 4	Average
Error (feet)	9.3	3.4	6.7	13.7	8.3
Failure Threshold	19.1	6.4	17.7	31.9	18.8
Confidence	51%	47%	62%	57%	54%
Error Reduction (feet)	-9.8	-3.0	-11.0	-18.2	-10.5

Reference Points

This analysis suggests that the use of permanent fixed reference points will be useful not only for commissioning the RTLS but to maintain the accuracy of the Wi-Fi RTLS by providing a means to continuously calibrate the system. Inexpensive Wi-Fi devices can be placed within a space to serve as Wi-Fi beacons. A number of wireless, connected devices that typically exist in offices can also serve as stationary reference points, such as Wi-Fi enabled television displays in conference rooms, office equipment such as printers and copying machines, cameras, sensors, and the APs themselves.

Placement of APs in the Space

The algorithm also allowed us to investigate how the placement of the APs affected the accuracy of the device location prediction. The LDA gave us the option to select which APs would be used to perform the trilateration calculations. By choosing the number and locations of the APs, we could investigate how the relative position of the Wi-Fi devices with the APs affected the accuracy of the location predictions. We found that the location prediction was more accurate when the device was positioned within the area bound by the three or more detecting APs. If the device was located outside this area, the predicted location was typically a greater distance away from the device's actual position. This suggests that the ideal placement for APs to provide good location predictions will be along the perimeter of the space being monitored. This is different from the typical AP placement for good Wi-Fi coverage in a space, which would place the APs more centrally. More central positioning of the APs also minimizes the number of APs needed to provide the wireless network, while a minimum of three APs is needed in a space for location prediction. Placing the APs along the perimeter to provide both good Wi-Fi coverage and accurate location predictions would likely require additional APs to be installed than if only Wi-Fi coverage is required.

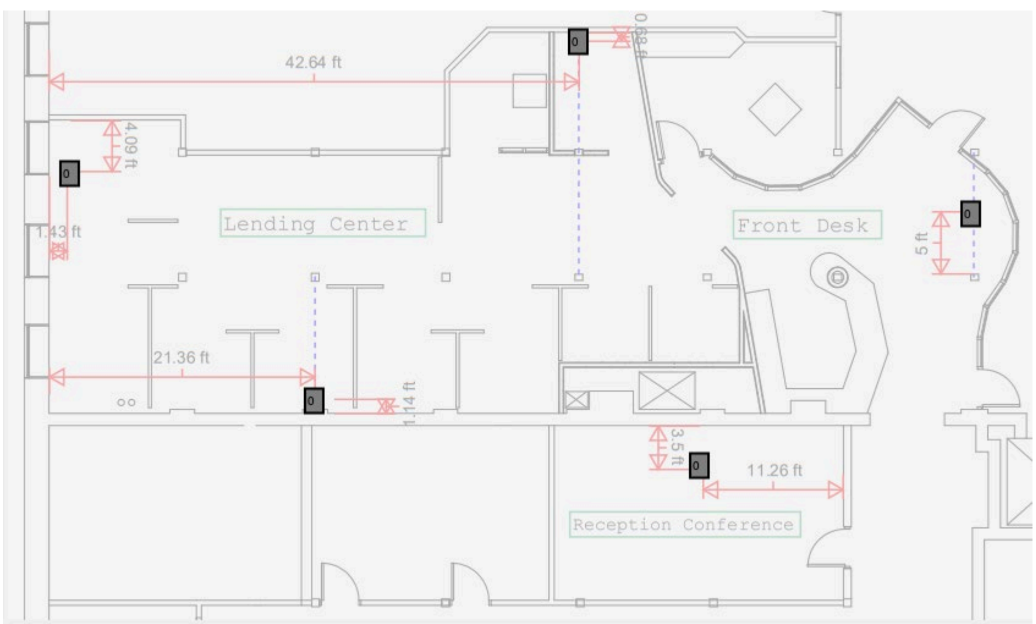
In-Situ Testing

The algorithm was tested using occupancy data collected from two sites: the CEE Lending Center and the Parallel Technologies' Innovation Lab. The testing performed at the Design.Garden office helped determine the steps needed to achieve accurate location estimates and occupant headcounts. The CEE Lending Center tests were performed to validate the algorithm for performing head counts in an office setting with some limited occupancy due to the pandemic. The Parallel Technologies' test continued the validation process and allowed comparison of the algorithm with the location analytics performed by the Cisco Meraki system.

CEE Lending Center and Admin Office

The Lending Center is occupied by CEE staff who approve home improvement and energy efficiency loans for qualified Twin Cities residents. Loan closings also take place in the Lending Center. The Wi-Fi LBS approach was tested to track occupancy and flow through the space. Four OpenMesh APs were placed along the perimeter of the Lending Center. Data from the APs were uploaded to the Design.Garden database server for analysis by the LDA. Wireless battery powered home security cameras[21] were placed within the Lending Center to create a visual record of occupancy in the space and to verify the calculations of the LDA. The cameras are Wi-Fi enabled and could be used as reference points. Figure 7 shows the floor plan with the locations of the APs.

Figure 7. Floor plan of the CEE Lending Center and reception area



[21] Blink Indoor Wireless Security Camera from the Amazon.com webpage. https://www.amazon.com/Blink-Indoor-Wireless-Security-Camera/dp/B07X4BCRHB

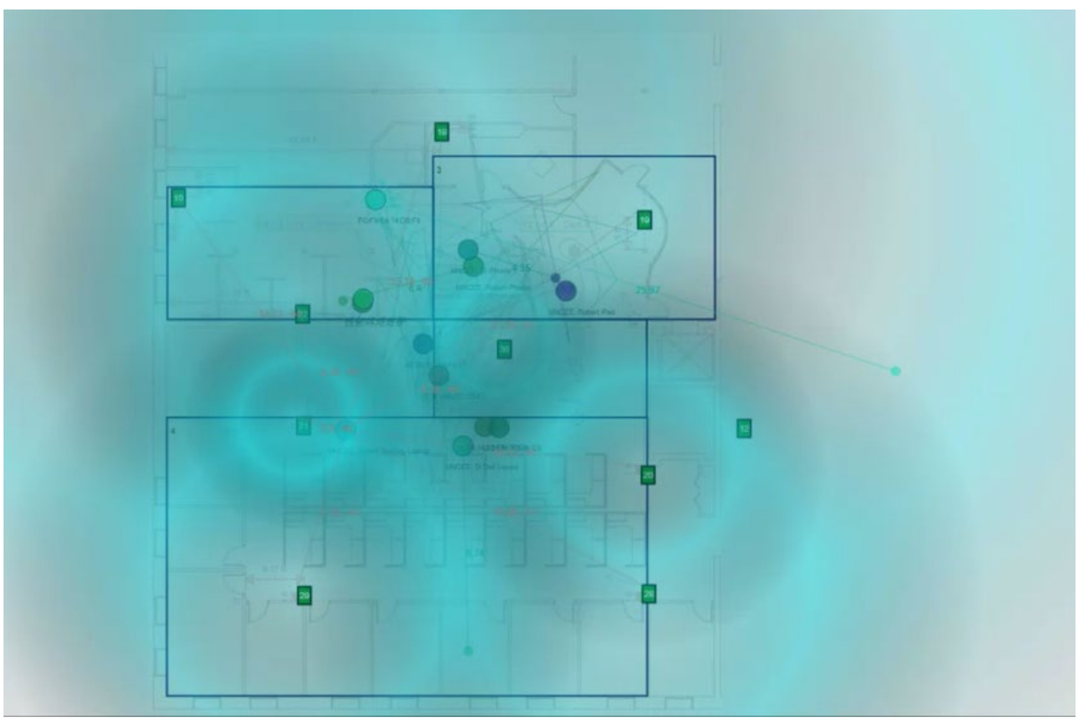
Occupancy Sensing Validation

Testing the LDA in the CEE Lending Center allowed us to determine the accuracy of the LDA to track motion and occupancy count compared to the information collected from the home security cameras. The photographic evidence also allowed us to determine the accuracy of occupant count based on the number and location of mobile devices (phones, tablets, and laptops) detected.

Even though the pandemic greatly reduced occupancy at the CEE Lending Center, the Lending Center typically had one or two staff working in the office per day and there was one administrative staff person present at the front desk. Applicants for energy and home improvement loans also come to the office for closings, which take place in the small meeting room in the Lending Center. CEE staff who do occasionally come into the office will enter through the doors at the front desk and then pass to the admin offices. So, some traffic will be detected passing through this area.

To improve the location prediction of the LDA, the algorithm was modified to show the probability distribution of the location of the signal (rather than the discrete ring that defines a specific estimated distance.) This is shown in Figure 8.

Figure 8. Heat map of the predicted location of a signal in the CEE Lending Center and reception area



Instead of just finding the overlap of the rings, it now looks at the overlap of the probability distributions of all the APs and then finds the location with the greatest overlap. This approach was found to provide a prediction that was at least as good as the previous approach and in some cases, an improvement.

Parallel Technologies' Innovation Lab

The next set of testing took place at the Parallel Technologies, Inc. (PTI)[22] Innovation Lab. The space is used for product demonstrations, testing, and training. It has a floor area of 5,780 square feet and is adjacent to their warehouse and office area. The existing PTI Wi-Fi network had one Cisco Meraki AP placed in the lab area, two Meraki APs in the adjacent warehouse, and one Meraki AP in the adjacent office area. For the test, seven OpenMesh APs were placed at locations in the lab, warehouse, and office area. Figure 9 shows the floor plan of the Innovation Lab (the area denoted with the 5,780 sq. ft. floor area) and warehouse space (the area denoted with the 5,258 sq. ft. floor area) with the locations of the OpenMesh APs denoted by the green dots and the locations of the Meraki APs denoted by red circles (where three of our APs were also placed).

Figure 9. Floor plan of the Parallel Technologies Innovation Lab

[22] Parallel Technologies homepage. https://www.paralleltech.com/

Since Parallel Technologies provides security system services, the Lab is also outfitted with a 360º camera and a camera at the door to the Lab that uses video analytics to perform occupant counting (entering and exiting the lab). These cameras provided photographic and video validation of the Wi-Fi LBS results. CEE staff were able to use the recorded footage from the camera to compare actual occupant counts and locations with those predicted by both the LDA and the Meraki location analytics at the corresponding dates and times.

Occupancy Sensing Validation

Because of the pandemic, the office area was typically vacant with most staff working remotely. The Innovation Lab did have some occupant traffic with deliveries taking place there, technicians entering and leaving through that area, staff performing work in the lab, and some traffic to the adjacent warehouse.

Two cases were performed for the validation. For the first case, two Wi-Fi-enabled devices with known MAC addresses (a laptop and a tablet) were placed at specific locations in the space and the accuracy of the LDA predictions was evaluated. The LDA consistently predicted the locations of the devices within our error margin of 10 ft.

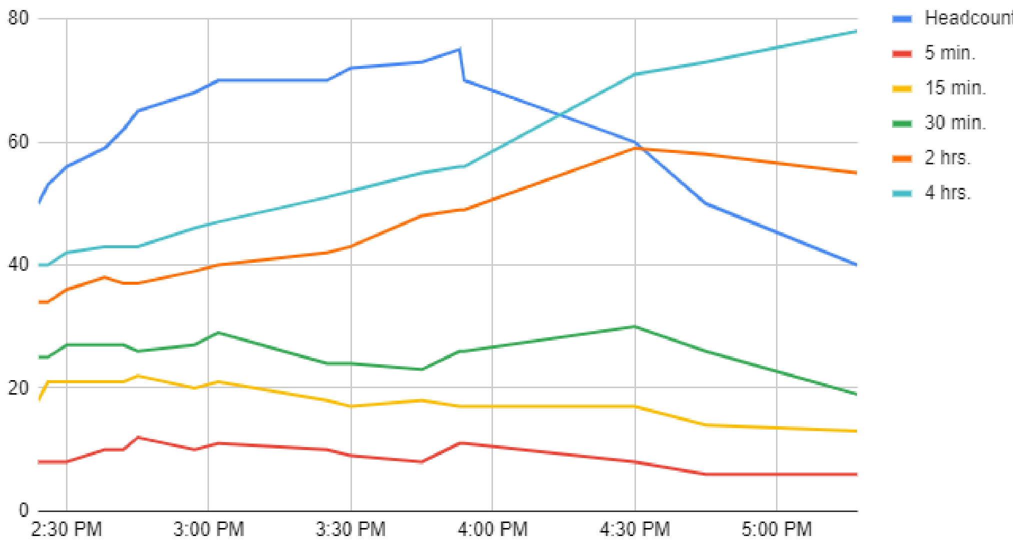
Having validated our system, we then validated the Wi-Fi LBS' ability to detect presence by comparing our presence guesses to presence detected by security cameras 25 times over two days. The LBS detected presence 16 times (64%) and detected the correct count of people over 13 times (52%). Because of the sparse occupancy in the space due to COVID restrictions, an error margin of a couple of devices would result in no occupant presence detected and greater percent error.

For the second test, the LDA was used to monitor occupancy during an open house that took place in the Innovation Lab. On October 28, 2021, Parallel Technologies hosted a client appreciation event in the Innovation Lab from 2 pm to 6 pm. Approximately 80 to 100 people attended. CEE staff attended to document the occupant count, location, and traffic. They also brought a number of Wi-Fi enabled devices with known MAC addresses. This allowed comparison of the LDA predictions with the devices' known locations at various designated times during the event.

First, we tested the LDA's ability to provide headcounts of large groups of guests (with unknown MAC addresses). The PTI lab includes several static Wi-Fi devices, so we began by identifying and excluding MAC addresses seen in the days before the event, then we confirmed a zero-device count both before and after the event. Next, we compared headcounts performed by CEE staff throughout the event to device counts calculated by the LDA using sampling periods of 5, 15, 30, 120, and 240 minutes.

As expected, we found that (1) lower sampling periods produced lower counts, at worst counting only 11% of the guests, whereas (2) higher sampling periods failed to acknowledge waning attendance, at worst counting 195% of the guests. In our opinion, a sampling period greater than 30 minutes is too long for responsive HVAC control, while a sampling period of 5 minutes is too short to count all the guests.[23] Therefore, we feel that a sampling period of 15 or 30 minutes is best, on average counting 30% and 42% of guests, respectively.

Figure 10. Headcount versus device counts (by sampling period) in the PTI Innovation Lab



Adapting the LDA to Import the Cisco Meraki System Location Analytics Data

PTI employs the Cisco Meraki Network platform for the Wi-Fi services in the office. The Network Administration and Management system includes the Location Analytics API that can export location data showing a user's presence, how much time they spend within the Wi-Fi area, and their approximate signal strength from each AP. Figure 11 shows the results of the Meraki location analytics during a snapshot in time as displayed on the dashboard floorplan.

Figure 11. PTI floorplan from the Meraki dashboard showing locations of detected Wi-Fi enabled devices

[23] It should be noted that per ASHRAE 90.1, periods of several hours are appropriate for averaging number of occupants in spaces of several thousand square feet or smaller.

The locations of the Meraki APs are denoted by the green inverted teardrop shapes outlined in dark gray. There are seven APs shown on the floorplan. The green cloud shapes show the location of Wi-Fi enabled devices that are connected to the PTI Wi-Fi network. The light gray dots are the estimated locations of the unaffiliated Wi-Fi enabled devices.

We found that the Meraki management system provided access to the Wi-Fi data collected by their APs (device MAC addresses and RSSI data) and the calculated locations of each Wi-Fi device relative to the floor plan defined in their Location Analytics API. We adapted the LDA to be able to import this data, allowing us to compare the ability of the two approaches to estimate the locations of the detected Wi-Fi signals. Consequently, we added an additional demonstration site — The Sinclair, Autograph Collection hotel — to explore the relative accuracy of the two location sensing methods.

Field Demonstrations

Four field sites were recruited to evaluate the performance of the LDA for occupancy sensing. Three commercial office sites and one hotel agreed to participate in the field demonstrations:

1. The State Administration Building located at the Minnesota State Capitol Complex in Saint Paul, Minnesota
2. ConEd's Research and Development (R&D) offices located in their Manhattan headquarters in New York City
3. The second-floor offices of Slipstream in their building located in Madison, Wisconsin
4. The Sinclair, Autograph Collection hotel located in Fort Worth, Texas

For the three office sites, we installed Open Mesh APs for Wi-Fi device detection to be used with the LDA. We chose Open Mesh because it fit the project's requirements (well known, has a presence API, and cloud-based management) and was inexpensive compared to the competition (Cisco Meraki and HP Aruba). Unfortunately, shortly after the decision was made and a number of Open Mesh Wi-Fi access points were acquired and configured, Datto purchased Open Mesh and began to sunset support of legacy Open Mesh hardware. Fortunately, rather than having to find another manufacturer and purchase a whole new set of devices, the large community of Open Mesh owners and enthusiasts resulted in a number of projects to create custom firmware to allow us to continue to use the legacy Open Mesh devices. We decided to use the approach offered by Plasma Cloud, one of the largest, most reputable hardware makers that supported Open Mesh APs. Through their onboarding program, we reprogrammed our Open Mesh APs with their firmware, bolstered our inventory with Plasma Cloud-branded APs, and were able to still maintain cloud-based management and the presence API, which was key to collecting field data.

For the three office sites, we also installed a cellular router onsite to upload the data from our APs directly to Design.Garden's server for processing with the LDA. Creating the cellular hotspot for our APs assuaged any cybersecurity concerns that the respective IT department might have about the project having access to the demo site's wireless platform. Equipped with a SIM card, the team purchased a prepaid phone data plan with a defined monthly bandwidth per month for the term that the router would be in use at the site. Based on Design.Garden's experience, Wi-Fi LBS can use a lot of data if there are many other Wi-Fi enabled devices in the space, possibly over 100 MB/day. The APs create a Wi-Fi mesh so only one of our APs needed to be connected to the router. Since we were only using the APs as Wi-Fi signal sensors, we disabled the APs' ability to create their own Wi-Fi network and prevented any devices from mistakenly connecting to them.

Measurement and verification at the three office sites were performed in the following manner.

1. Several Android phones (up to six) were placed at known locations within each office space to serve as reference points to verify the accuracy of the LDA in detecting the mobile devices and in calculating their location. These phones were kept at those fixed locations throughout the testing period for each office.
2. At recorded dates and times, a staff person logged the head count of occupants who were present in defined zones and spaces of the offices. This information was submitted to us to correlate with the measured head counts calculated by the LDA.

For the fourth site, the LDA was used to detect occupancy on one floor of guest rooms using the Wi-Fi data collected by the hotel's Cisco Meraki wireless network. This allowed a direct comparison of the location detection capabilities of the LDA with the Meraki Location Analytics API.

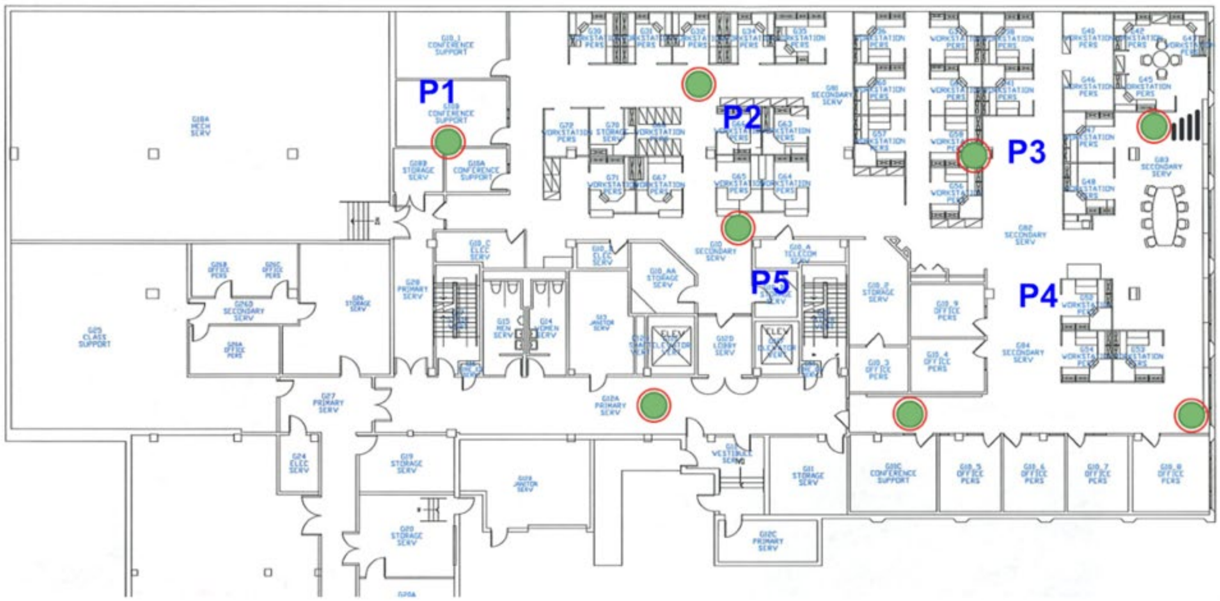
Minnesota Administration Building, Saint Paul, Minnesota

The Wi-Fi LBS demonstration was performed in the offices of the Minnesota Department of Administration Materials Management and Plant Management Divisions located in the Administration Building at the State Capitol Complex. The three-story office building was built in 1967 and has a building area of 80,144 square feet. The offices of the Materials Management and Plant Management Divisions are located on the ground level of the building.

Figure 12. Minnesota Admin Building, Saint Paul, MN.

For their wireless network, the State uses eight Honeywell APs. For the demonstration, we placed eight OpenMesh APs at the same locations as the Honeywell APs to replicate the existing Wi-Fi coverage. All APs were placed above the tiles of the suspended ceiling. Note that any equipment installed in an above-ceiling plenum space must be plenum-rated or installed within a plenum-rated enclosure, as required by national building code. 120VAC line voltage was provided to power our APs. Figure 13 shows the locations of the APs on the floor plan of the offices. The green dots represent our OpenMesh APs and the red circles represent the locations of the Honeywell APs. The cellular router was placed in the suspended ceiling and connected to the AP shown in the southeast corner of the building (i.e., the upper right-hand corner of the floor plan and denoted by the cell phone strength icon).

Figure 13. Floor plan of the Minnesota Department of Administration Offices showing the locations of the APs



Measurement and Verification

Five Android phones were placed in the offices to serve as fixed reference points for measurement and verification (M&V). Their locations are denoted by the blue numbered Ps shown in Figure 13. During the monitoring period, the Android phone located in the storage room (P5) was mistakenly disconnected and discarded by an office worker. Of the four phones that remained in the space, only two provided signals that could be detected and analyzed by the LDA. Figure 14 shows the LDA-calculated locations of the two phones compared to their actual locations. The actual location of the phone is denoted by the smaller circle and is denoted by the uppercase blue P. The LDA-calculated location is shown by the larger circle and labeled by the lowercase blue p. The line connecting the two circles measures out the distance in feet between the associated circles and represents the error of the LDA location estimation. Table 5 shows the average error in feet of the LDA-calculated locations for each phone, ranging from 2.1 feet to 18.2 feet.

Figure 14. Comparison of LDA-calculated reference point locations with actual locations at the Admin Building.

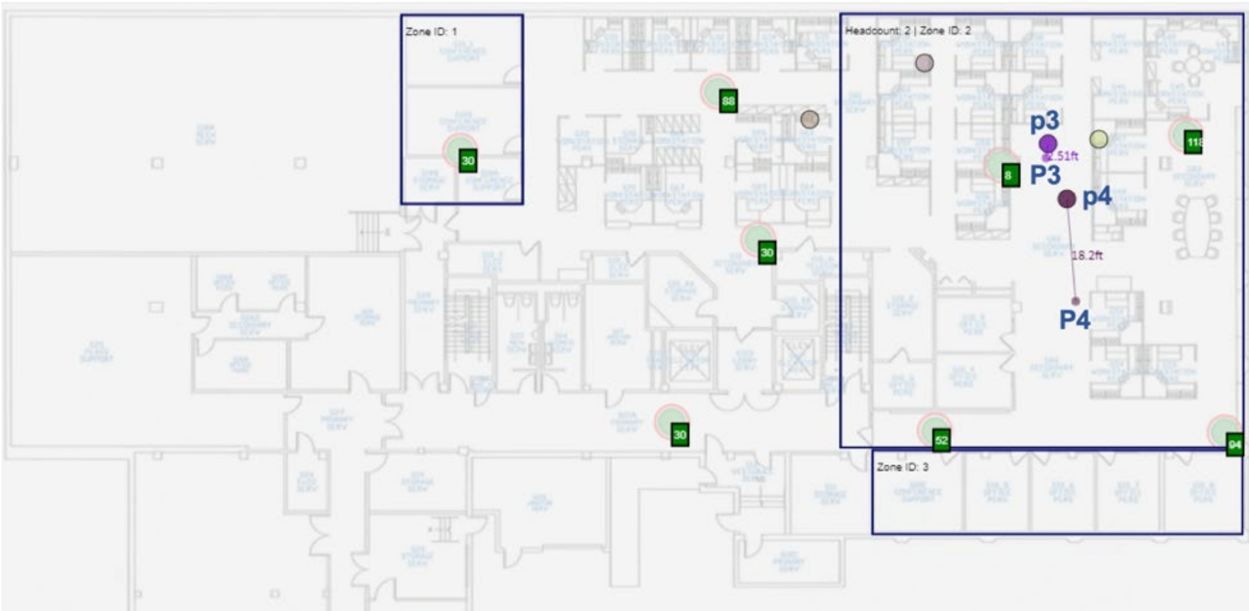


Table 5. Differences in the LDA-calculated locations with the fixed reference point locations at the Admin Building.

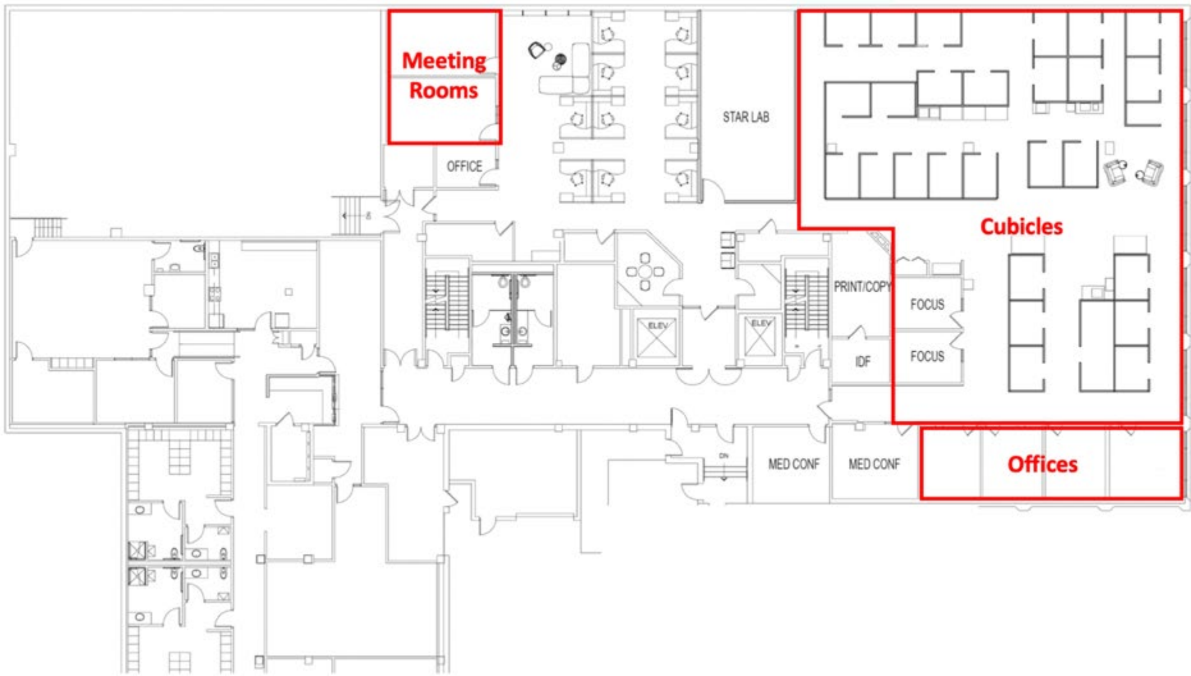
Phone	Average Error (in feet)
P1	–
P2	–
P3	2.1
P4	18.2

The average error of the LDA for the two fixed reference point phones was 10.1 feet with a standard deviation of 11.4 feet.

Validating Space Occupancy

Within the office space, Admin staff typically occupied three zones: assigned open office cubicles, private closed offices, and two meeting rooms. These three zones are shown in Figure 15.

Figure 15. Occupancy zones in the Admin Building.



Over about a month period from late June and into July of 2023, an Admin staffer recorded office occupancy in each of the three zones at five specific times. No one was assigned to any other workspaces in the offices. This occupancy data was then compared to the headcounts predicted from the Wi-Fi data by the LDA. Table 6 shows the comparison of the data.

Table 6. Comparison of observed head counts with LDA-detected values for the Admin Building

Date	Time	Head Count											
		Total			Cubicles			Offices			Meeting Rooms		
		Actual	LDA	Delta	Actual	LDA	Delta	Actual	LDA	Delta	Actual	LDA	Delta
6/27/2023	2:00 PM	13	15	-2	12	13	-1	1	0	1	0	2	-2
7/7/2023	11:50 AM	13	12	1	13	11	2	0	1	-1	0	0	0

The LDA headcounts had good agreement for the large area of the cubicle space and this carried over for the headcount of the entire space. The office spaces and meeting rooms had smaller footprints and inaccuracies of the LDA provided poorer agreement with these spaces.

Occupancy Patterns

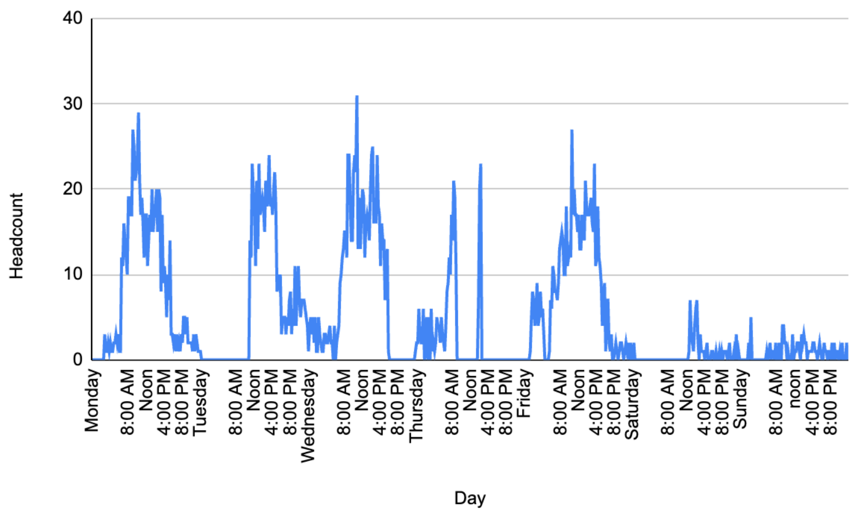
The LDA was used to determine the occupancy patterns within the Admin office over a week to inform the determination of an occupancy schedule for the space. An algorithm was created in order to define a headcount for the space based on the number of devices detected by the LDA. A square was circumscribed around the floorplan and the headcount was defined by the number of devices that the LDA determined were located within the square. Figure 16 shows locations of detected Wi-Fi enabled devices on June 26, 2023 at 9:45 am. The total headcount based on devices detected in the perimeter of the floorplan is 22.

Figure 16. Distribution of detected Wi-FidEnabled devices in the Minnesota Department of Administration Offices on June 26, 2023, at 9:45 a.m.

Figure 17 shows the variation of the estimated headcounts in the space over the week beginning on Monday, June 26, 2023. Data was collected at 15-minute increments for the week time frame. Outages resulted in some gaps in the data with gaps occurring:

- Midnight to 2:30 a.m. on Monday
- 12:15 a.m. to 10:45 a.m. on Tuesday
- 5:45 a.m. to 11:30 p.m. on Wednesday
- 9:00 a.m. to 1:30 p.m. and 2:30 p.m. to 11:45 p.m. on Thursday
- Midnight to 1:00 a.m. and 4:30 p.m. to 5:15 p.m. on Friday
- 1:30 a.m. to 12:15 p.m. on Saturday
- 10:45 p.m. to 11:15 p.m. on Sunday

Figure 17. LDA-estimated headcount over the week of June 26, 2023, in the Minnesota Department of Administration Offices



For the entire floor (as shown in Figure 16), the average headcount for the week was 5.0 occupants with a minimum of 0 occupants, a maximum of 31, and a standard deviation of 7.0. From the data collected for this week, the hours of occupancy on the floor are typically from about 6:30 a.m. to about 5:45 p.m.

The maximum occupancy of the space can be inferred from the number of cubicles, offices, and meeting rooms' chairs shown in the floor plan. Table 7 shows an estimate of the maximum occupancy of the Admin Department space.

Table 7. Maximum occupancy of the Minnesota Department of Administration Offices

Sites	Cubicles	Offices	Meeting rooms	Maximum Occupancy
Admin	27	5	36	68

Comparing the headcount values from Figure 19 with the maximum occupancy shown above, the office occupancy approaches about 46% at its highest level of occupancy but typically not more than 30% occupancy (typically about 10–20 people with a maximum of about 30 people).

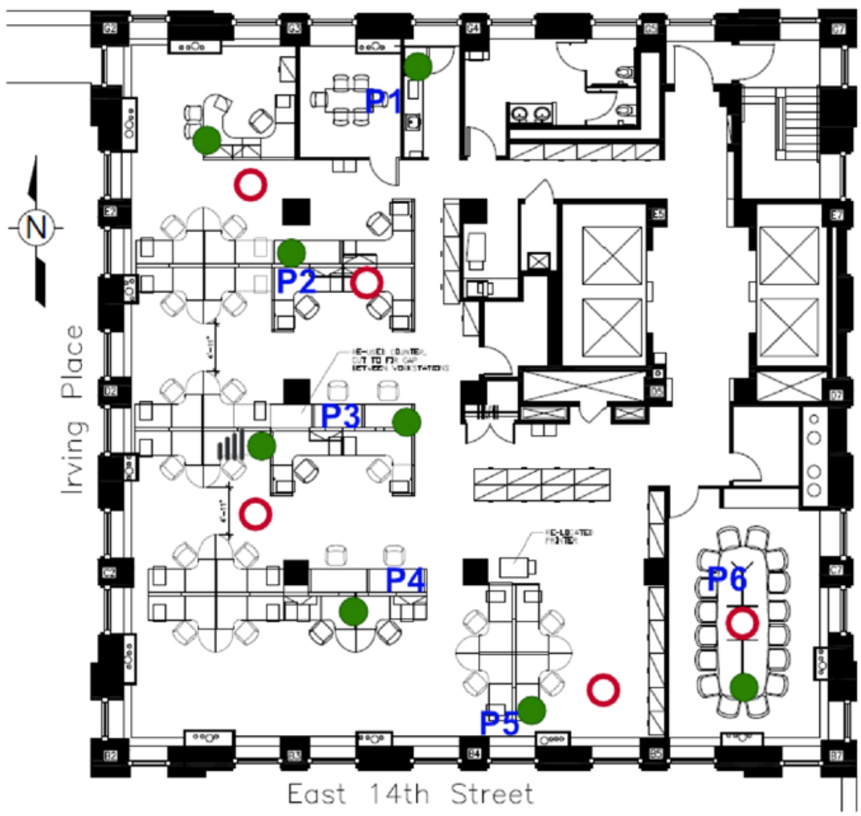
Consolidated Edison Building, New York City, New York

The Manhattan headquarters of ConEd are located in the Consolidated Edison Building at 4 Irving Place, a historic landmark building constructed in 1911 by Consolidated Gas, predecessor of Consolidated Edison. It is a 26-story building originally built in 1911 and is a New York City designated landmark.

Figure 18. The Consolidated Edison Building at 4 Irving Place, New York City, NY

The Wi-Fi LBS testing was performed in the offices of ConEd's Research and Development (R&D) department and located on the building's 22nd floor. This space was selected because: 1) the space is surrounded by condos, apartments, and commercial spaces, representing a busy downtown mix-use zone, 2) it can be assumed that each apartment and office space has their own Wi-Fi, offering an opportunity to test robustness of the LBS algorithm in presence of wi-fi and mobile device interference, and 3) the historical building space is ideal for LBS technology in that minimal infrastructure changes are needed to adopt the usage of LBS. The offices are served by five APs to provide their office Wi-Fi. The locations of these APs are denoted by the red circles on the floorplan in Figure 19. A total of eight OpenMesh APs were installed in the space for the Wi-Fi LBS occupancy sensing demonstration and are denoted by the green-filled circles.

Figure 19. ConEd Manhattan R&D Offices floor plan with the locations of the APs



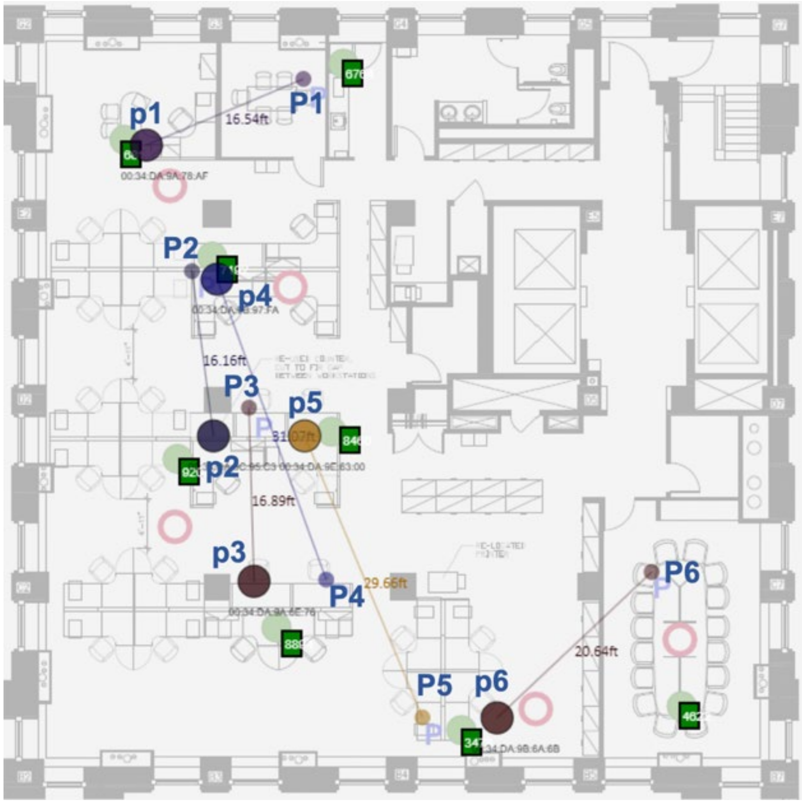
The placement of the cellular router is shown by the cell phone signal strength icon and is located near P3.

There were a few non-ideal conditions that the experiment had to contend with from the placement of the OpenMesh APs. Originally these APs were to be placed at the same locations as the ConEd APs but because of to power source availability, the OpenMesh APs had to be placed on top of desk spaces. As a result, these APs would be more prone to directional signal attenuation due to office furniture and people traffic. Ideally, the APs would have been installed on the ceiling where line of sight from AP to device is more likely. Multi-path interference caused by reflections of the signal from mobile devices is another type of interference that would subtract or add to the signal as received by the APs, contributing to additional error.

Measurement and Verification

Six Android phones were used as fixed reference points at the ConEd site and were placed at locations throughout the offices of the R&D department. Figure 19 shows the reference point locations (denoted by the blue numbered Ps) and the comparison of the LDA-calculated locations of the phones with their actual locations is shown in Figure 20. The actual locations are indicated by the smaller circles and labeled with the uppercase blue Ps, while the corresponding estimated locations are shown by the larger connected circle and labeled with the lower-case ps.

Figure 20. Comparison of LDA-calculated reference point locations with actual locations at the ConEd R&D offices



The error (in feet) between the LDA-calculated locations is shown in Table 8.

Table 8. Differences in the LDA-calculated locations with the fixed reference point locations at the ConEd R&D offices

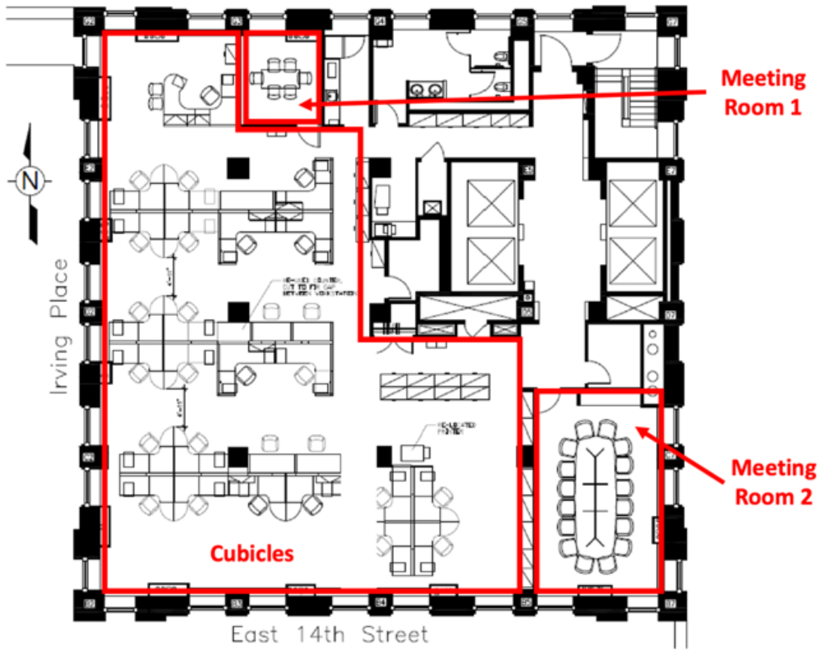
Phone	Average Error (in feet)
P1	43.1
P2	5.6
P3	15.8
P4	33.9
P5	43.1
P6	21.4

The error in the LDA location predictions range from 5.6 feet to 43.1 feet, with an average error for all reference points of 27.2 feet and a standard variation of 15.4 feet.

Validating Space Occupancy

Three zones could be defined within the ConEd R&D department office space: the open office cubicle space, meeting room 1 which is used for small groups and/or privacy calls, and meeting room 2 which is used for larger meetings with audio–visual (AV) equipment for remote video conferencing. Figure 21 shows the locations of the three zones on the ConEd R&D office floor plan.

Figure 21. Occupancy zones in the ConEd R&D department office space



As with the Minnesota Admin Building site, our contact in the ConEd R&D department agreed to record head counts on select dates and times to allow us to compare with the LDA-calculated headcounts. The results of the comparison are shown in Table 9.

Table 9. Comparison of observed headcounts with LDA-detected values for the ConEd R&D offices

Date	Time	Head Count							
		Total			Cubicles	Meeting Room 1	Meeting Room 2		
		Actual	LDA	Delta	LDA	LDA	Actual	LDA	Delta
8/17/2023	11 a.m.–12:30 p.m.	**15**	**16**	**-1**	13	1	15	2	13
8/22/2023	12:30 p.m.–5:00 p.m.	**11**	**16**	**-5**	14	1	11	1	10
8/23/2023	8:30 a.m.–5:30 p.m.	**10**	**18**	**-8**	15	0	10	3	7

For the total space, averaging the deltas in head count for the three time periods shows that the LDA overpredicted occupancy by 4.7 people. Given the location prediction errors observed with the Android phone fixed reference points, it is not surprising that the LDA had difficulty in accurately determining the headcount in the smaller Meeting Room 2 space and that the LDA located many devices in the larger cubicle space.

Occupancy Patterns

Figure 22 shows the locations of the Wi-Fi enabled devices in the offices of the R&D department in the ConEd building that were identified by the LDA at 10:30 a.m. on August 25, 2023. The seven devices detected are used as the occupancy headcount for this time period.

Figure 22. Distribution of detected Wi-Fi enabled sevices in the R&D department for the ConEd building on August 25, 2023, at 10:30 a.m.

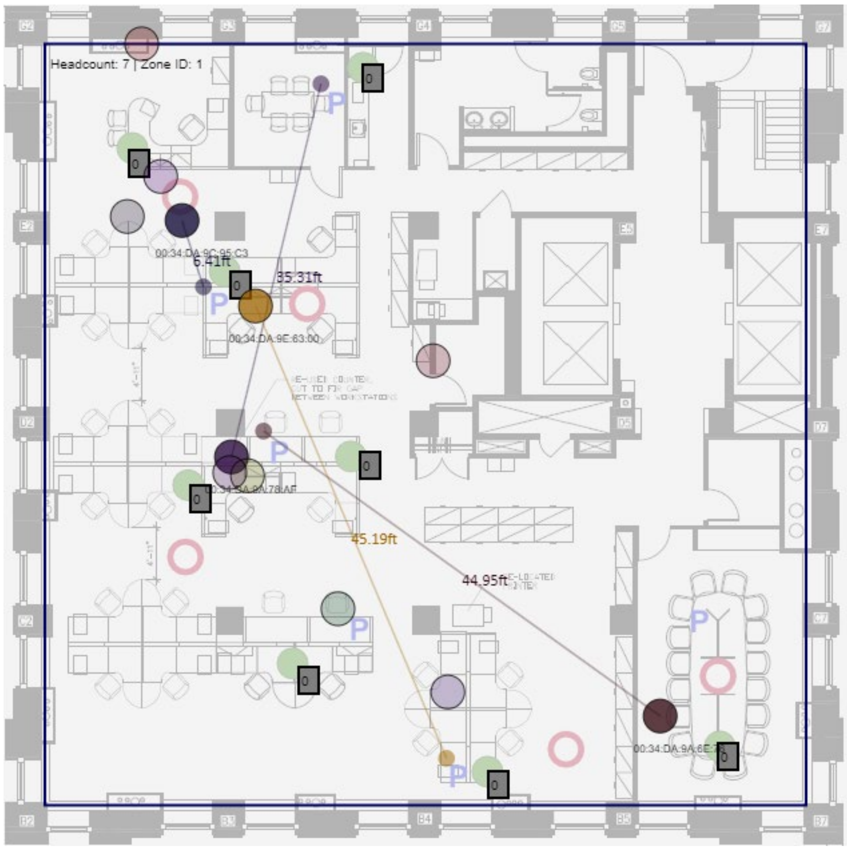
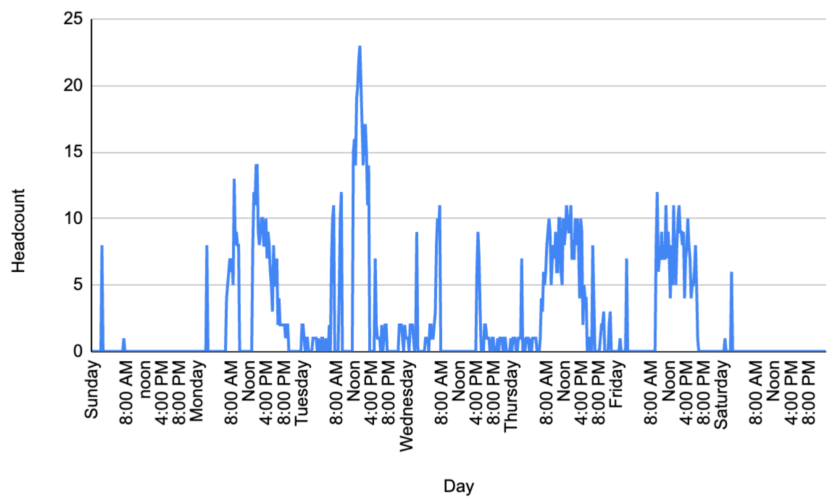


Figure 23 shows how the estimated occupancy (collected every 15 minutes) varied in the offices over the week beginning on Sunday, August 20, 2023. Unfortunately, outages in the data collection were experienced during the week. These outages occurred:

- 8:45 a.m. to 11:30 am and 8 p.m. to 10:45 p.m. on Monday
- 12:45 a.m. to 1:15 a.m., 6:30 a.m. to 7:30 a.m., 8:15 a.m. to 10:30 a.m., 2:30 p.m. to 3:30 p.m., and 6:45 p.m. to 9:00 p.m. on Tuesday
- 1:30 a.m. to 2:15 a.m., 6:45 a.m. to 2:45 p.m., and 4:00 p.m. to 4:30 p.m. on Wednesday
- 2:30 a.m. to 7:45 a.m. on Friday
- 5:00 a.m. to 7:45 a.m. and 10:15 a.m. to 5:30 p.m. on Saturday

There were no outages on Sunday or Thursday.

Figure 23. LDA-estimated headcount over the week of August 20, 2023, in the ConEd Offices



The average estimated headcount for the week was 2.2 occupants with a minimum of 0 occupants, a maximum of 23, and a standard deviation of 3.6. Based on the data collected for this week, the hours of occupancy on the floor are from about 5:30 am to 5:30 pm.

Based on the number of cubicles and meeting rooms' chairs shown in the floor plan, Table 10 shows an estimate of the maximum occupancy of the ConEd R&D space.

Table 10. Maximum occupancy of the ConEd R&D offices

Sites	Cubicles	Offices	Meeting rooms	Maximum Occupancy
ConEd	28	0	22	50

Using the calculated headcounts from the LDA, occupancy of the offices approaches 50% at its highest level of occupancy but typically not more than 20% occupancy. Feedback from ConEd staff found these findings are consistent with they observed. Because staff are often out in the field or traveling, a typical slow week would see occupancy in the range of five to eight while a major meeting would see office occupancy around 25. August is typically a popular month for staff to take vacations before school starts, so occupancy can be expected to be lower than usual during this time.

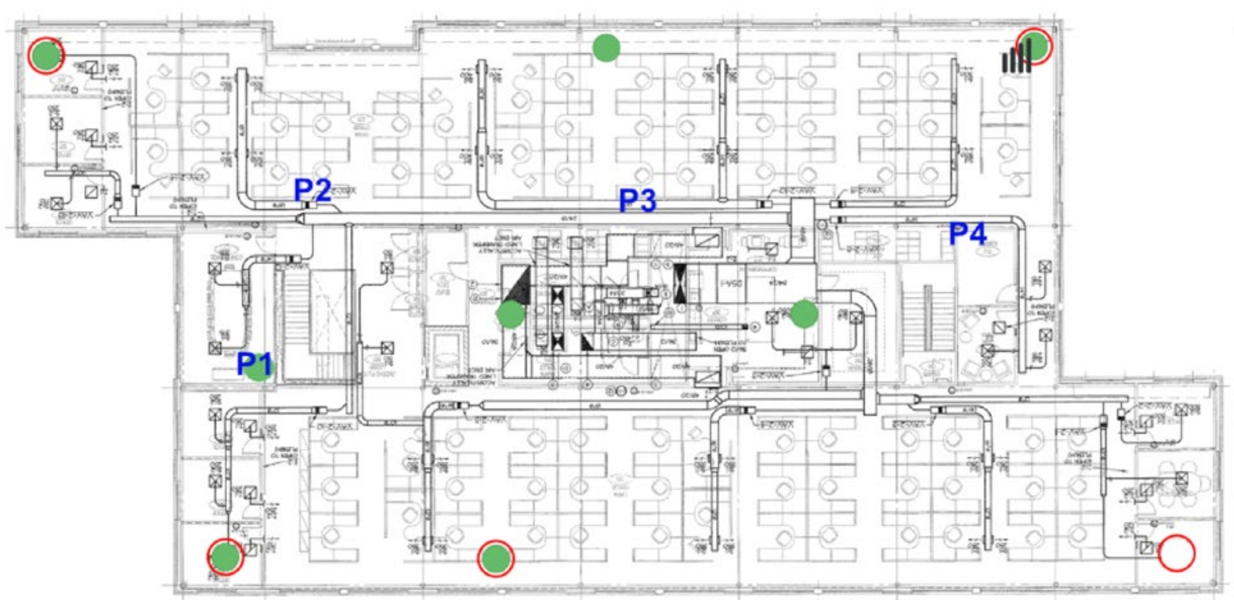
Slipstream Offices, Madison, Wisconsin

The Slipstream Wisconsin offices are located in a two-story office building in Madison, Wisconsin.

Figure 24. The Slipstream offices, Madison, WI

The testing was performed in their second-floor offices where five Ubiquiti UAP-AC-Pro APs support their Wi-Fi network. We placed eight of our OpenMesh APs in the space, five at the same locations as the Ubiquiti APs and another three provide additional coverage to evaluate the accuracy of the trilateration calculations of the LDA. The floorplan of these offices is shown in Figure 25. The green dots denote the AP locations and red circles show the locations of the five Slipstream APs. Our APs received power via PoE with cables running back to a PoE network switch in their server room. The cellular router was placed in the Slipstream second-floor server room and is denoted by the cell phone strength icon in the bottom left corner of the floor plan.

Figure 25. Floor plan of the Slipstream offices showing the locations of the APs



The Ubiquiti APs and Wi-Fi system do not store the MAC addresses and RSSI data that they receive, so they cannot be used for comparison with the OpenMesh AP data or the Wi-Fi LBS occupancy sensing.

Measurement and Verification

Four Android phones were placed at fixed locations throughout the second floor of the Slipstream offices for the M&V of the LDA. The reference point locations (indicated by the numbered Ps) are shown in Figure 25. Signals from three of the four Android phone fixed reference points were collected by the LDA and the locations of those three phones were calculated. Figure 26 shows the comparison of the LDA-calculated locations of the phones with their actual locations. The actual location of the phone is denoted by small circle and the upper-case blue P, and its corresponding LDA-calculated location is the larger connected circle, labeled with the lower-case blue p.

Figure 26. Comparison of LDA-calculated reference point locations with actual locations at the Slipstream offices

The average errors (in feet) of the LDA-calculated locations for each reference point are shown in Table 11, ranging from 5.5 feet to 8.0 feet.

Table 11. Differences in the LDA-calculated locations with the fixed reference point locations at the Slipstream offices

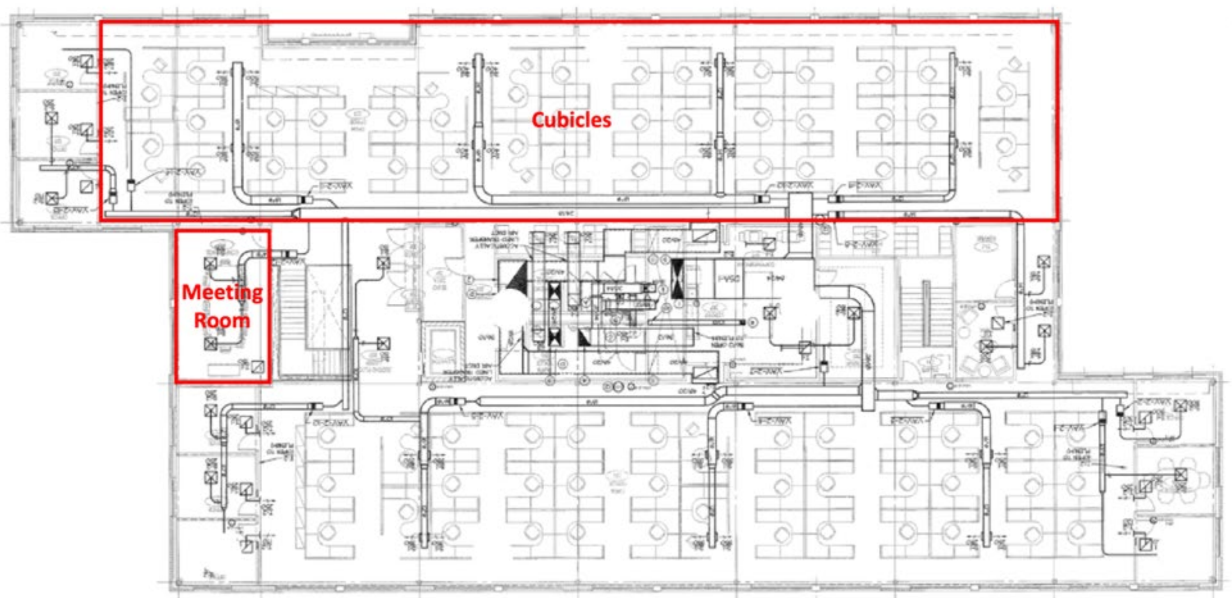
Phone	Average Error (in feet)
P1	5.5
P2	7.7
P3	8.0
P4	–

The average error of the LDA for all of the reference points was 7.1 feet with a standard deviation of 1.4 feet.

Validating Space Occupancy

Two zones were defined for the second floor of the Slipstream office building. One zone was the open cubicle space that housed Slipstream's research department and the second zone was their meeting room. These two zones are identified in Figure 27 below.

Figure 27. Occupancy zones in the Slipstream Madison Headquarters

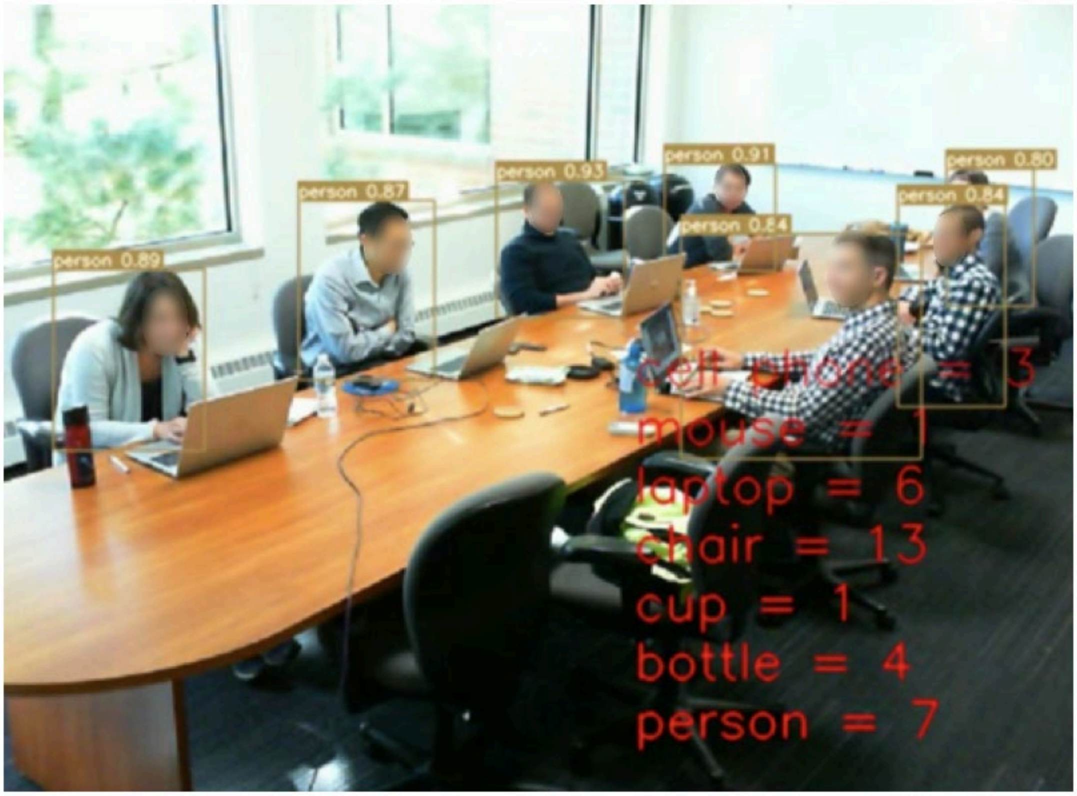


In addition to having a staff person record headcounts in each of the zones at certain dates and times, we also investigated the use of computer vision to record occupancy. For our first test, we placed a laptop and an external USB camera in the meeting room to identify occupants and algorithmically perform headcounts.

Initial Computer Vision Testing in the Meeting Room

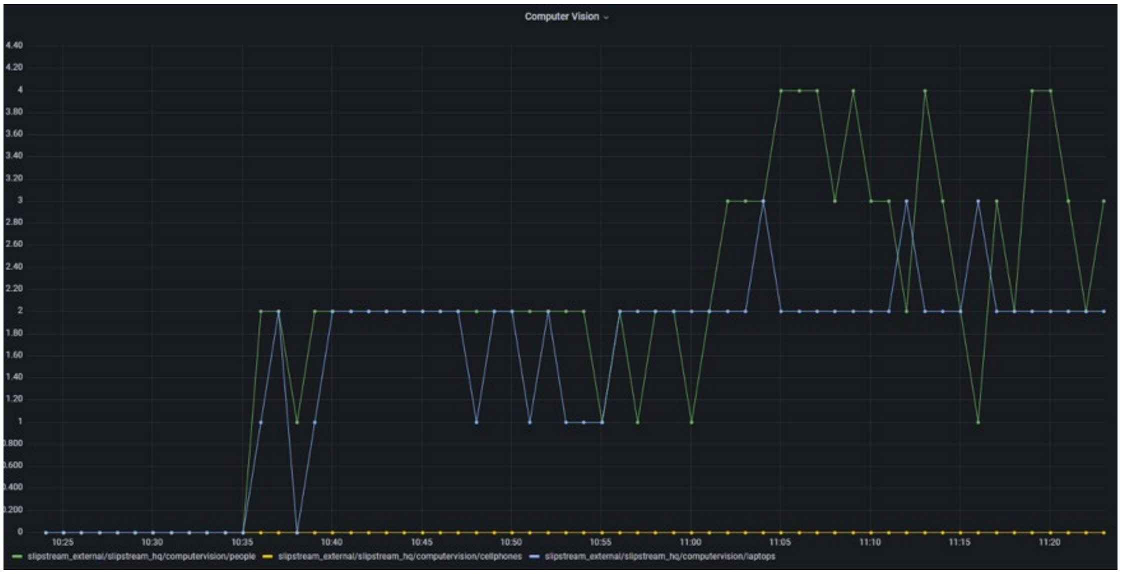
A simple custom Python-based computer vision software application was developed by Slipstream, which applied the latest technological improvements in artificial intelligence and machine learning algorithms called YOLO version 7 to perform object detection and recognition. This enabled the computer to identify and categorize objects within an image or video stream. In the Slipstream meeting room, a computer vision routine was integrated into the existing VOLTTRON IoT platform onsite to log the people, laptop, and cell phone counts which are standard object detection classes of YOLO version 7. Figure 28 shows an example of the output from the computer vision routine of the laptop placed in the Slipstream meeting room.

Figure 28. Computer vision interface of a staff meeting at Slipstream



Notice that in addition to the number of people in the line of sight of the laptop camera, computer vision was also able to identify and count cell phones, computer mice, laptops, chairs, cups, and bottles. In this way, computer vision provided an additional means to document the occupancy of the meeting room zone. Figure 29 displays the computer vision data being classified in real time which is then integrated via IoT to the existing Slipstream VOLTTRON platform that harnesses a time series database and a Grafana dashboard. The YOLO version 7 application does not log data but only classifies objects in real time. An external application logs the data so that the historical data can be studied with a visualization tool like a Grafana dashboard.

Figure 29. Computer vision output of a staff meeting at Slipstream on Grafana dashboard



Enhanced Computer Vision Approach for the Meeting Room and Cubicle Space

Based on the success of using computer vision in the meeting room, Slipstream expanded the effort by harnessing additional computer vision techniques with the latest version of YOLO (version 8), running on an Edge AI Device equipped with NVIDIA Jetson Orin™ Nano GPU technology. Ace IoT[24] was brought in to further develop this technology. Slipstream's original conceptualized computer vision technology could only handle a single camera at approximately 1 frame per second (FPS). The Ace IoT app achieved an impressive 10 FPS. The app supports asynchronous processing of multiple cameras simultaneously and allows more general deployment within a building through the use of temporary IP cameras or existing security camera systems. Within the Slipstream space, IP cameras were strategically installed in each zone to allow asynchronous processing of multiple video feeds simultaneously by the NVIDIA AI edge device. This enabled the compilation of results, which were compared to the performance of LDA. Figure 30 to Figure 32 show the device recognition displayed on Ace IoT's computer vision web browser dashboard for three of the cameras temporarily deployed in Slipstream's meeting room and cubicle office space. The YOLOv8 computer vision app developed by Ace IoT is available at the free open-source GitHub repository.[25]

[24] Ace IoT Solutions homepage. https://aceiotsolutions.com/

[25] Ace IoT Solutions YoloOcc VOLTTRON™ Agent GitHub webpage. https://github.com/ACE-IoT-Solutions/volttron-yolo-occupancy

Figure 30. Web camera 2 showing the meeting room

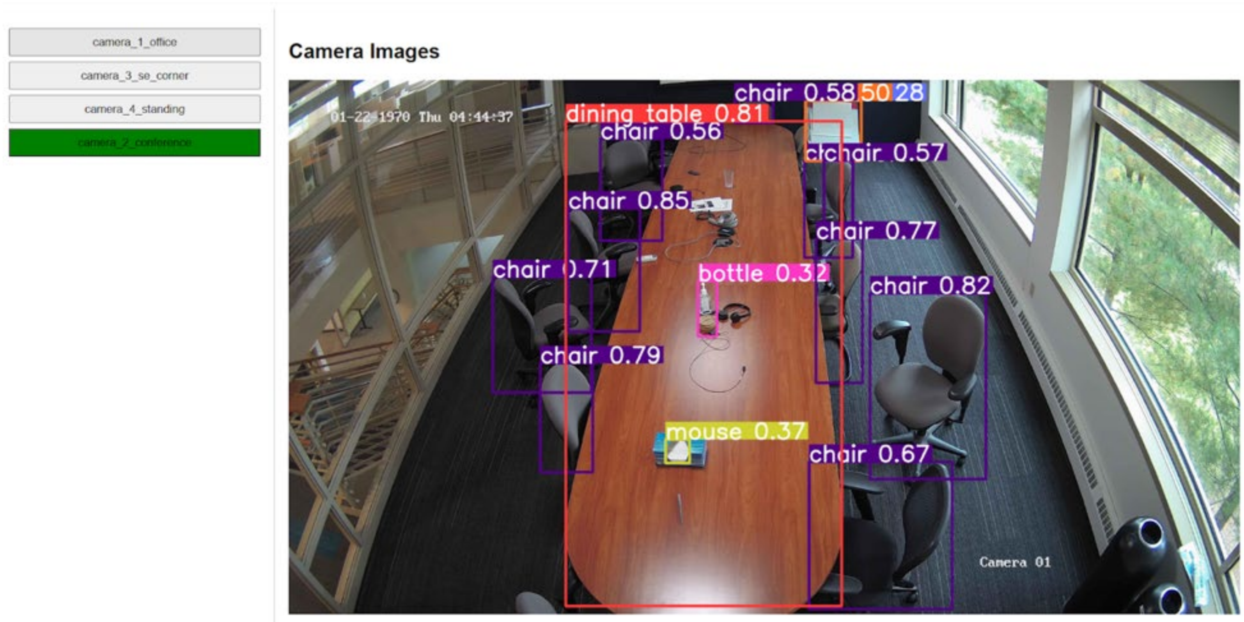


Figure 31. Web camera 1 showing the office cubicle space

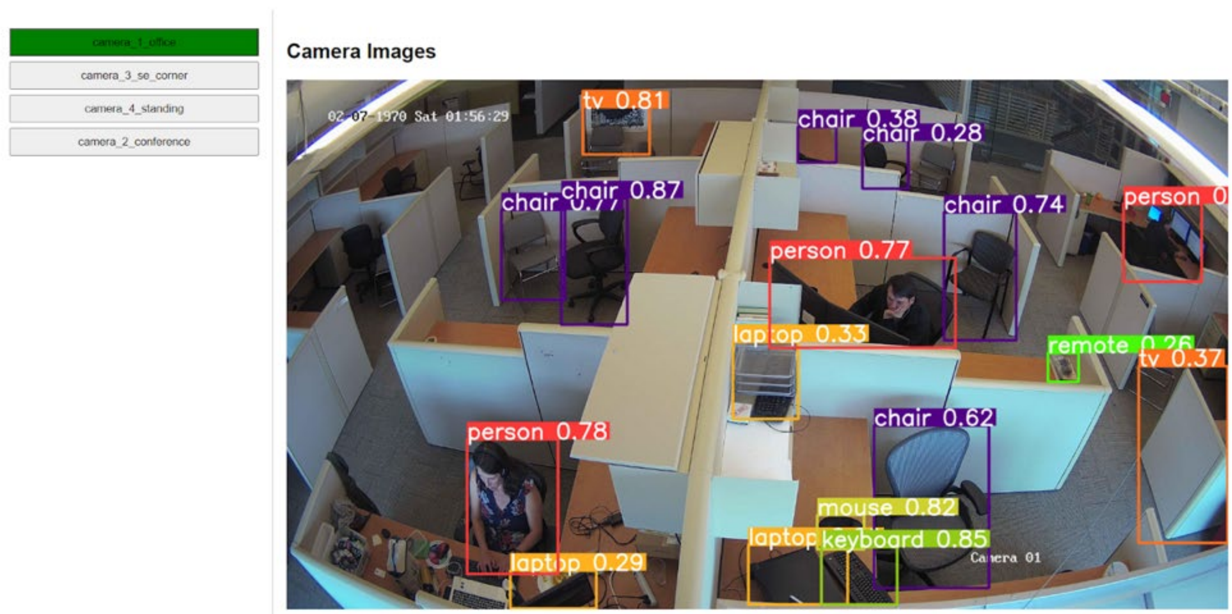


Figure 32. Web camera 3 showing the office cubicle space (SE corner)

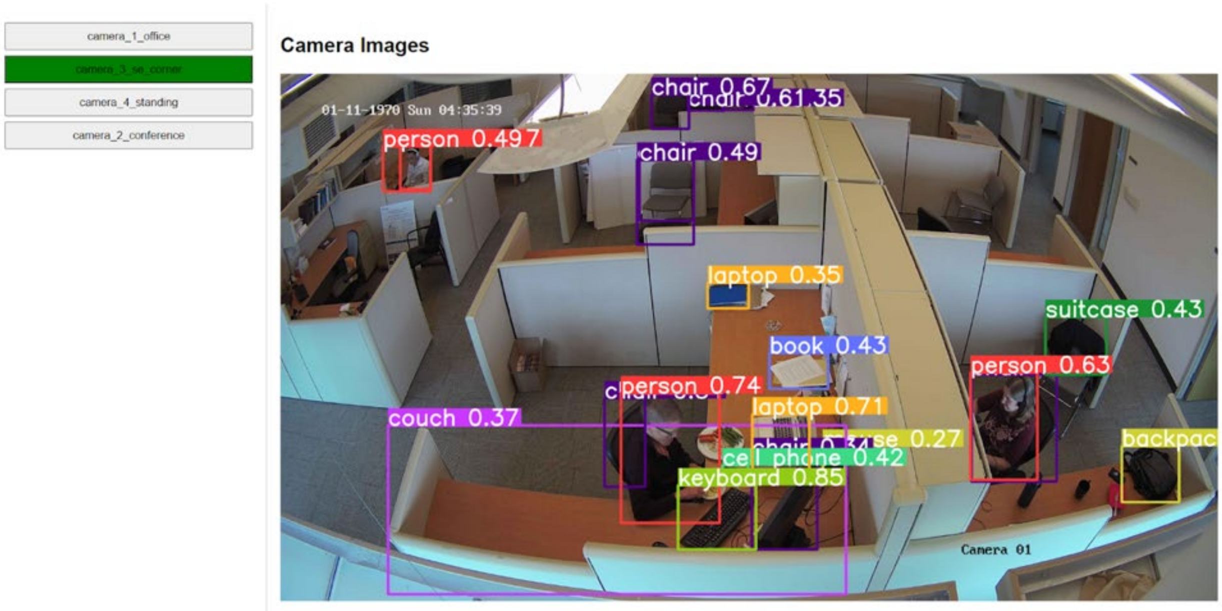


Table 12 compares the observed head counts with the head counts calculated by the LDA during the same recording dates and times.

Table 12. Comparison of observed head counts with LDA-detected values for the Slipstream offices

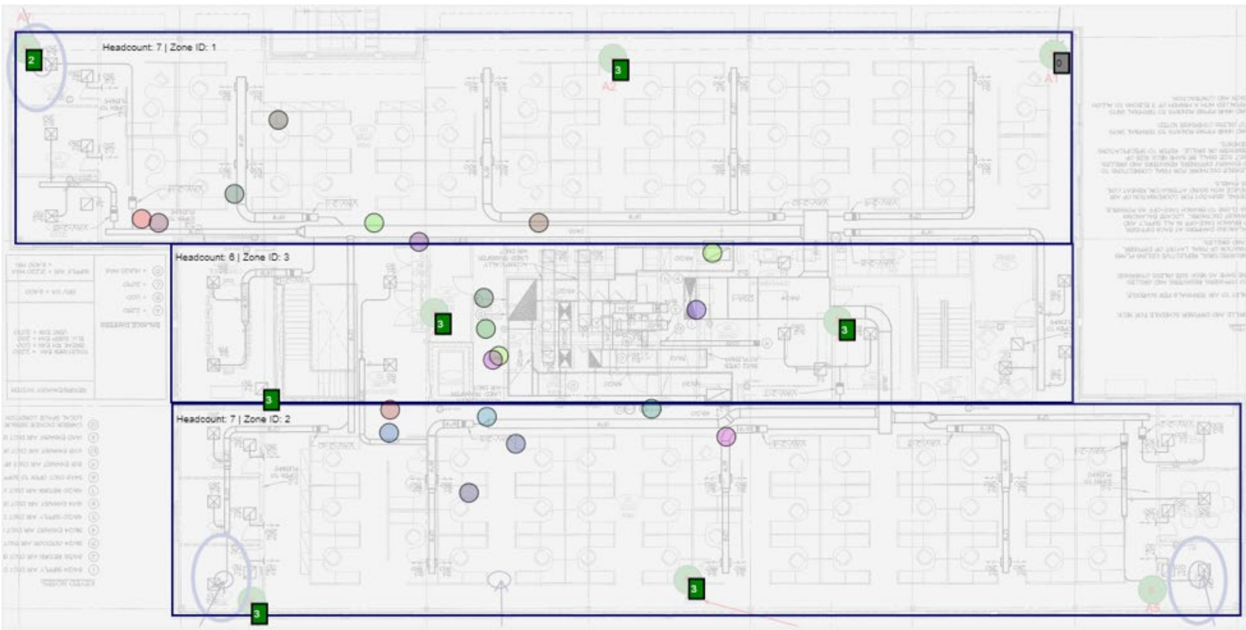
Date	Time	Head Count								
		Total			Cubicles			Meeting Room		
		Actual	LDA	Delta	Actual	LDA	Delta	Actual	LDA	Delta
9/20/2023	10:30 a.m.	5	8	-3	0	6	-6	5	2	3
9/26/2023	1:45 p.m.	0	13	-13	0	11	-11	0	2	-2
9/27/2023	10:45 a.m.	1	5	-4	1	5	-4	0	0	0
9/28/2023	10:25 p.m.	9	11	-2	0	6	-6	9	5	4
9/28/2023	2:15 p.m.	5	8	-3	5	6	-1	0	2	-2

The average difference between the head count calculated by the LDA and the actual occupancy is 5.0 people for the total space, 5.6 people for the cubicles zone, and 0.6 people for the meeting room zone.

Occupancy Patterns

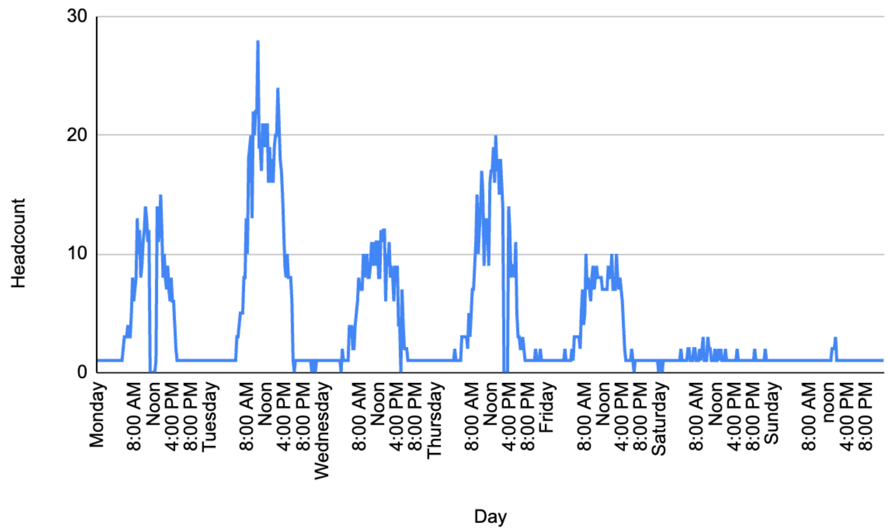
Figure 33 shows the locations of the Wi-Fi enabled devices that were identified by the LDA at 9:30 a.m. on September 26, 2023, on the second floor of the building. The 20 devices detected are used as the occupancy headcount for this time.

Figure 33. Distribution of detected Wi-Fi enabled devices on the second floor of the Slipstream building on September 26, 2023, at 9:30 am



For the week beginning on Monday, September 25, 2023, headcounts were collected every 15 minutes. Figure 34 shows how the calculated occupancy varied in the Slipstream second floor space over the seven days, from Monday to Sunday.

Figure 34. LDA-estimated headcount over the week of September 25, 2023, in the Slipstream offices



The average estimated headcount for the week was 3.9 occupants with a minimum of 0 occupants, a maximum of 28, and a standard deviation of 5.1. Given that during non-work hours the LDA is often detecting one device, we can assume that this device is typically left in the office and should not be a sign of occupancy. There were two periods of outages when no data was collected, on Monday from 11:15 a.m. to 12:15 p.m. and on Thursday from 2:45 p.m. to 3:30 p.m. Based on the data collected for this week, the following hours of occupancy on the floor is presented in Table 13.

Table 13. Hours of occupancy of the second floor of the Slipstream offices for the week of September 25, 2023

Day	Occupancy
Monday	5:30 a.m. – 4:45 p.m.
Tuesday	5:45 a.m. – 5:30 p.m.
Wednesday	5:45 a.m. – 6:00 p.m.
Thursday	5:45 a.m. – 7:00 p.m.
Friday	5:45 a.m. – 4:45 p.m.
Saturday	8:30 a.m. – 1:00 p.m.
Sunday	12:45 p.m. – 1:30 p.m.

By counting the available seating shown in the floorplan of the space, the maximum occupancy of the second floor of the Slipstream building is shown in Table 14.

Table 14. Maximum occupancy of the Slipstream second floor offices

Sites	Cubicles	Offices	Meeting rooms	Maximum Occupancy
Slipstream	75	8	17	100

From the headcount results shown in Figure 19, typical occupancy in the space is around 10% of the maximum occupancy and the greatest utilization of the space is about 25% of the maximum occupancy. Feedback from Slipstream staff confirmed that the headcount numbers obtained from the LDA reflected their observed occupancy levels for the space.

Four of the Android phones were placed on the first floor to determine the extent that the LDA detected Wi-Fi signals from the floor below. Only one of the phones was detected by the APs on the second floor of the building and the phone that was detected was placed in an area near the stairway that was open between the two floors. Otherwise, it could be assumed that there was sufficient shielding between the floors that the data collected by the second floor APs was indicative of the second-floor occupancy.

BAS Integration of LDA Occupancy Data

The team assessed how the data from the LDA could be integrated into the existing building automation system (BAS) to control the ventilation to particular HVAC zones. Specifically, the team was interested in augmenting existing occupancy sensors, such as occupancy sensors for BAS or lighting, with the LDA data to toggle the status of a zone served by a variable air volume (VAV) box between the "occupied" and "unoccupied" states, or an “occupied-standby” sequence as defined by ASHRAE 62.1 version 2022.[26]

Integrating LDA data into a BAS at a site is feasible if the BAS has the capability to make HTTP requests to a cloud-based API and if the IT department permits internet access for the BAS. It's important to note that traditional operations technology (OT) systems, such as BAS, were initially designed to function independently without relying on IoT connectivity. When considering such integration, it is important to determine whether the BAS has logic in place to handle an occupied-standby sequence and can depend on a cloud API. Additionally, it is crucial to plan for contingencies in case of internet connectivity loss, including the implementation of default values within the BAS.

It is worth mentioning that the skillset required for IoT HTTP protocol data communication is not typically found among BAS contractors and field technicians who predominantly work with BACnet communications integrated into BAS software configuration tools. Therefore, integrating a cloud-based API into a BAS system may require expertise beyond the traditional HVAC controls contracting industry skillset. This expertise might be found among master systems integrators (MSI) or specialists in IoT technologies. In summary, while the logic and sequencing aspects of BAS integration are manageable, the challenge lies in data ingestion,

[26] ASHRAE. ANSI/ASHRAE Standard 62.1-2022, Ventilation and Acceptable Indoor Air Quality. Atlanta, GA. https://www.ashrae.org/technical-resources/bookstore/standards-62-1-62-2

particularly if the BAS lacks API compatibility or if the OT technician's skillset does not encompass working with APIs and handling JSON payloads.

We investigated the BAS integration of the LDA headcount data at two of the demonstration sites. At the Slipstream site, we were permitted access to their BAS and were able to develop and test an approach to integrate LDA data directly into their BAS within the VOLTTRON environment. At the Minnesota Admin Building site, for security reasons, the State Capitol buildings operation and IT departments were reluctant to provide us access to their Honeywell BAS but tasked us with outlining potential approaches for integrating occupancy data into their Honeywell system for their future consideration.

Slipstream VOLTTRON BAS Integration

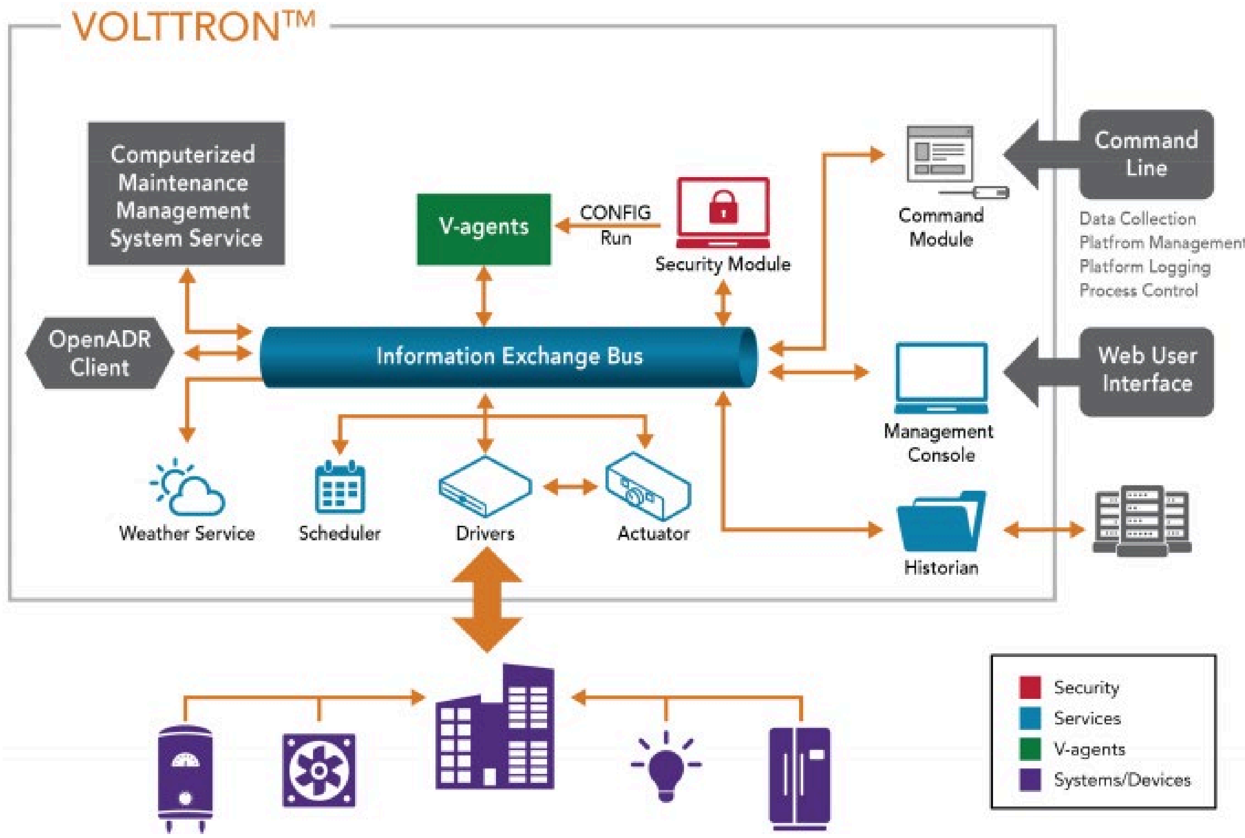
VOLTTRON[27] is implemented on the Trane BAS installed at Slipstream's Madison offices as an IoT integration mostly via LAN using BACnet/IP protocol. VOLTTRON is an open-source distributed control and sensing software platform intended for IoT projects in buildings. It is an ideal platform for us to integrate our Wi-Fi LBS occupancy data and test its use with building operation.

VOLTTRON

Pacific Northwest National Laboratory (PNNL) was funded by DOE to develop the VOLTTRON platform and PNNL currently maintains it. VOLTTRON is Linux-based and developed in Python, and the VOLTTRON framework facilitates IoT functionality by enabling data logging to the cloud, if desired. It supports commonly used communication building automation and IoT protocols including BACnet, MODBUS, DNP3, REST, MQTT, and OpenADR (automated demand response). VOLTTRON has a host environment with core platform services that can be used to facilitate third-party integration. These services include ZeroMQ or RabbitMQ, which acts as a message bus that allows for data exchange between multi-platform VOLTTRON connections or a single machine VOLTTRON deployment that can act as a gateway device. The BACnet driver for the VOLTTRON framework is built on an open source Python-based library called BACpypes, which allows for the interaction via BACnet with the building systems. VOLTTRON only supports direct BACnet "writes" or commands to the BAS as a method of control via remote procedure call (RPC) to the VOLTTRON framework actuator agent. At the moment the VOLTTRON framework does not support discoverable read-only BACnet objects where BAS side logic (implemented by a controls contractor) could be utilized for the control of HVAC based on occupancy information provided by the LDA algorithm. The VOLTTRON driver framework also includes APIs for ChargePoint, Ecobee, IEEE 2030.5, Obix, The Energy Detective (TED), postgresQL database, Mongo database, Influx database, and a variety of weather APIs. Figure 35 shows a schematic of the VOLTTRON platform.

[27] VOLTTRON home page, https://volttron.org/

Figure 35. Schematic of the VOLTTRON platform



The Information Exchange Bus is the central location where data/information comes in and is published. VOLTTRON was originally developed as a platform to create a low-cost "software only" BAS for small- and medium sized commercial buildings but it can also be used as a data-bridge or gateway to a commercially-available BAS.

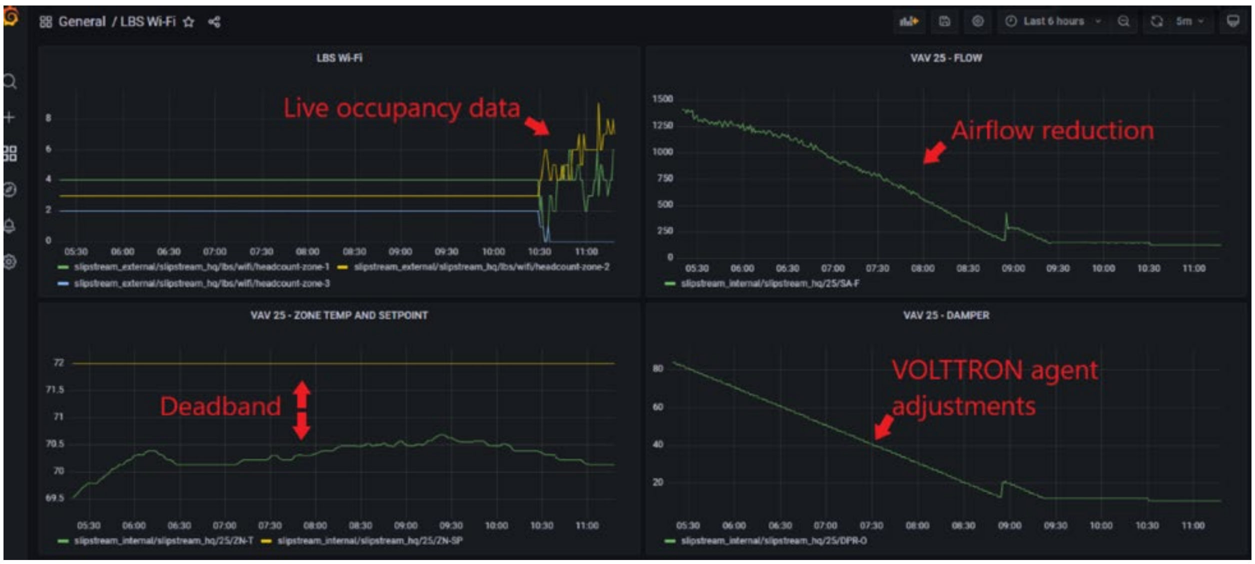
Occupancy Data Integration with VOLTTRON

The occupant data calculated by the LDA is provided to Slipstream's VOLTTRON implementation running along the perimeter of the building via a RESTful API call over the Internet to the Design.Garden server in the cloud. The Slipstream queries the Design.Garden server using a JSON API in the form of a queryable URL route that includes inputs/outputs (such as time range, building ID, zone ID, and predicted headcount/occupancy data). The app then transforms the headcount data into a VOLTTRON instance that is seamlessly integrated into the Slipstream SQL/Grafana system. VOLTTRON uses the occupancy data passed by the JSON object to guide HVAC operation in the defined zone in a custom VOLTTRON agent, which can be used to control the HVAC system via BACnet protocol. The Slipstream office HVAC system is a variable air volume (VAV) air handling unit system (AHU) that consists of a mixture of Trane and JCI field level devices controlling individual HVAC zones.

Within the edge environment, the VOLTTRON agent plays a crucial role in managing data ingestion through the Design.Garden API. It leverages a customized Python-based sequence for

HVAC control, incorporating variations of ASHRAE 62.1 and 90.1,[28] specifically focusing on the *occupied standby* mode. It is worth noting that the prevailing mechanical code in Wisconsin follows the ASHRAE 2013 version of 62.1, which lacks the occupied standby provision found in the 2022 version. However, Slipstream has successfully demonstrated the potential for IoT integration, enabling near real-time updates of occupancy counts in zones with occupied standby sequences. The Python-based sequence operates by computing a 62.1 ventilation requirement for the HVAC system, based on a rolling average of occupancy data recorded at one-minute intervals, followed by a five-minute rolling average. This requirement encompasses CFM per square foot of the zone and a CFM per person requirement. Notably, the occupied standby features include minor adjustments to the VAV box air damper, typically 1%, if the zone temperature falls within ±2 degrees of the setpoint, with the aim of achieving the calculated ventilation setpoint, as illustrated in Figure 36 below.

Figure 36. VOLTTRON agent at work adjusting the HVAC system VAV box zone



It is essential to exercise caution when developing sequences of operations to implement occupied standby and thoroughly investigate the limitations of the building automation system (BAS) hardware. An illustrative case can be found at the Slipstream office, where JCI-branded VAV boxes present a unique challenge. These VAV boxes do not allow for direct alteration of the air flow ventilation setpoint through BACnet communication. Consequently, the VOLTTRON agent must take control and override the air damper to achieve the desired air flow setpoint. Furthermore, Trane VAVs introduce their own set of constraints. They transmit data in metric units via BACnet, necessitating unit conversion. While adjustments can be made to the airflow setpoint, the air damper command remains unmodifiable, requiring distinct control logic for these two devices to reach the desired outcome.

Additional considerations may need to account for ASHRAE 62.1 airflow requirements. This becomes particularly relevant if real-time calculations of the air handling unit's percentage of

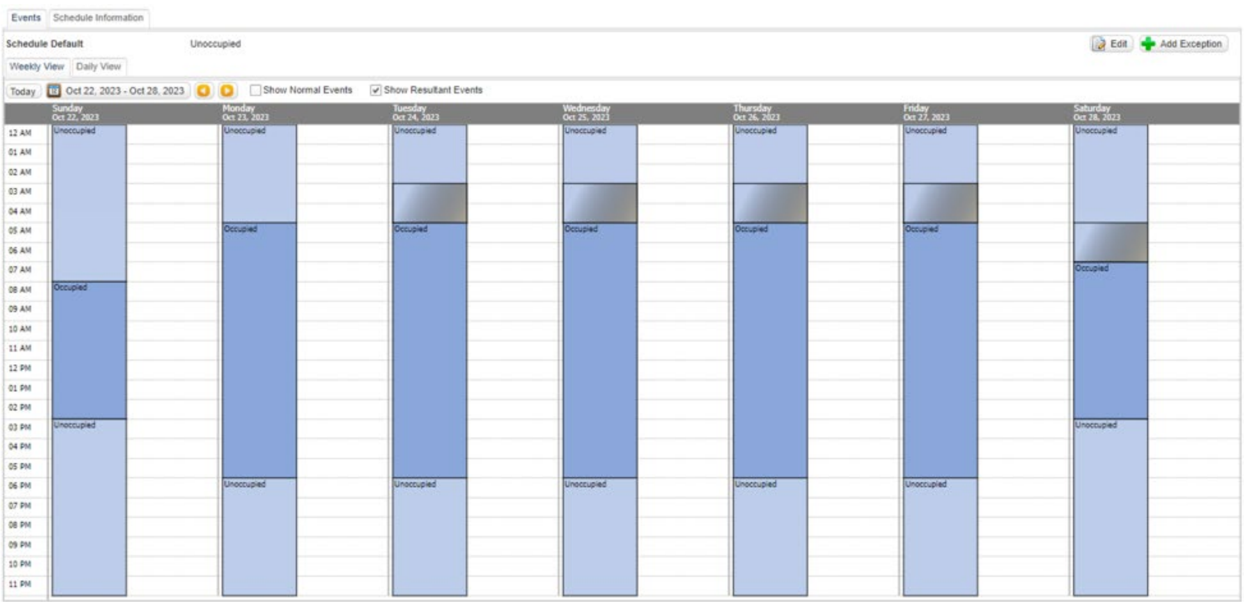
[28] ASHRAE. Standard 90.1-2022—Energy Standard for Sites and Buildings Except Low-Rise Residential Buildings. Atlanta, GA. https://www.ashrae.org/technical-resources/bookstore/standard-90-1

outside air are essential. The process is relatively straightforward when an AHU is equipped with an outdoor airflow measuring station (AFMS). However, in cases like the Slipstream office where no AFMS is available, determining the percentage of outside air introduced into the building relies on a combination of AHU mixing, return and outside air temperature sensors, and totalized VAV box air flow readings. This calculation can significantly influence the 62.1 ventilation requirement, particularly when the AHU predominantly operates in an economizer cooling mode with nearly 100% outside air or in a minimum outside air mode, typically associated with heating or mechanical cooling.

Opportunities for Occupancy-Based Building Ventilation

Figure 37 shows the building occupancy schedule programmed into the Slipstream BAS.

Figure 37. Slipstream BAS building schedule



A comparison of the building occupancy schedule programmed into the Slipstream BAS with the occupied time detected by the LDA is shown in Table 15.

Table 15. Comparison of LDA-detected occupancy with the BAS-programmed occupancy schedule

Day	Occupancy	
	LDA-Detected	**BAS Schedule**
Monday	5:30 a.m. – 4:45 p.m.	5:00 a.m. – 6:00 p.m.
Tuesday	5:45 a.m. – 5:30 p.m.	5:00 a.m. – 6:00 p.m.
Wednesday	5:45 a.m. – 6:00 p.m.	5:00 a.m. – 6:00 p.m.
Thursday	5:45 a.m. – 7:00 p.m.	5:00 a.m. – 6:00 p.m.

Friday	5:45 a.m. – 4:45 p.m.	5:00 a.m. – 6:00 p.m.
Saturday	8:30 a.m. – 1:00 p.m.	7:00 a.m. – 3:00 p.m.
Sunday	12:45 p.m. – 1:30 p.m.	8:00 a.m. – 3:00 p.m.

The headcount data obtained from Wi-Fi LBS could be used to create a more accurate BAS occupancy schedule that would result in some energy savings.

Proposed Minnesota Administration Building Honeywell BAS Integration

The Administration Building at the State Capitol complex uses a Honeywell Enterprise Building Integrator (EBI) BAS that supports both a top-down and a bottom-up approach for integrating the data from the LDA. The top-down approach requires that the application layer of the BAS, in this case, the Honeywell EBI, requests data from the LDA periodically via the LDA API. The LDA would return the data (headcount by zone) in the form of a text file, which the application layer would use to update an internal database table. Based on the values in this database table, the EBI would use its automation engine to send the appropriate messages to the VAV controllers on the network. While it is technically possible, it is currently not typical for the Administration Building staff to use the EBI automation engine to carry out specific low-level actions like controlling VAV boxes. The bottom-up approach would make use of a BACnet interface card to request JSON data from the LDA via HTTP, then translate it into BACnet messages to send directly to the plant controllers on the VAV boxes. For this approach, the interface card is extra hardware that would essentially duplicate a function that the application layer could perform, so it is a better fit for systems with less capable application layers.

General Steps for BAS Integration

In general, to perform this data integration, the BAS should be able to initiate an HTTP GET request to a cloud-based API, enabling it to retrieve a JSON payload containing occupancy data. In cases where the BAS operates in an edge environment or within an operations technology (OT) LAN, it will become necessary to incorporate a BACnet IoT gateway to work around the BAS's limitations. For instance, a software engineer can leverage open-source Python-based BACnet stacks to develop a BACnet server. This server can then interact with the cloud-based API to obtain the JSON data representing the Wi-Fi occupancy data, subsequently translating it into discoverable BACnet AnalogValue points for integration into the BAS. Historically, BASs and OT in general, have traditionally functioned as closed-loop systems, intended to operate independently of IoT connectivity. This paradigm can pose a significant challenge to OT, particularly for OT technicians who may not possess proficiency in the HTTP protocol or interfacing with cloud-based APIs. However, as OT continues to evolve, the need for these skills may become more prevalent.

The Sinclair Hotel, Fort Worth, Texas

The Sinclair[29] is a Marriott Autograph Collection luxury hotel in Fort Worth, TX built in 1929. Sinclair Holdings LLC remodeled the 16-floor office building into a DC-powered, 164-room hotel in 2019.

Figure 38. The Sinclair Hotel in Fort Worth, TX

The hotel's wireless platform is provided by a Cisco Meraki system with its location analytics capabilities. At this demonstration site, occupancy sensing was tested on a representative floor containing guest rooms. Figure 39 shows the floorplan for a typical floor of guest rooms with the locations of the APs. The green dots represent AP locations.

[29] Sinclair Hotel homepage. https://www.thesinclairhotel.com/

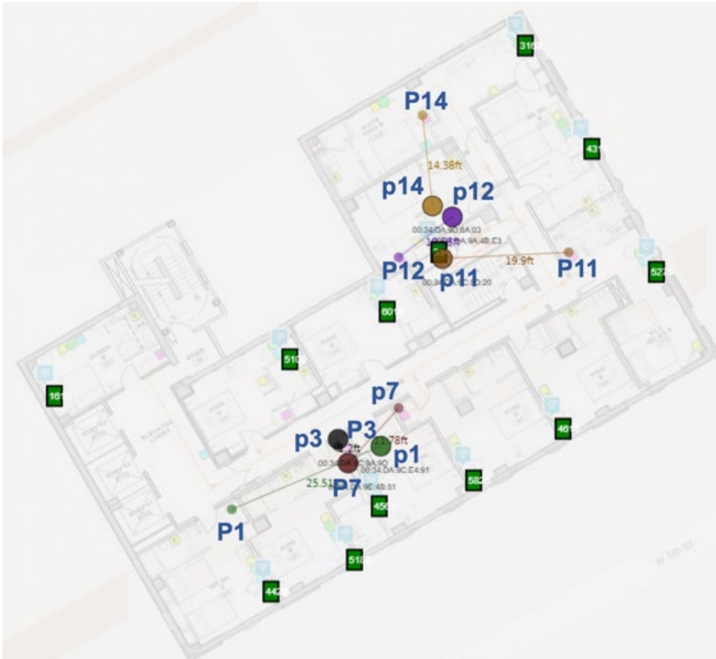
Figure 39. Floor plan for a typical floor of The Sinclair, Autograph Collection guest rooms with the AP locations

As with the other demonstration sites, Android phones were placed in each of the guest rooms to provide fixed reference points to test the accuracy of the location detection calculations of the LDA. On the twelfth floor of the hotel, the phones were placed in the locked cabinets of the guest rooms where the phones could be powered by the PoE network switches secured in the cabinets. The cabinets were located in the guest rooms' closets. For this site, rather than installing our own APs, we were able to use the MAC addresses and RSSI signals collected by the hotel's Cisco wireless network. With this data, we used the LDA to calculate the locations of the phones. Because we had access to the Meraki Location Analytics API of the hotel's wireless network, we also collected the locations of the phones as calculated by the Meraki system. Knowing the actual locations of the phones, we could compare the relative accuracies of the two location detection algorithms.

Comparison of the LDA with the Meraki Location Analytics API

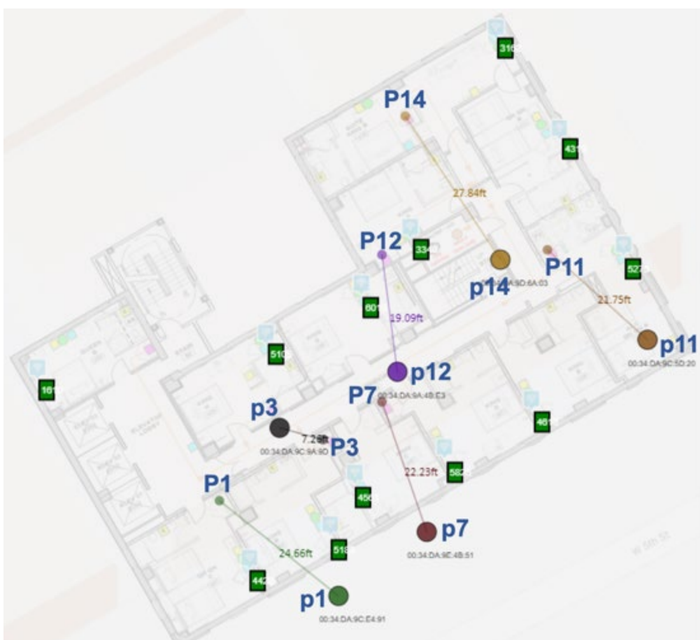
Of the twelve phones that were distributed throughout the hotel guest room floor, the Meraki wireless network detected the phones in six of the guest rooms: 1201, 1203, 1207, 1211, 1212, and 1214. Figure 40 shows the calculated locations of the six phones from the LDA compared to the phones' actual locations.

Figure 40. Comparison of LDA-calculated reference point locations with actual locations at the Sinclair Hotel



In comparison, Figure 41 shows the phones' locations calculated by the Meraki API.

Figure 41. Comparison of Meraki Location Analytics API-calculated reference point locations with actual locations at the Sinclair Hotel



A more direct comparison of the location accuracy of the two algorithms is provided by Table 16, which shows the error in feet of the algorithm's location calculation with the corresponding phones' actual locations.

Table 16. Differences in the LDA-calculated and Meraki Location Analytics API-calculated locations with the fixed reference points at the Sinclair Hotel

Room	Phone	Error (in feet)		
		LDA	Meraki	Delta
1201	P1	25.4	24.1	-1.3
1202	P2	–	–	–
1203	P3	4.4	18.9	14.6
1204	P4	–	–	–
1205	P5	–	–	–
1206	P6	–	–	–
1207	P7	13.9	22.8	8.9
1209	P9	–	–	–
1211	P11	27.0	21.7	-5.2
1212	P12	10.5	17.9	7.5
1213	P13	–	–	–
1214	P14	14.3	26.9	12.6

The average error for the LDA calculated locations was 15.9 feet, ranging from 4.4 feet to 27.0 feet and with a standard deviation of 8.7 feet. The Meraki API calculated locations had an average error of 22.1 feet, ranging from 17.9 feet to 26.9 feet and with a standard deviation of 3.3 feet. The average difference in accuracy of the location predictions of the two algorithms was 6.2 feet with the Meraki algorithm showing greater error for four of the six phones. Notice also that the LDA placed all the phones within the perimeter of the building.

Occupancy Patterns

Figure 42 shows the comparison of the occupancy patterns on the twelfth floor of the Sinclair Hotel determined by the LDA and the Meraki API over the week of April 6, 2023. The estimated headcounts are derived from the Wi-Fi enabled devices that were detected by each of the location detection algorithms.

Figure 42. Comparison of the LDA and Meraki headcounts over the week of April 6, 2023, on the 12th floor of the Sinclair Hotel

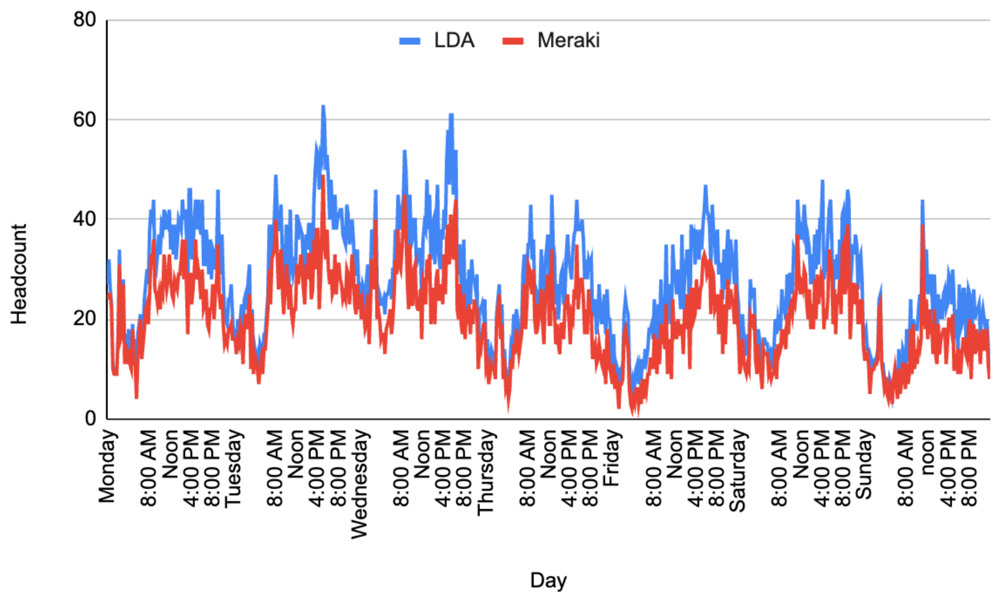


Table 17 compares the statistics or aggregate functions of the week-long data sets from the two algorithms.

Table 17. Statistics/aggregate functions of the LDA and Meraki headcount datasets for the week of April 6, 2023

	LDA	**Meraki**
Mean	27.5	20.1
Min	5	2
Max	63	49
Std Dev	11.2	8.4
Median	27	20
Mode	38	22

As described previously, the headcounts were determined by counting the number of devices located within a box drawn around the floorplan. Based on the data that we collected and analyzed, we found that the LDA has a higher tendency to place devices near the APs and inside the perimeter of the space while the Meraki API has a higher tendency to put devices anywhere inside/outside of the floorplan. Thus, based on the way that we determine headcount, it is expected that the LDA will typically have a higher headcount than the Meraki API. This is not evidence that one approach is necessarily more accurate than the other in calculating headcount since there are many other variables to consider such as whether devices are being detected that may be located on floors above or below the floor we are interested in.

Occupant Surveys

Three surveys were distributed among workers in large office environments to understand how they perceived their office environment and the role it plays in their jobs, as well as to inform technological developments in occupancy tracking using Wi-Fi data. The first survey was performed in 2019 at the beginning of the project while the remaining surveys were performed at the end of the project in 2023. These last two surveys also allowed us to understand the impact of the COVID-19 pandemic on remote work trends and office environment trends.

Each survey had about 400 respondents and they worked in three markets corresponding to the locations of the three office demonstration sites: Minneapolis/St. Paul, Madison/Milwaukee, and New York, with responses equally distributed between locations in both time periods. Respondents worked for organizations with at least 50 employees at their office location and held full-time positions (92–93%) in a variety of roles, with the highest proportion in management, director, or supervisory roles (37–39%) or administrative, office support, or assistant roles (24-27%). Women had slightly higher representation in the responses (58–60%) compared to men (40–42%), and age was distributed across groups, from 18 to 55+.

Technology and Location Sensing

Nearly all workers (98%) reported having some type of access to Wi-Fi in their workplace, which varied between building-wide, business-wide, office-specific, or public/guest access. With regard to the use of Wi-Fi enabled technologies, nearly all workers (96%) reported carrying a smart phone during their workday. 17% carry more than one smartphone, and 67% of 2023 survey respondents said they carry one laptop during their workday, significantly higher than the 44% of respondents in the 2019 survey. Smart watch use also increased from 19% in 2019 to 34% in 2023. On average, workers reported having 2.6 devices that use Wi-Fi, down from an average of 3.6 devices in 2020. The average number of devices that use Bluetooth (1.4) and cellular data (1.5) were consistent with 2019 survey results. Assuming that all these devices are Wi-Fi enabled, we would expect that the Wi-Fi LBS approach to occupancy sensing would overpredict the headcount by about 160% or so (on average, 2.6 Wi-Fi-enabled devices per office worker).

Related to devices provided by employers, we continue to see a decrease in telephones (65%) and desktop computers (54%) and an increase in laptops (61%) as compared to the 2019 survey results (79% telephones, 62% desktops, and 48% laptops). This might be expected as the workforce has transitioned from individuals having fixed workspaces to requiring mobility to support remote work.

The 2019 survey found that about a third of the respondents turn off their Wi-Fi or Bluetooth while in the office and about 10% turn off their phones while at work. The 2023 survey found that fewer workers took steps to limit Wi-Fi and Bluetooth access to their mobile devices while at work, and a larger percentage said they are not bothered by Wi-Fi and Bluetooth access (50% for Wi-Fi and 65% for Bluetooth). In 2023, only 25% said they turn off Wi-Fi and 9% turn on airplane mode to limit Wi-Fi. Even fewer 2023 respondents said they turn Bluetooth off (18%) or turn off their phone (7%) to limit Bluetooth access. This trend is encouraging for Wi-Fi location tracking applications because greater use of Wi-Fi will increase the utility of Wi-Fi locating applications.

In the 2019 survey we asked the respondents if they were aware of location sensing apps in retail stores, malls, and museums and 28% said that they currently use them, 29% would use them if they were aware of them, 17% weren't interested, 15% would avoid using them, and the remaining 11% weren't sure. They were then asked if they would like their workplace to use location sensing for greater individual comfort, improved working conditions, and greater safety and security, and 61% said yes, 23% said no, and the remaining 16% didn't care. The respondents' main concern about location sensing at work was privacy, while they were interested in location sensing for temperature and lighting control. The survey also found that about a third of the respondents turn off their Wi-Fi or Bluetooth while in the office and about 10% turn off their phones while at work.

Only 19% of workers said they currently use apps with location sensing in public spaces for help, directions, information, etc., but nearly half (43%) said they would use them if they were aware they existed. Only 6% specified that they would avoid these apps, and 33% said they didn't care or weren't sure. Those younger than 55 were more likely to use location sensing apps, while those 55 or older were more likely to avoid using them.

63% of workers said they think location sensing in the office could be valuable, compared to 24% who thought it would not be valuable or too intrusive. The location sensing functions people were most interested in were assistance with navigating the building and the ability to adjust lighting and temperature for both personal comfort and conservation of energy resources. Some were also interested in security features, such as limiting access to building spaces or providing security assistance; locating items and people in the office; and monitoring employee presence and performance.

Related to location sensing in the office, workers were most concerned with potential invasions of privacy or the intrusiveness of being monitored. People worried that sensing data could be compromised or misused and were skeptical about the anonymity of tracking. They were uncomfortable with the idea that employers could use employee movement and activity data as a management tool. Some people also noted possible technical problems and the cost implications of implementing a location sensing system.

Workplace Comfort

The responses from both the 2019 and 2023 surveys found that personal temperature and temperature control received the lowest ratings in terms of satisfaction for staff working in both their individual workspaces and the office's conference rooms/common areas. When workers were not satisfied with temperature levels in both individual workspaces and conference rooms/common areas, the most frequently reported problem was that the temperature was too cool. The second most frequently reported problem with the temperature was that it was inconsistent throughout the day. Workers with low satisfaction with their workplace environment were more likely to desire greater control over their environment, while those who were highly satisfied did not express a greater desire for environmental control. Male respondents were more likely to be satisfied with office environments than female respondents. When dissatisfied with space temperature, women were more likely to say it was too cool while men were more likely to say their office temperature was too warm.

When workers were not satisfied with lighting levels in individual workspaces, the most frequently reported problem was that lighting was too bright. In conference rooms and common areas, lighting problems were reported as being too bright or inconsistent throughout the day.

The workplace physical environment was rated as having a lower impact on overall job satisfaction in 2023 than in 2019 (59% vs. 65%). This may have been the result of a change in occupancy patterns post-COVID-19.

Occupancy Patterns

After going through a couple years of remote working due to COVID-19, the workforce has been returning to the workplace, but hybrid working has become accepted practice. This was confirmed by our survey results. In 2019 workers reported spending and average of 38.1 hours per week working in an employer office location and 7.0 hours working away from the office. In 2023, workers reported spending an average of 33.3 hours per week in the office and 9.6 hours away from the office. The proportion of people working from home or an alternate location at least some of the time significantly increased, from 77% to 91% between 2019 and 2023. The proportion of people spending time at an office location other than their home office significantly decreased to 16% in 2023 from 34% in 2019. In 2023, an average of 23% of work was reported as being done remotely, equating to just over one day per week spent remotely and nearly four days in an office.

In the past year, 19% of workers reported their time spent working remotely decreased and 10% said it increased. Only 11% anticipated a decrease in remote work in the next year and 13% anticipated an increase. About three-fourths of workers anticipated that their level of remote work will remain the same in the next year. Respondents under 45 years old reported a significantly higher number of hours working in an office location than respondents older than 45. If we can infer age with level within the organization, this suggests that upper management enjoyed greater flexibility with remote working, while there was a greater emphasis on having lower-level workers performing their duties in the office. It is also interesting to note that younger respondents were more likely to expect an increase in remote work in the future, either reflecting an expected trend toward more hybrid work or an expected promotion within the organization.

Interestingly, there was regional variation in attitudes towards remote work. Respondents in New York were most likely to anticipate a decrease in remote work in the next year, support employer mandates to return to the office, have a permanent employer office location available to them, and want to work 100% in the office. (While not stated in the study, this could be because of more limited personal space at home in this area.) Respondents in Minneapolis/St. Paul were most strongly opposed to return to office mandates and most likely to view remote work as a benefit when considering employers and to change jobs if forced to return fully to the office.

With a large majority seeing no change in their remote work time between last year and the upcoming year, a full return to office work for most employees is not expected in the near future, though more than half of surveyed workers (55%) stated their employer is actively trying to bring people back to office locations. About a quarter (27%) said their employers are not.

It will be worth keeping an eye on the commercial real estate market to see whether commercial office vacancy rates return to pre-pandemic levels and whether remote and hybrid work will trigger a rethink of office space design and utilization.

Emerging Technologies

Residential technologies influence the technologies adopted in the workplace. Smart home technologies are increasing in maturity and adoption. During the pandemic, many remote employees worked in home offices and spent more time interacting with their smart home devices than pre-pandemic. It could be speculated that employees who interacted with their smart homes to control their personal environments might expect access to similar amenities in the workplace.

In order to explore the role smart devices and emerging artificial intelligence (AI) technology might play in the workplace, the 2023 survey included questions that weren't asked in 2019. There was familiarity with and use of voice-based digital assistants, and 79% of respondents reported having used them. Of those who have used voice-based digital assistants, half (51%) said they use them at least daily, and another 26% use them weekly. Those 55 and older were least likely to have used a voice-based digital assistant.

When asked if they would be interested in using a voice-based digital assistant to control their workspace environment, submit a comfort complaint, or file a work order, 41% of workers said yes and 24% were not sure, while 35% said they would not. Those who said they would like greater control over their comfort in their personal workspace were also much more likely to be interested in using voice-based digital assistant for that control. Based on the responses, it seems likely that additional education is needed to teach office workers about how voice-based digital assistants could be used to control their workplace environment.

OpenAI's ChatGPT, a chatbot based on a large language model (LLM), made its public debut on November 30, 2022, and at the time became the fastest-growing consumer software application in history. ChatGPT quickly captured the public's attention. AI, particularly generative AI, became a hot topic in 2023 and was predicted by the media to be the most influential new technology since the internet. In anticipation of future AI capabilities for controlling and interacting with buildings, 2023 survey respondents were asked about their experiences and attitudes toward AI technologies.

Nearly half of workers (49%) said they have not used an AI chatbot. In addition, of those that had used a chatbot, 27% said they have never used one for their work. ChatGPT was the most popular AI chatbot, with 36% of workers saying they had used it. Only 19% of those who have used a chatbot, use it for work on at least a daily basis. Weekly and monthly use were more common. Workers aged 25–44 were more likely to have tried AI tools than those older and younger. Those 18–24 years old were more likely to have tried ChatGPT, and those 45 and older were more likely to not have tried any AI chatbots. Men were more likely to have tried ChatGPT (and any chatbot) than women.

There was mixed agreement with statements of interest in learning about and using AI, with mean scores around 5.0 on a scale of 1=*Totally Disagree* to 10=*Totally Agree* and 22%–34% in the top three agreement responses. 22% agreed that AI can be used to improve their office environment and work experience and would love a tool that used AI to adjust a room to their comfort needs. Workers generally disagreed that AI is a fad that will fade in the coming years. Men were more interested in learning about AI than women. Those in offices of larger size were both more likely to have used AI tools and more interested in learning about them.

When asked if they would be interested in using an AI chatbot to control their workspace environment, submit a comfort complain, or file a work order, 39% of workers said yes and 32% were not sure, while 29% said they would not. Those who expressed interest had a positive sentiment toward AI, generally, and saw benefits for convenience, efficiency, and comfort in allowing AI to control their environment. Those who were unsure expressed familiarity with how they adjust their environment themselves and a need for more information and understanding of allowing AI to do that, especially related to data privacy and more specific functionality. Those who said they are not interested in AI controlling their environment expressed their general reluctance and skepticism toward AI and preference for human interaction and manual control. They feel they are self-sufficient and autonomous, and AI is unnecessary for their work or office environment.

Prospective adopters of AI chatbot technology tended to be strong adopters of technology in general. Those who have used AI chatbots are more likely to have various types of personal and company-provided electronic devices in their workspace. They also said they have about twice as many devices that use Bluetooth or cellular capabilities than those who have not used chatbots. There was not a significant difference in the number of Wi-Fi enabled devices, but those who have used chatbots were more likely to say they have turned off the Wi-Fi on their devices while in the office and leave wireless devices at work when they are away. Those who said they would like greater control over their comfort in their personal workspace were also much more likely to be interested in using an AI chatbot for that control.

While the percentage of those who were interested in voice-based digital assistance is similar to those interested in using an AI chatbot for workplace control, a higher percentage said they would not be interested in using a voice-based digital assistant than an AI chatbot for these purposes at work. The reasons people were interested in using a voice-based digital assistant were similar to the benefits seen in using AI, with the addition of it being a hands-free option for controlling the environment. These people were especially excited and eager to implement this technology they are already familiar with in their work settings. Those who were unsure of or not interested in using voice-based digital assistants at work shared very similar problems and concerns as those expressed with using AI to control their work environments.

As voice-based digital assistants and AI chatbots mature, we can anticipate that adoption will increase and employees will become more aware of their ability to interact with their workplaces. Additional education and experience with these tools will help drive adoption for intelligent buildings.

Discussion

In this section, we cover in more complete detail the work we performed in this project and the results obtained in the field demonstrations and surveys.

Wi-Fi Enabled Device Detection

A number of issues concerning Wi-Fi device detection were encountered during the site demonstrations. These involve the wireless network's APs not being able to detect some of the Android phones used for fixed reference points s in the collected data due to outages. There are three sources for these problems:

- The Wi-Fi device that emits the signal
- The APs and wireless network that receives the signal
- System outages

Wi-Fi Device Signal

The two primary issues with the Wi-Fi device sending out a signal are the frequency at which the device is searching (or pinging) for a wireless network and the strength at which the signal is sent out. According to Meraki's Location Analytics documentation,[30] the frequency of probe requests varies based on the device's state: about once a minute when asleep and 10–15 times per minute when in standby, and a device might not send probe requests when already associated with an AP. Additionally, we assume that the frequency also varies greatly among different operating systems and installed applications (for example, an active app on a smartphone can cause it to probe more frequently, even when the device is in a sleep state).

AP Receiver

We noted limitations in some of the APs' ability to read signals, including issues related to signal obstruction, multipath interference, antenna orientation, and distance from devices. This was particularly evident in environments with complex layouts or where APs were not ideally positioned.

System Outages

Occasional server outages and internet connectivity issues led to gaps in the collected data. The ingest server at Design.Garden that receives and stores data was unable to consistently keep up with the increasing number of APs and would occasionally require manual intervention to continue collecting data. We also observed that some offices would occasionally stop sending data for periods of time, leaving us to assume they lost internet connectivity.

[30] Cisco Meraki, "Location Analytics, Location Data Collection" webpage.
https://documentation.meraki.com/MR/Monitoring_and_Reporting/Location_Analytics#Location_Data_Collection

Device Location Accuracy

The accuracy of device location varied significantly across different environments. Factors such as antenna orientation, physical obstructions within the space, and inherent limitations of the Wi-Fi LBS technology influenced the accuracy of our Location Detection Algorithm (LDA). Instances occurred in which the algorithm failed to correlate RSSI readings to location accurately, leading to significant errors in device positioning. This was exemplified in our tests at the Sinclair Hotel, where devices were often incorrectly located.

Our initial expectation for the Location Detection Algorithm (LDA) was that the error in translating RSSI to distance would be less than 10 feet, a benchmark derived from literature on Wi-Fi RSSI-to-distance transformations and confirmed in our laboratory testing. However, the complexity and variability of commercial building environments meant that we did not have complete control over the placement of APs, leading to situations where the RSSI was often translated to distance with a larger error than anticipated. This deviation from our expected accuracy necessitated an adaptation of our LDA, as described in our section regarding in-situ testing for occupancy sensing validation.

Wi-Fi LDA Failure

As discussed, Wi-Fi LBS requires a correlation between a device's distance from a sensor and the RSSI. However, in our field demonstrations we observed several instances where there simply was no discernible correlation. In these instances, the LDA cannot be used to confidently determine the location of the device.

For example, the device labeled P11 in the Sinclair was placed in room 1211, but was often calculated by our LDA to be across the hall in room 1203. Looking at the RSSI of each sensor averaged over one hour, we determined the issue: sensors across the hall were reporting strong RSSIs. In our "X_a Tuning" section, we have demonstrated how we can account for this by calculating an estimated mean, X_μ, but this is inapplicable when a monotonic RSSI-to-distance transformation, where RSSI increases with decreasing distance, cannot be reasonably inferred.

Each row in Table 18 shows the actual distance between the phones P3 and P11 to an AP, (identified by its MAC address), along with the RSSI. To illustrate the issue, we've highlighted the closest phone and strongest symbol in each row. Note that we should expect to see the closest phone providing the strongest signal (both highlighted numbers in one row should belong to the same phone, P3 or P11); however, instead we see the opposite, that the RSSI is consistently stronger for the furthest phone.

Table 18. Comparison of distances of Android phones P3 and P11 from APs at Sinclair Hotel

AP MAC	P3		P11	
	RSSI (DBm)	Actual Distance (ft)	RSSI (DBm)	Actual Distance (ft)
e0:cb:bc:47:**6e:fd**	-23	8.4	-13	49.3
e0:cb:bc:47:**6c:aa**	-23	15.5	-4	58.3

e0:cb:bc:47:**78:2b**	-11	18.8	-3	48.1
e0:cb:bc:47:**db:5e**	-26	19.6	-16	37.6
e0:cb:bc:bd:**1d:5d**	-20	24.4	-11	31.3
e0:cb:bc:47:**da:eb**	**-5**	33.9	-14	25.6
e0:cb:bc:47:**ce:b6**	**-7**	35.9	-11	22.5
e0:cb:bc:47:**cf:e7**	**-8**	56.7	-34	11.9

Unfortunately, our ability to troubleshoot this issue was limited given that this only occurred during our field demonstrations, where we lacked the ability to rapidly review and test the system. Therefore, we did not identify the cause of this issue during this project. Instead, we can offer the following notes:

- We can't simply assume that obstructions or faulty hardware caused these discrepancies because neither easily explains why some Access Points received very strong signals.
- This issue was most profound at the Hotel Sinclair, which used Meraki access points, but we also encountered this issue for some reference devices at the offices of ConEd's R&D department and at Slipstream, which used Open Mesh access points connected to Plasma Cloud.
- Mislabeled access points or reference devices would exhibit a similar symptom; however, we worked with staff at each site to confirm all device positions.

Occupancy Detection

Our project aimed to correlate the number of detected Wi-Fi enabled devices to actual headcounts. Survey results indicated that occupants typically carry multiple Wi-Fi-enabled devices, leading to the expectation that the number of detected devices would exceed the actual headcount. However, our findings showed a good correlation between the detected number of devices and the actual headcount, suggesting the effectiveness of our filtering and consolidation methods for MAC addresses (cf. the section on Filtering Devices).

In addition to the initial occupancy detection efforts, our second test at the Parallel Technologies Innovation Lab provided further insights. During this test, the LDA was employed to monitor occupancy during an open house event, a setting significantly different from the regular office environment due to the large and fluctuating number of attendees, who may have been moving about more than typical office workers sitting in a single location for most of the time.

During the event, headcounts performed by staff were compared against device counts calculated by the LDA using varying sampling periods. Interestingly, we found that shorter sampling periods tended to undercount the guests, while longer periods failed to accurately reflect changes in attendance, such as when guests began to leave. This discrepancy highlighted the importance of choosing an optimal sampling period that balances responsiveness with accuracy. We concluded that a sampling period between 15 to 30 minutes struck the best balance, correctly accounting for approximately 30% to 42% of guests, respectively.

Commissioning

Differences between lab test results (errors of less than 10' with X_a turning) and field demonstrations (errors ranging from 2' to 43' with an average for all the sites of about 18' and a standard deviation of 13') underscored the need for careful commissioning and calibration of the LDA in each unique environment. This process includes fine-tuning parameters such as the X_a value in the Hato-Okumara model, which accounts for signal attenuation due to environmental factors such as walls, furniture, and other obstructions. Having fixed reference points such as the Android phones used at the demonstration sites or fixed office equipment like Wi-Fi enabled printers, copiers, and displays could allow for ongoing commissioning of the space.

Cybersecurity Considerations

The IT departments of all of the field sites were interested in the Wi-Fi LBS technology that we were studying but were reluctant to allow us access to their wireless network and APs. Their concern was that the technology used for occupancy load detection via Wi-Fi APs can expose vulnerabilities both in the building and over the internet related to local network, man-in-the-middle, and server attacks.

- Local network attacks involve the intruder gaining access to the Wi-Fi network inside the building to exploit or manipulate the data.
- *Man in the middle* attacks could manipulate data sent from the APs during transmission to the cloud for processing and/or manipulate data sent to the IoT system in the building that uses the processed occupant load data to operate the HVAC system. The use of TLS on API endpoints provides encryption of the data across the web and the use of common API authentication techniques secures the endpoints themselves.
- Server attacks involve a hacker gaining access to data sent by the Wi-Fi APs to the cloud-based database. Personal data such as the MAC addresses of smartphones could be retrieved if a hacker gained access. A one-way hash function could be used to store and protect personal information on the server after the AP has sent the data via the web to the cloud.

Furthermore, the end device that uses the occupant load data to adjust setpoints on the HVAC system is susceptible to corrupt data, whether the data is manipulated or incorrectly reported. To protect HVAC equipment from unwanted equipment cycling that can lead to premature wear, the IoT or BAS could be protected to respond to the occupant load information on allowable percent change per hour.

This project demonstrated the communications pathway that the LDA receives the data of the Wi-Fi devices detected by the APs and sends the headcount data to the BAS. This can all be done behind the firewall set in place by the IT department. This should allay any concerns that this functionality will introduce additional cybersecurity vulnerabilities beyond those that are currently being defended against.

Potential Energy Savings from Occupancy-Based Ventilation Rates

A proprietary calculator designed for use with commercial HVAC programs at the Center for Energy and Environment was modified to measure the impact of adjusting building ventilation rates based on actual occupancy. While this calculator is less robust than an energy model using EnergyPlus, for example, it has the advantage of easily allowing isolation and control of the supply fan for parametric studies of relative energy use.

The calculator assumes a simple RTU that has only time schedule and thermostatic control. For these systems, the two factors that have the greatest impact on energy consumption are the temperature set points(s) and the occupancy status of the space. Higher setpoint temperatures require more heating and less cooling. When the space is unoccupied, if the RTU supply fan is set to auto, it operates only when needed to distribute heating or cooling—otherwise it is off, saving fan energy. When the space is occupied, the supply fan is always on at full power, as required for 100% occupancy (the basis of design). This is the attribute that was varied for our analysis. Rather than being always on, the fan speed was regulated based on the ventilation requirements for the level of occupancy.

For this analysis, the characteristics of the four sites were normalized to a 5,000 square foot area. The system heating and cooling capacities were determined by the design temperatures for each location. Based on our observations in this study, we rarely saw space occupancy greater than 75% of the design level, and frequently observed occupancy of 25% or less. Table 19 shows the range of savings using technical potential that represents the maximum amount of energy use that could be theoretically displaced by an efficiency measure.[31] The conservative savings estimate shown in the table is based on half of all buildings implementing controls that average 75% occupancy and the rest making no change; the aggressive savings estimate is based on half of all buildings implementing controls that average 75% occupancy, one quarter implementing controls that average 50% and one quarter implementing controls that average 25% occupancy.

Table 19. Estimated energy savings based on technical potential

	Total EUI	Heating EUI	Ventilation EUI	% Total Savings	% Heating Savings	% Ventilation Savings
Conservative Scenario	64.7	19.7	12.4	1.4%	2.0%	4.0%
Aggressive Scenario	62.5	18.7	11.2	4.8%	7.0%	13.3%

[31] EPA (U.S. Environmental Protection Agency). 2007. Guide for Conducting Energy Efficiency Potential Studies. Washington, DC: EPA. http://www.epa.gov/cleanenergy/documents/suca/potential_guide.pdf.

These calculations assume that the supply fan operates at full power when it is on. Fans are now available with multiple operating speeds or fully modulating motors; these could produce even larger savings, but the controls would be more complex. Appendix A provides a more complete description of this analysis.

Impact of COVID-19 on Office Occupancy

The COVID-19 pandemic had a major impact on this project when office staff began working remotely and occupancy in buildings (and at our field sites) was negligible. In addition to the delays this caused to our project, we also encountered low and variable occupancy once the offices in our field study began to reopen. A few years removed from the pandemic, remote working continues to be practiced even though businesses are encouraging a return to the office. Many companies have required staff to work in the office for at least a few days of the week. Given this trend, adjusting building ventilation rates based on actual occupancy should be a practice that is promoted. The failure to have this measure in place during COVID was an opportunity lost.

Program Recommendations for Implementing Wi-Fi LBS

A number of opportunities are available to encourage the operation of building HVAC systems based on actual occupancy and, specifically, the use of Wi-Fi LBS. Utility provider incentive programs that focus on retro-commissioning (RCx) and monitoring-based commissioning (MBx) could expand their offerings to include a Wi-Fi LBS energy saving/management program. These programs should be encouraged to use MBx and analytics to continuously verify the effectiveness of the LBS Wi-Fi strategy by monitoring and documenting reductions in building fuel consumption over time. Incentives would be beneficial for both contractors and building owners to participate. A number of stakeholders would also need to be enlisted and trained to promote effective adoption. This includes:

- Engaging consulting firms or contractors regarding task allocation for setting up LBS platforms or systems to optimize building energy use.
- Requiring architectural/engineering (A/E) consulting firms to perform HVAC design calculations incorporating variations in occupancy as part of the system setup.
- Training IoT contractors to implement wireless networks that effectively deliver LBS occupancy detection along with good Wi-Fi coverage.
- Educating local engineering consultants in commissioning the LBS systems to ensure the proper functionality and integration of the LBS system.

Future Work

Based on the results of this project, there are a number of follow-up research topics that are worth exploring. While it was found that locating mobile devices like smartphones provides a good way to sense occupancy, the inability of the LDA to accurately and consistently determine the locations of these mobile devices is still the major limitation of the approach. Given the use of dedicated apps to provide accurate RTLS for applications in retail stores and museums, investigation of these approaches should be considered to determine if the limitations of the LDA can be overcome or whether these apps make use of other mobile device signals such as

Bluetooth or GPS. These dedicated apps require the user to download the app, open the app, and log the device into the wireless network. This might be expected for employees but would require benefits for other occupants to incentivize use of the app. More accurate location of occupants could allow finer control of lighting, plug loads, and space conditioning/personal comfort, as well as non-energy benefits such as greater building security and safety and open office workplace customization. Use of dedicated apps could result in additional privacy concerns that would need to be confronted.

The onsite field demonstrations showed the quantity and placement of the APs for the LDA to provide good results. If this approach is to gain wider adoption, a commissioning approach that can be performed by in-house IT staff is needed. Since the APs will be used to provide both wireless network coverage and occupancy sensing, a greater number of APs will be required and the LDA would also need to be tuned for greater location accuracy using fixed reference Wi-Fi beacons to account for obstructions within the space. An ongoing commissioning of the LDA with the fixed reference points would be desirable.

Real-time occupancy sensing will require the development of HVAC design algorithms that building operators can implement to provide more accurate occupancy-required ventilation, heating, and cooling.

Conclusions

This project found that using Wi-Fi data collected from mobile Wi-Fi enabled devices can provide reasonable real-time occupant presence and count data. Using actual detection of occupant presence would improve on the inefficiencies produced by predefined occupancy schedules which can result in elevated energy use and comfort issues. Despite the uncertainty in the LDA's headcount estimate due to occupants carrying multiple Wi-Fi enabled devices and the ability of the APs to consistently detect the mobile devices' Wi-Fi signals, the headcount numbers were found to reflect the actual occupancies of the spaces monitored. The average typical occupancy for the three sites (Minnesota Admin Building, ConEd R&D Office, and Slipstream second floor offices) was about 20% of the maximum occupancy of the sites (ranging from 10% to 30%). The average highest occupancy detected was about 40% (ranging from 25% to 46%). Using ventilation rates based on real-time occupancy rates for demand-controlled ventilation as opposed to schedules assuming full occupancy would provide significant opportunities for energy savings. For building-wide or floor-wide HVAC system operation, headcount estimates provided by the LDA could best be applied by using a rule-based approach to occupancy-based ventilation. Table 20 shows the calculated electrical and heating energy savings using occupancy-based supply fan operation for 25%, 50%, and 75% occupancy levels. As described in Appendix A, these results were obtained from simulations of office buildings located in the cities where the monitored building sites were located.

Table 20. Energy savings based on occupancy-based supply fan operation

Actual Occupancy (vs. Design)	Electrical Energy Savings	Heating Energy Savings
25%	22% ± 2%	12% ± 3%
50%	15% ± 2%	8% ± 2%
75%	8% ± 1%	4% ± 1%

Negligible cooling savings were found (less than 1%). To estimate the total energy savings for all commercial buildings in the U.S., a weighted average of square footage was used by principal building activity using the electricity consumption rates from CBECS. The median energy savings from ventilation controls was 16.7 TWh annually and 6.9 million metric tons of CO_2 emissions avoided. If the mobile device RSSI and MAC address data collected by the APs of the wireless network is available for location analytics, no further investment in occupancy sensing equipment is needed. This would then be a software-based retrofit that would be a cost-effective approach to building occupancy sensing and occupancy-monitored HVAC operation.

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Appendix A – Estimating Energy Savings Potential

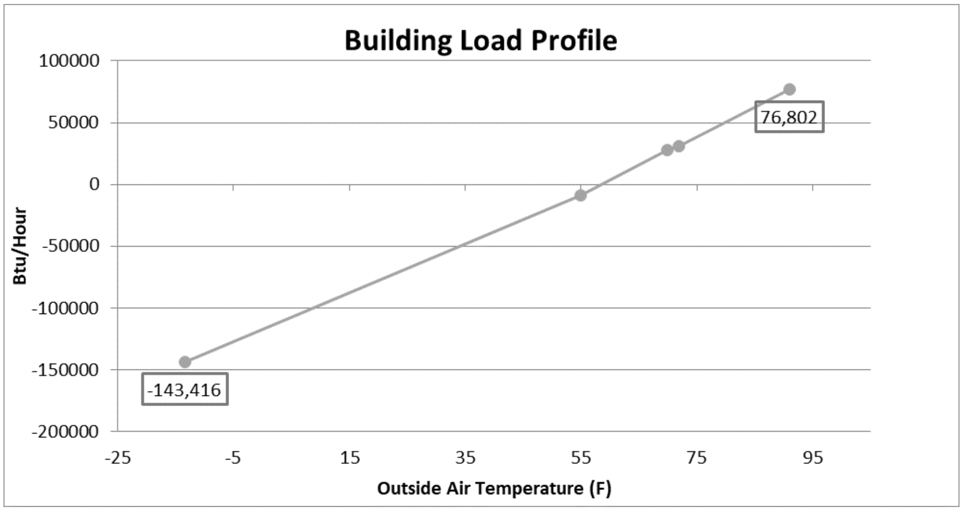
A proprietary calculator designed for use with commercial HVAC programs at Center for Energy and Environment was modified to measure the impact of adjusting building ventilation rates based on actual occupancy. This tool was originally developed to calculate energy use of a rooftop unit (RTU) using standard engineering algorithms for energy consumption based on building heating and cooling loads. Hourly energy use is calculated using TMY3 data for outdoor temperature, setpoints for the indoor temperature and the building's balance point. The building load curve defines the capacity of the heating or cooling system based on the design temperature for the location. The hourly energy required for heating, cooling, and ventilation is summed to obtain the total annual energy use. While this calculator is less robust than an energy model using EnergyPlus, for example, it has the advantage of easily allowing isolation and control of the supply fan for parametric studies of relative energy use.

The calculator assumes a simple RTU that has only time schedule and thermostatic control. For these systems, the two factors with the greatest impact on energy consumption are the temperature set point(s) and the occupancy status of the space. Higher setpoint temperatures require more heating and less cooling. When the space is unoccupied, if the RTU supply fan is set to auto, it operates only when needed to distribute heating or cooling—otherwise it is off, saving fan energy. When the space is occupied, the supply fan is always on at full power, as required for 100% occupancy (the basis of design). This is the attribute that was varied for our analysis: rather than being always on, the fan speed was regulated based on the ventilation requirements for the level of occupancy.

For this project the characteristics of the four sites were normalized to a 5,000 square foot area. The system heating and cooling capacities were determined by the design temperatures for each location. These in turn define a building load curve, such as that shown in Figure 43 (for the St. Paul location), which is the starting basis for the calculations.

Figure 43 shows the building load curve using the St. Paul design temperatures. The values in the boxes are the heating (-143,416 Btu/h) and cooling (76,802 Btu/h) loads at the design temperatures. The load is for the building shell only; it excludes ventilation.

Figure 43. Building load profile using St. Paul design temperatures



The heating and cooling energy for the building load is:

$$((\text{System Capacity} / \text{efficiency}) * (OAT - T_{Balance}) / (T_{Design} - T_{Balance})) * (\%\ \text{Capacity at Design})$$

where:

OAT = Outside air temperature and
$T_{Balance}$ = Building balance point temperature.

The building performance curve is generated by adding ventilation to the building load. This is shown in Figure 44. The total heating or cooling required at design is increased by a factor of about 2 compared to the load of the building shell. The increase is required to meet the additional load required for conditioning outside air ('fresh air") based on *ASHRAE 90.1, Energy Efficiency Standard for Sites and Buildings Except Low-Rise Residential Buildings*, as shown in Figure 44.

There are two causes of the increase in energy for ventilation energy .Energy is required for the supply fan whenever it distributes and circulates air. The electric energy required to operate the supply fan (SF) is:

$$((\text{Occupied hours}) + (\text{Unoccupied hours} * (OAT - T_{Balance}) / (T_{Design} - T_{Balance}))) * \text{SF power}$$

SF power is measured in kilowatts and the fan only operates for long enough to meet the building heating or cooling load during unoccupied hours. When the space is occupied the SF uses full power continuously. This will be changed by the occupancy control discussed below.

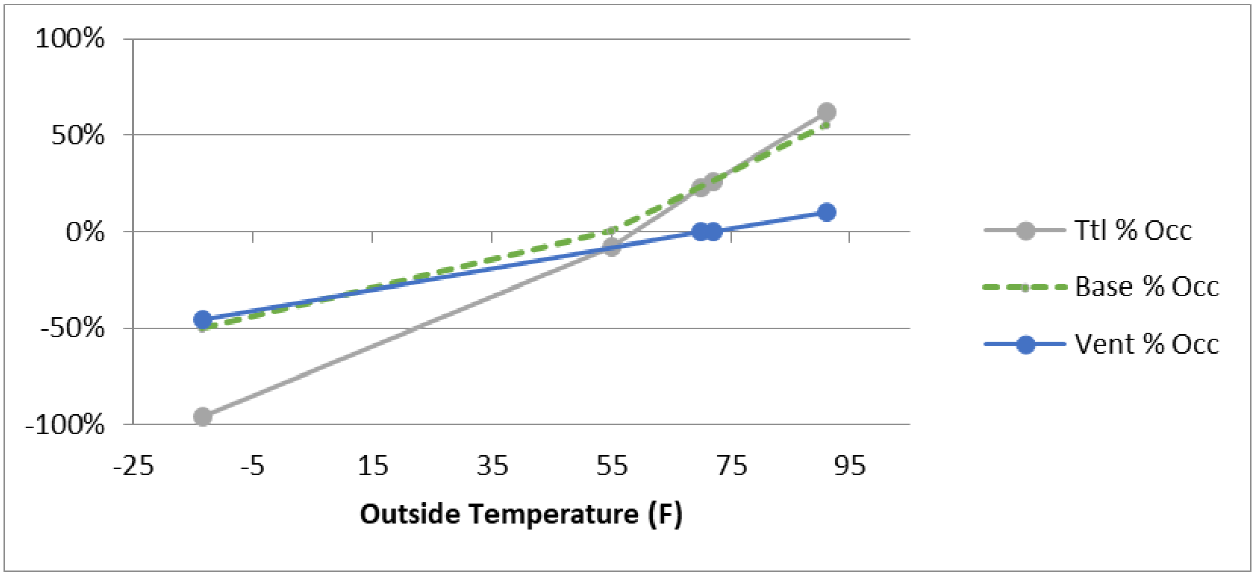
In addition, heating or cooling energy is required to condition the outside air brought into the space. The additional heating or cooling energy required for the outside air is:

$$SA\ cfm * min\ OA\% * |RAT - OAT| * 1.085$$

where RAT = Room air temperature and |RAT-OAT| is always a positive number,

SA cfm = the supply air flow rate (cubic feet/minute (cfm)), and
Min OA% is the percentage of outside air that is mixed with the returning air.

Figure 44. Building performance curve with ventilation added to the building load



Building performance curves showing the impact of conditioning outside air (blue line) compared to no outside air (dashed green line). The gray line is the total load.

The TMY3 for each of the four project sites (St. Paul, MN; Madison, WI; Manhattan, NY; Fort Worth, TX) is used with the design temperatures shown in Table 21.

Table 21. TMY3 design temperatures

Location	Heating design temperature	Cooling design temperature
St Paul, MN	-13.4°F	91°F
Madison, WI	-12.3°F	93.1°F
Manhattan, NY	12.6°F	92.2°F
Fort Worth, TX	18.8°F	100.3°F

Location-Specific Inputs

The inputs used for a 5,000 square foot office occupied 60 hours/week at each location are listed below in Table 22. The heating and cooling system capacity values were determined by the building load model using the design temperatures in Table 21. The fan power values are based on a database of approximately 2,000 RTUs installed on commercial buildings. The flow rate of 400 CFM/ton of cooling capacity is an industry standard. The outside air percentage is based on ASHRAE 90.1 requirements for a 5,000 square foot space with 45 occupants (110 square feet per occupant).

Table 22. Location-specific inputs for the energy savings calculations.

	City				Notes
	Minneapolis	Madison	NYC	Fort Worth	
Rated heating input (btu/hr.)	120,000	115,000	75,000	65,000	from load modeling
Rated cooling capacity (tons)	6.0	6.3	6.2	7.4	from load modeling and field data
Cooling eff (EER)	10.2	10.2	10.2	10.2	Field data
Condensing fan power (Amps) 208 V, single phase	1.9	1.9	1.9	3.0	Field data
Supply fan power (Amps) 208V, three phase	5.5	5.5	5.5	7.0	Field data
Flow rate	2,400	2,520	2,480	2,960	400 CFM/ton
Min vent rate	22%	21%	21%	18%	ASHRAE 90.1 requirements

ASHRAE Ventilation Requirements

The ASHRAE Standard 62.1 has often been cited as a reason that the supply fan must run at full speed during all occupied hours.[32] However, this is not required by the standard; rather the supply of outside air must meet a minimum value that adds two values together, one proportional to the total area of the space (essentially a baseline minimum) and a variable term proportional to the number of occupants in the space. Section 62.1 states, "The design outdoor airflow required in the breathing zone of the occupiable space or spaces, V_{bz}" is determined by this equation:

$$V_{bz} = R_a A_z + R_p P_z$$

where:

R_p the "People Outdoor Air Rate," is the airflow rate per person, 5 cfm for office spaces,
P_z is the population of the zone,
R_a the "Area Outdoor Air Rate," is the required minimum for the building area, 0.06 cfm/ft^2 for offices, and

[32] ASHRAE. ANSI/ASHRAE Standard 62.1-2022, Ventilation and Acceptable Indoor Air Quality. Atlanta, GA, 2022.

A_z is the building area in square feet.

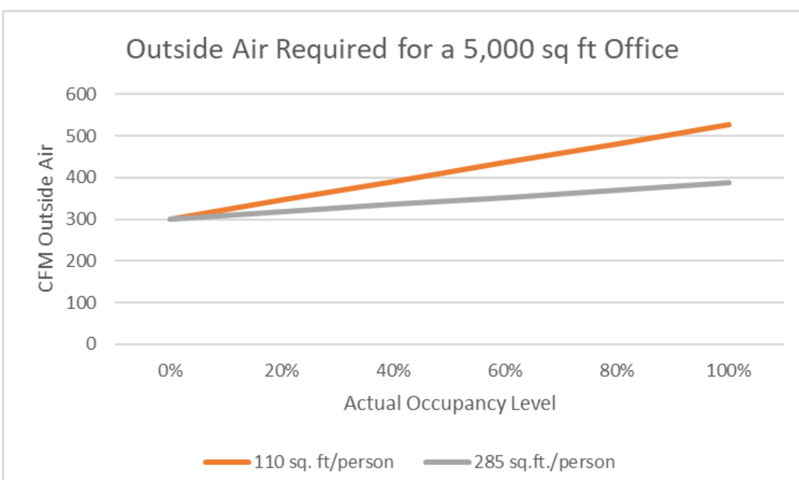
Table 23 shows the ventilation rate at full occupancy for a range of office densities (based on square feet per occupant).

Table 23. Full occupancy ventilation rates for various office densities

Square feet per worker	Building Area, Sq ft, A_z	Occupants (design), P_z	R_aA_z Area based cfm	R_pP_z Occupancy based cfm	V_{bz} Total cfm
100	5,000	50	300	250	550
150	5,000	33	300	167	467
200	5,000	25	300	125	425
250	5,000	20	300	100	400
300	5,000	17	300	83	383
350	5,000	14	300	71	371
400	5,000	13	300	63	363

This table illustrates the potential for saving energy with control of the fan operation based on actual occupancy, which our study found to be as small as 20% of the design. The offices we studied had an average of 112 ft.^{2} per person with a range from 73 to 170. In a previous study of 28 Minnesota office spaces we observed an average of 285 ft.^{2} per person. Figure 45 shows the ventilation required as a function of the actual space occupancy for two offices, one with 110 ft.^{2}/person (this study) and one with 285 ft.^{2}/person. While the larger area per person may be more representative of typical office spaces, this as-built value may be much less dense than the original building designs, which are reflected in the plans for the spaces in the current project. CBECS 2018 records an average of 507 ft.^{2} /person in office buildings overall, but that includes all spaces in the building (common areas such as lobbies, basements, etc., not just active office space).

Figure 45. Comparison of outside air requirements by space occupancy



Analysis of Energy Savings

The calculator was augmented to look at the impact of changing the supply fan run time, and thus ventilation, as occupancy varies. The ASHRAE ventilation requirements were incorporated by this, changing the *Occupied Hours* term in the equation for fan power to *Effective Occupied Hours*:

$$((\textit{Effective Occupied hours})+(\textit{Unoccupied hours}*(OAT - T_{Balance})/(T_{Design} - T_{Balance}))) * \textit{SF power}$$

where for each hour,

$$\textit{Effective Occupied hour} = R_aA_z + R_pP_z*(P_{z\ actual} / P_{z\ design})$$

The impact on heating and cooling is incorporated by adjusting the outside air supply, SA, from the fixed value specified under design conditions with the ventilation required for the actual number of occupants:

$$R_aA_z + R_p\, P_{z\ actual} * (RAT - OAT) * 1.085$$

where:

> *SA cfm * min OA%* is replaced by ($V_{bz} = R_aA_z + R_pP_{z\ actual}$) using observed population instead of design population, for P_z.

Section 6.2.5 of the ASHRAE standard addresses *Design for Varying Operating Conditions,* including specifying the time duration to use when occupancy fluctuates during the day with this relationship:

$$T(hrs)= 3 * (\text{volume of the zone in cu. ft.}) / (V_{bz}).$$

For this study, these times range from 3.5 hours for the “high density” office at design to 5.8 hours for the low-density office at 50% actual occupancy. For this analysis we used a constant occupancy rate for each day as short-term variations were observed over much shorter periods (often less than an hour), but daily averages were much more stable.

Table 24 shows the electrical energy savings, as a percentage of total annual energy use without the occupancy control, for the supply fan at each of the four locations. The occupancy percentages are based on the observations in this project; the 50% and 75% values are higher than any of our observations but are added assuming that the low levels observed were largely due to the impact of COVID-19 and reduced occupancy levels (although there are indications that offices may take many years to return to pre-COVID densities).

Table 24. Electrical energy savings based on occupancy-based supply fan operation

Actual Occupancy (vs. Design)	St Paul, MN	Madison, WI	Manhattan, NY	Ft. Worth, TX	Average and Standard Deviation
15%	25%	26%	27%	21%	25% ± 3%
21%	23%	25%	25%	20%	23% ± 2%
25%	22%	23%	24%	19%	22% ± 2%
50%	15%	16%	16%	13%	15% ± 2%
75%	8%	8%	8%	7%	8% ± 1%

Table 25 shows that smaller savings were also found for heating, due to the reduced volume of outside air requiring heating to the indoor setpoint temperature.

Table 25. Heating energy savings based on occupancy-based supply fan operation

Actual Occupancy (vs. Design)	St Paul, MN	Madison, WI	Manhattan, NY	Ft. Worth, TX	Average and Standard Deviation
15%	10%	11%	16%	18%	13% ± 4%
21%	9%	10%	15%	16%	13% ± 3%
25%	9%	9%	14%	16%	12% ± 3%
50%	6%	6%	9%	10%	8% ± 2%
75%	3%	3%	5%	5%	4% ± 1%

Negligible cooling savings were found (less than 1%).

Results from Modeling with Scout and EnergyPlus™

This section summarizes the modeling using DOE's tools that was performed in the first part of this project.[33] The report describes the results of a feasibility analysis of Wi-Fi LBS to provide the necessary information and accuracy to perform occupancy sensing for energy efficient building operation. Energy modeling was performed to define the necessary benchmarks that were then used for assessing the successful application of Wi-Fi LBS to building operations.

The Scout tool was used for estimating the energy and carbon impacts of various energy conservation measures (ECMs) on the U.S. residential and commercial building sectors[34] and

[33] "Energy Savings Analysis of the Use of Wi-Fi Location-Based Services (LBS) for Occupancy Sensing." Sui, Di, and Shen, Lester. DE-EE000008684 Deliverable 2.2.1 Energy Savings Analysis Report, January 2020.
[34] https://scout.energy.gov/

EnergyPlus™ whole building energy simulation program.[35] Scout was used to calculate the national energy savings potential and EnergyPlus™ simulations were performed to model the energy savings potential for specific reference building types.

Energy savings were calculated for each group of measures using the DOE reference building models[36] as the baselines. Current energy codes were used in the simulations. The energy savings were calculated using reference models based on ASHRAE 90.1-2016. To model the impact of each group of measures, the key simulation parameters were updated based on the level of controls. These parameters include: occupancy schedules, temperature control schedules, temperature setpoint schedules, ventilation schedules, fan schedules, lighting schedules and power densities, and plug load schedules.

The EnergyPlus simulations predicted total average savings for the five commercial building types (Small, Medium and Large Office Buildings, Primary and Secondary Schools) from 11% to 34% with an average savings of 21% for a total of 1.34 Quads when applied to all commercial buildings using Scout. The average savings by end use from the simulations are combined with the most recent CBECS data in Table 26 to estimate energy savings potential by end use.

Table 26. Potential Savings in Trillion Btu by End Use

End Use	LBS Savings	Office	All buildings
Space Heating	30%	98	650
Cooling	23%	19	135
Ventilation	15%	32	109
Water Heating			
Lighting	42%	55	298
Cooking			
Refrigeration			
Office Equipment	16%	2	8
Computing	16%	14	43
Other	9%	17	97
Total	**20%**	**236**	**1,341**

[35] https://energyplus.net/
[36] https://www.energy.gov/eere/buildings/commercial-reference-buildings

The reductions in carbon emissions associated with these savings are and carbon savings by fuel for office buildings and all commercial buildings. The annual emissions savings potential for all commercial buildings is 108 million metric tons of CO_2 shown in Table 27.

Table 27. Potential carbon dioxide emission reductions from LBS controls, Millions of metric tons by energy source[37]

Building Type	Electricity (Site)	Natural Gas	Fuel Oil	District Energy	Total Emissions Reduction
Office Buildings	15.8	3.9	0.3	0.1	20.0
All Buildings	74.4	25.7	6.8	0.6	107.5

Estimating Energy Savings Potential from Ventilation Control

As an alternative to the Energy Plus/Scout simulation approach, we also calculated the impact of broad implementation of occupancy-based control of ventilation based on the actual sites in this study to estimate the *Technical potential*. Technical potential represents, in theory, the maximum amount of energy use that could be displaced by an efficiency measure.[38] The most recent Commercial Buildings Energy Consumption Survey (EIA, 2018, CBECS) includes this information on office buildings in the U.S., as shown in Table 28.

Table 28. Average of selected energy end use for office buildings[39]

Building Activity	Total building space (millions of ft.^{2})	Total kBtu/ft.^{2}	Heating kBtu/ft.^{2}	Cooling kBtu/ft.^{2}	Ventilation kBtu/ft.^{2}	% Total Energy for Ventilation	% Electricity for Ventilation
Office	16,662	65.6	20.1	5.1	12.9	20%	28%
All Comm Buildings	96,423	71.6	25.0	7.0	8.0	11%	19%

Using these values with our findings, Table 29 shows the range of savings based on the technical potential. The conservative savings estimate shown in the table is based on half of all buildings implementing controls that average 75% occupancy and the rest making no change; the aggressive savings estimate is based on half of all buildings implementing controls that average 75% occupancy, one quarter implementing controls that average 50%, and one quarter implementing controls that average 25% occupancy.

[37] Portfolio Manager Greenhouse Gas Emissions August 2023, accessed February 22, 2024, portfoliomanager.energystar.gov/pdf/reference/Emissions.pdf

[38] Center for Energy and Environment, Optimal Energy, and Seventhwave. Minnesota Energy Efficiency Potential Study: 2020–2029. Minnesota Department of Commerce, Division of Energy Resources, 2018. https://mn.gov/commerce-stat/pdfs/mn-energy-efficiency-potential-study.pdf

[39] U.S. EIA CBECS webpage.https://www.eia.gov/consumption/commercial/pba/office.php

Table 29. Estimated energy savings based on technical potential

	Total EUI	Heating EUI	Ventilation EUI	% Total Savings	% Heating Savings	% Ventilation Savings
Conservative Scenario	64.7	19.7	12.4	1.4%	2.0%	4.0%
Aggressive Scenario	62.5	18.7	11.2	4.8%	7.0%	13.3%

These calculations assume that the supply fan operates at full power when it is on, while fans are now available with multiple operating speeds or fully modulating motors. These could produce even larger savings, but the controls would be more complex.

To estimate the energy savings for all buildings, a weighted average of square footage was used by principal building activity using the electricity consumption rates from CBECS Table E.5 with the relevant columns reproduced in Table 30. The PBA Savings Factor is an estimate of the savings potential of Wi-Fi Location Based Services in the building type. This is a rough approximation based on the expected occupancy level of the buildings, the stability/variability of occupancy over the occupied hours, the number of occupied hours per week (the only time savings will be realized) and the likelihood that building systems could use this control system.

Table 30. Electricity consumption (in kWh) by end use, 2018 (CBECS Table E5, Release date: December 2022)

	Total electricity consumption (billion kWh)					
	Total	**Space heating**	**Cooling**	**Ventilation**	**PBA Savings Factor**	**Vent kWh (billion)**
All buildings	1,196	70	170	213		168
Principal building activity					79%	
Education	128	7	26	19	50%	9.5
Food sales	54	2	2	4	50%	2.0
Food Service	61	4	7	7	75%	5.3
Healthcare	96	2	10	29		-
Inpatient	65	1	8	19	50%	9.5
Outpatient	31	1	2	10	75%	7.5

Lodging	100	7	12	25	75%	18.8
Mercantile	180	12	21	34		
Retail (other than mall)	71	3	9	18	100%	18
Enclosed and strip malls	109	9	12	16	100%	61
Office	227	13	23	63	100%	63
Public assembly	87	8	28	8	75%	6
Public order and safety	21	1	4	3	50%	1.5
Religious worship	27	2	6	5	100%	5
Service	45	3	7	5	50%	2.5
Warehouse and storage	95	6	15	7	25%	1.8
Other	70	2	8	5	25%	1.3
Vacant	5	(*)	1	(*)	0%	

With these values, the electrical savings are estimated in Table 31 for all buildings in GWh, and the CO_2 savings in millions of metric tons.[40] The median energy savings from ventilation controls alone is 16.7 TWh annually and 6.9 million metric tons of CO_2 emissions avoided, which is consistent with the simulation results using Scout and EnergyPlus for all end uses.

Table 31. Total Energy Savings and Emissions Reductions from Ventilation Controls

Building Activity	Controllable Ventilation Energy (TWh)	Low Savings (TWh)	Median Savings (TWh)	High Savings (TWh)	Low CO_2 Savings (megatonnes)	Median CO_2 Savings (megatonnes)	High CO_2 Savings (megatonnes)
All Commercial Buildings	168	7.8	16.7	26.1	3.2	6.9	10.8

[40] US Average emissions values published for 2022 by the EPA in eGRID, were 373.3 metric tons per GWh for all electric generation. Starting with 1,196 TWh of total electricity used in commercial buildings, and 213 TWh for ventilation, reducing to 79% for the likely penetration of the measure.

Appendix B – Links to Code

The software that was developed for this project is open-source and available free to the public via the GitHub platform. Table 32 lists the software packages with a description of each and the GitHub link where it can be downloaded.

Table 32. Open source software developed by this project

Software	Description	Link
Wi-Fi Location-Based Services (LBS) Calculation Demo	This project demonstrates a Wi-Fi Location-Based Services (LBS) system, providing a platform to visualize and calculate wireless signal-based location tracking within a defined area (like an office). It utilizes various technologies including JavaScript, Konva.js for canvas-based rendering, and jQuery for DOM manipulations.	https://github.com/DesignGarden/WiFi-LDA
YoloOcc VOLTTRON Agent	This project provides an Eclipse VOLTTRON™ Agent for determining occupancy count of a space using the YoloV8 Model and nVidia CUDA acceleration. The model will also run on CPU resources, but will be considerably slower. The application was tested on a Jetson Nano 8GB Developer Kit, where it delivered frame rates of 10–15 FPS, or 10–15 different camera feeds at 1 FPS. The camera interface was designed for Hikvision DS-2CD2185FWD-I 8MP cameras, but should work with any camera that supports a simple JPEG snapshot URL. The interface was also designed to be easily extensible for other authentication methods.	https://github.com/ACE-IoT-Solutions/volttron-yolo-occupancy