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Air quality metrics and wireless technology to maximize the energy efficiency of HVAC in a working auditorium

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ABSTRACT

HVAC is the single largest consumer of energy in commercial and residential buildings. Reducing its energy consumption without compromising occupants' comfort would have environmental and financial benefits. A wireless testbed consisting of a retrofitted wireless Condensation Particle Counter (CPC), 25 wireless temperature sensors, 2 HVAC-embedded temperature and CO_2 sensors, and a webcam was deployed in a working auditorium, to monitor the air quality, temperature, and occupancy of the room. The main objectives were to identify particle sources using the retrofitted CPC, map the temperature variability of the room and select an optimal sensor location for HVAC control using clustering algorithms, and examine possible energy savings by operating the HVAC only during periods of occupancy using calendar-based scheduling and air quality indicators as proxies of occupancy. All air quality metrics increased with higher occupancy rates, although HVAC-modes changes were also identified as a source for particle numbers. Operating the HVAC using calendar-based scheduling resulted in energy savings of between 8 and 79%, increasing if occupancy events were scheduled close together. Finally, CO_2 was the strongest predictor of occupancy counts with an R^2 of 0.62 ($p < 0.001$) during simple regression analysis. Incorporating particle numbers and temperature improved estimates of occupancy only slightly ($R^2 = 0.67$), however incorporating a particle metric may enable the general air quality to be monitored, and identify when filters should be replaced.

1. Introduction

In 2010, the US primary energy consumption was 98 Quadrillion Btu, representing 19.2% of the world's energy consumption, second only to China [1]. Of this, 41.1% was consumed by the building sector – almost half by commercial buildings; and there is no slowdown in sight [2]. A large proportion of this energy was used on heating, ventilation and air conditioning (HVAC) [3]. Any HVAC system must operate within certain constraints overseen by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers [4] which states that HVAC must 1) be capable of ventilating at a rate of 5×10^{-4} m^3/s for every 9.3 m^2 of occupiable space or 3.6×10^{-3} m^3/s per occupant, and 2) maintain CO_2 concentrations at no more than 700 ppm above outside concentrations, or at an indoor concentration of less than 1000 ppm. While indoor air standards are becoming ever more stringent, reducing HVAC energy consumption is increasingly sought. Therefore improving HVAC efficiency without compromising indoor air quality or occupancy comfort could resolve these seemingly contradictory goals resulting in large energy and financial savings, as well as significant reductions in CO_2 emissions.

Occupants play an important role in indoor air quality, not only as a source of indoor particulates, heat and CO_2, but also as the constraint whose wellbeing and happiness must be satisfied through effective HVAC control [5]. Many HVAC systems operate using a schedule-based approach: switching between off- and on-modes at predetermined times, and delivering airflow based on a full-capacity scenario [6]. By failing to differentiate between a room that is occupied or unoccupied, and by assuming full-capacity, energy wastage is inevitable. Frequently the focus of many studies is on an occupancy-based HVAC control, delivering fresh air only when the room is occupied. Predicting times of occupancy can

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be accomplished in several ways. Numerous studies have proposed various CO_2-based demand controlled ventilation systems, in which occupancy is assumed based on an indoor CO_2 concentration, and ventilation air provided accordingly [7,8]. Other studies have used room temperature or occupants' temperature preferences in order to determine airflow [6]. Some studies have advocated a multi-agent control system with different combinations of, for example, environmental (CO_2, temperature) data, occupancy counts, and energy data [6,9,10], while several studies have assessed different HVAC scenarios for providing localized airflow, both ventilation and heat, to isolated zones within a larger space [11,12]. Energy savings of between 23% and 66% have been reported in these studies. One study took a different approach and tried to minimize occupant exposure by altering HVAC function to use less outdoor air during times of poor outdoor air quality [13]. By measuring indoor and outdoor $PM_{2.5}$ simultaneously they were also able to calculate filter efficiency. Incorporating sensing technology, and more specifically wireless sensors, enables efficient delivery of multiple data streams with which to inform HVAC function [14,15].

However, the majority of these studies focus on simulation modeling, and although indoor air quality is considered [13,16], few studies compare actual air quality measurement data, for example real-time particulate or CO_2 concentrations, with real-time occupancy counts. Nor do they assess whether the temperature sensors used for HVAC control are optimally placed and representative of the entire space the HVAC is servicing. The overall objective of this study was to monitor the indoor air quality of a university auditorium, and assess the energy-savings potential of its HVAC system through the implementation of a dense wireless sensor network incorporating real-time environmental data, whilst maintaining a healthy and comfortable environment. The first objective was to investigate the air quality of the auditorium using a Condensation Particle Counter (CPC), retrofitted to wirelessly transmit continuous particle measurements that could be logged remotely. The sources and sinks of particles were examined. The second objective was to assess the thermal environment of the auditorium, through the installation of a dense wireless network of temperature sensors. The optimal number and location of sensors needed to represent the thermal distribution across the entire room was investigated, and the optimal sensor location with which to control the HVAC identified. The final objective was to assess the benefits of using 1) a calendar-based schedule, and 2) air quality indicators, including particulates and CO_2, to determine occupancy and thus pinpoint the times at which HVAC should operate in on-mode, resulting in significant energy savings.

2. Methods

2.1. Building description

The test building is located on the northeast corner of Washington University in St Louis' Danforth campus, approximately 100 m from the intersection of 2 major roads and roughly.

300 m from the beginning of Forest Park, a 5 km^2 urban park. It was constructed as part of the university's commitment to greener buildings and received its Leadership in Energy and Environmental Design (LEED) certification for a new construction version 2.2 Gold in 2010 (WUStL, 2010). It is insulated with recycled blue jeans, has a high-albedo roof and a low-energy lighting system, and was constructed using only low-volatile organic compound (VOC) materials to promote good indoor air quality; indeed subsequent testing demonstrated negligible VOC emissions. A hi-tech digital control system displays real-time energy and water consumption using a touchscreen dashboard that is mounted in the foyer, and a high-efficiency HVAC system promotes the thermal comfort of workers [17,18].

2.2. Auditorium and HVAC function

The building's basement auditorium was the testbed for the project. It is a windowless multifunction conference room hosting seminars, classes, meetings and other unofficial events. Measuring 11 m in length, 12 m in width at the front and 16 m at the back, and 4–6 m in height from back to front, it can hold approximately 90 occupants, and is equipped with a computer, 2 projectors and lighting systems. Outside air enters an air handler unit that is equipped with 2 deep, minimum efficiency reporting value (MERV) 10 pre-filters followed by final filters with an MERV rating of 14. Here the chiller cools the air to 12.8 °C (or the boiler heats it to this required temperature). Recirculated air is warmed and mixes with this cooled air to obtain the required supply air temperature. This is the Supply Airflow (SAF), and is controlled by 4 Variable Air Volume (VAV) devices; when the room temperature drops to 21.6–0.6 °C, the VAV dampers open allowing additional warm air to enter the room. Conversely, when the room temperature increases to 21.6 + 0.6 °C, the VAV dampers close. Two temperature sensors, utilized to inform control decisions in the HVAC system, mounted on the walls on either side at the front of the auditorium (the stars in Fig. 1) control these VAVs. Additional SAF is allocated to the auditorium when CO_2 concentrations exceed 700 ppm.

The HVAC is currently programmed to switch from off-mode (unoccupied) to on-mode (occupied) at 6:00AM, and back to off-mode at 9:00PM. This schedule is repeated daily, including the weekend. A maintenance person cleans the room between 5 and 6:30AM each weekday morning. The HVAC-embedded temperature and CO_2 as well as airflow data are recorded and stored on a local server for 72 h at resolutions between 10 and 30 min before being stored permanently on a server external to the university. The HVAC data was downloaded every 24 h by logging into this server.

2.3. Experimental design

Measurements were collected between January 29th and April 29th, 2013. A wireless testbed consisting of a reconfigured wireless Condensation Particle Counter (CPC 3022A, TSI Inc, St Paul, MN), 39 wireless temperature sensors, and a webcam were deployed in the

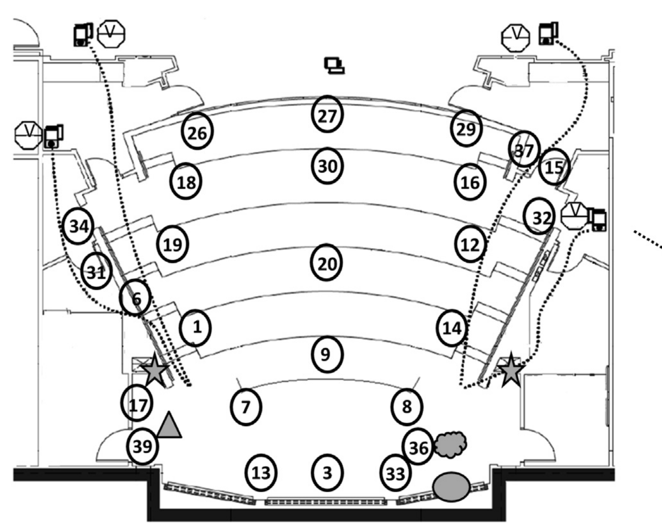

Fig. 1. A map of the auditorium depicting temperature sensor locations, CO_2 and thermostat sensors, wireless CPC, speaker podium and webcam.

auditorium to monitor the air quality, temperature, and occupancy of the room. This was in addition to the two HVAC-embedded CO_2 and temperature sensors that were used to inform HVAC operation, as well as airflow data that was collected every 15 min. Together, a comprehensive profile of the air quality and thermal variability of the auditorium was assessed. Fig. 1 presents a schematic of the auditorium highlighting the location of the HVAC VAVs, temperature sensors, CPC and seating arrangements. The following paragraphs present further information regarding each of the instruments deployed in the auditorium.

2.3.1. Particle counts

A CPC 3022A counts airborne particle numbers with a diameter between 0.07 and 3 μm, at concentrations up to 9.99×10^6 cm^{-3} (with an accuracy of ±10% for concentrations up to 5×10^5 cm^{-3}), using butanol and photometric technology. For this project the CPC was retrofitted, using its RS-232 connection, with a connectBlue OBS-421 classic Bluetooth RS-232 cable replacement device. In addition to the wire replacement, some reverse engineering of the CPC's protocol to extract and record the data into a correlated format with the temperature readings (described in the next section) was performed, which is more useful and easier to work with than attempting to combine the data after the fact. Data were transmitted wirelessly, and detected and recorded using packet sniffing software on a base station computer equipped with a similar Bluetooth device for the connection to the laptop RS-232 port, and located under the speaker podium at the front of the room. This computer logged and correlated the data and uploaded it to a cloud server thus ensuring continuous collection and long-term storage of data with increased ease and security, as well as off-site accessibility from any shared computer. Particle data were collected every 20 s. To ensure that any instrument error would be immediately detected, the software was configured to send an error warning to a predetermined email address so that any issues could be promptly resolved. It would be possible to collect data from multiple wireless CPCs using just one bay station.

2.3.2. Temperature sensor network

Thirty-nine wireless temperature sensors - White-Rodgers F145RF-1600, manufactured by Emerson, were repurposed for distributed monitoring and positioned along the walls, desks and podium of the auditorium at different heights (0.5–3 m), in order to capture real-time fine-grained spatiotemporal dynamics of the room. These sensors communicate using Bluetooth™ v2.1 EDR. Each sensor required modifications to the firmware in order to remove the limit on the number of supported sensors that could be connected to the system (4), and to enable the passing of sensor ID to the base station. Although the address of each sensor is known, the header that is transmitted to the receiver with this information was stripped at the hardware level prior to being passed to the base station. These sensors have an accuracy of ±0.5 °C. When they detected a temperature change greater than 0.1 °C, the new temperature value was transmitted to the base station, which was then sent to a database in the cloud. In the event that no temperature change occurred, a response was sent every half hour, to assure the host that the sensor was still operational. All of the temperature sensors were battery-operated enabling them to be placed throughout the room at minimum cost. This temperature network was in addition to the two HVAC-embedded temperature thermostats currently used to inform HVAC operation. Although 39 wireless sensors were deployed in the auditorium, only those sensors installed on desks and on walls near to the ground, and displaying stable measurements (25 sensors) were included in this analysis since they best represented occupancy comfort. Those sensors installed on the upper walls and ceilings will be analyzed in future work to generate a more comprehensive temperature distribution profile of the auditorium.

2.3.3. Occupancy detection

A Wi-Fi enabled webcam (DCS-2132L) manufactured by D-Link, was deployed at the front of the auditorium to monitor occupancy at a rate of 1 image every 15 min. The optimal location for the webcam was decided by installing it in multiple locations and comparing the seats captured. The location finally decided upon was able to capture the most relevant seating: the auditorium tended to fill up on the right-hand side first (the side where the speaker stood), in the middle and back. The front tended to fill-up more slowly, especially the very front seats and the ones on the left. More often than not the auditorium was not filled to full-capacity and therefore many of the front and left-hand seats would go unoccupied.

From its optimal location, the camera was able to capture over 90% of the seating capacity of the auditorium. These images were then sent to the backend server over a campus-wide Wi-Fi network. The number and location of occupants were counted offline by visual inspection of the images. When an image contained many occupants it was printed out and a head count was performed by manually checking-off each occupant with a pen. The process was made easier by the date and time stamp included on each image, which allowed the counts to be easily cross-checked. The random cross-checking that was subsequently performed ensures that the final occupancy counts are presented with confidence.

2.4. Data analysis

All data were checked for accuracy prior to analysis for quality control purposes. A glitch in the system caused some of the automated airflow and CO_2 data to output replicated data which had to be removed, and instrument error meant that 5 days of particle data were lost. The temperature sensors collected 3 measurements at a time, for validity purposes. If any of these temperatures deviated too far from the average of the 3 they were rejected and the measurement cycle repeated. If too many were rejected, the sensor would send a failure message indicating transducer failure. Thus any malfunctioning sensors were identified and removed from the network. Of the retained temperature sensors 7 days were lost due to system error.

The webcam was able to capture more than 90% of the occupancy of the auditorium, and therefore a slight underestimation of occupants is possible. Each variable was recorded at different temporal resolutions; data was therefore converted to hourly averages, the lowest common denominator. All but 2 instances of occupancy occurred during the weekday. For this reason analysis and reported results pertain only to weekday data. The final dataset used in this study consisted of 25 temperature sensors, 2 HVAC-embedded temperature and CO_2 sensors, 1 wireless CPC and 1 webcam. Several matrices were generated using the retained weekday data for further analysis. All analysis and graphics were performed using R (version 2.11.0, R Foundation for Statistical Computing), MATLAB (version 7.10 R2010a, The MathWorks, Inc.), and SigmaPlot (version 11.0, Systat Software, Inc.).

3. Results and discussion

3.1. General description

The mean outdoor temperature during the measurement period was 6.5 °C, and ranged from −6.5–29.2 °C. Mean airflow into the auditorium from the HVAC system was approximately 0.118 m^3/s (off-mode) to 1.180 m^3/s (on-mode), increasing to more than 1.89 m^3/s with high occupancy numbers. Out of almost 3 months of data (2046 h), the room was occupied for just 304 h, approximately 14.8% of the time. When only the on-mode is considered, this increases to 20%. It is also important to note that while occupancy levels ranged from 0 to 82 persons, just under the full capacity of the auditorium, 36% of the time that it was occupied, this was by only one person, predominantly a maintenance or cleaning crew member, and 62% of the time it was occupied by fewer than 10 people. Mean CO_2 concentrations were approximately 456 ppm (SD 36), while particle numbers and temperature (HVAC-embedded sensor) were approximately 1110 cm^{-3} (SD 2093) and 20.5 °C (SD 0.74) respectively. These concentrations tended to increase with higher occupancy rates, although for particle numbers the relationship was more complicated.

3.2. *Particle number concentrations*

Particulate matter is an important ambient air quality indicator for which legally-binding standards exist [19]. Indoor particulate matter comprises primary particles that have infiltrated from the outdoors, primary particles generated from indoor sources, and secondary particles generated from precursors emitted both indoors and outdoors [20]. The influence of ambient outdoor aerosols on the indoor environment depends on a particle's ability to penetrate a building, and its fate once inside. The Infiltration Factor is defined as the equilibrium fraction of ambient particles that penetrate indoors and remain suspended [21], and depends on the ambient outdoor concentration, the strength of indoor sources, structural characteristics of the building and building condition (presence of gaps, cracks), air exchange rates, indoor flow patterns, types of ventilation, the position and size of inlet and outlet vents, the presence of windows and double-glazing, construction materials of the walls, the characteristics of the wind system operating around the house, and the penetration coefficient of the particle [21–24]. A particle's composition dictates how far it is transported away from source and how readily it can penetrate into a building: those comprised of volatile species will experience reduced infiltration due to volatilization, while particles comprised predominantly of elemental carbon will infiltrate more readily [25]. Indoor/outdoor studies have demonstrated reduced penetration rates for the smallest (<100 nm) and largest (>1000 nm) particles [21,24]. Once inside, attenuation, deposition and resuspension become dominant processes [26]. The rate of attenuation and deposition depends on the presence of air filtration systems, the size, quantity and nature of interior furnishings, surface space, cleaning activities, and the type of floor material, for example carpet or linoleum [27,28]. Conversely, resuspension is caused by the presence of people, and cleaning activities such as sweeping and vacuuming, or the use of fans [26].

A CPC was successfully configured to wirelessly transmit continuous particle number data to a base station located on the other side of the auditorium. This data was used to assess the aerosol environment within the auditorium – identifying any particle number trends and possible sources and sinks. In order to ascertain these trends it is important to understand whether outdoor particle concentrations may be influencing indoor concentrations. This was achieved by comparing nitrogen oxides (NO_X) concentrations measured at a fixed site monitor (FSM) located 4.8 km away in Forest Park and operated by the United States Environmental Protection Agency (USEPA). The correlation between NO_X and particle numbers, especially ultrafine particles (UFP) (particles with an aerodynamic diameter below 0.1 μm), is well established, and is often stronger than the correlation between UFP and other particle metrics. This is particularly true within urban areas, due to their shared source: vehicle exhaust emissions [29–32].

Fig. 2 compares hourly averages for the 3 months of particle number data, outdoor NO_X concentrations from the same time period, and occupancy counts. A decrease in particle number concentrations can be observed from late night/early hours of the morning until around 6:00AM where a steady increase until 8:00AM is noted. This increase in concentrations somewhat coincide, with some time delay, with an increase in outdoor NO_X concentrations which begin to increase at approximately 4:00AM, peaking around 7:00AM, indicative of morning rush hour. However, the peak also directly coincides with the HVAC switching from off- to on-mode at 6:00AM. It is around this time that the auditorium also receives its daily cleaning. The 2 principal peaks in particle number counts occur at 11:00AM and 3:00PM, which corresponds with the most common times for well-attended classes and seminars, demonstrated by the corresponding occupancy data. Particle numbers continue to decline during the late afternoon and evening until around 9:00PM when they begin to increase again. Despite the slight increase in NO_X concentrations around this time, it is unlikely to have caused the peaks observed indoors. This is however, also the time when the HVAC switches from on-to off-mode. The hourly data indicates that the principal sources/activities influencing particle numbers are occupancy, or activities occurring during occupancy, and HVAC mode change. The auditorium appears to be by and large unaffected by outside influences. To confirm this, Pearson's product correlation was performed for hourly particle number and NO_X data. This was performed multiple times for different time lags (real-time, 1-, 2-, and 3-h delays). No statistical correlation was observed. Similar analysis was conducted between UFP and outdoor ambient temperature. Again no statistical correlation was observed.

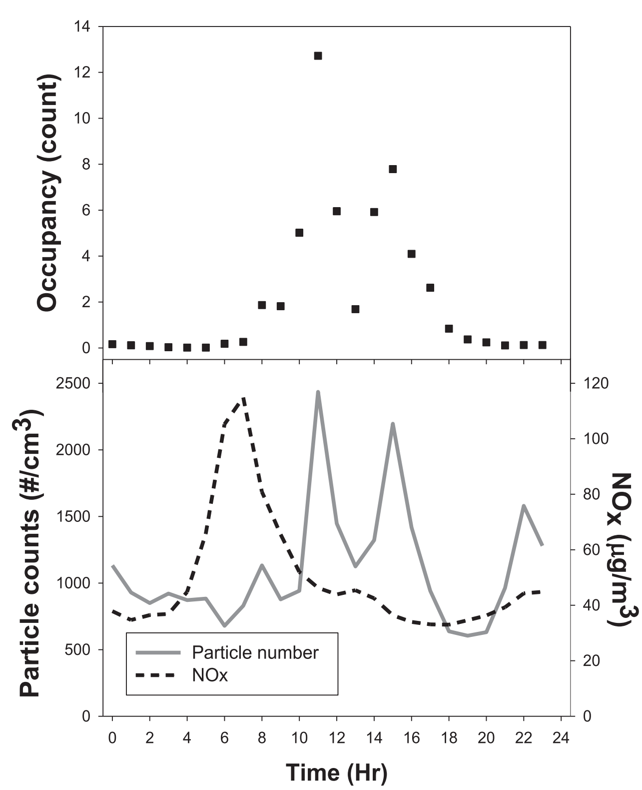

Fig. 2. Weekday hourly average occupancy counts (top), particle number and NO_X concentrations (secondary axis) (bottom).

Fig. 3 presents a time-series depicting particle number counts, occupancy and airflow in the auditorium during a typical work-week. The highest concentrations of particles occurred during high occupancy events: concentrations as high as 27,000 cm^{-3} and 12,500 cm^{-3} were observed for seminars with 39 and 42 occupants respectively. In fact the highest observed particle number counts of 39,781 cm^{-3} occurred during a high-occupancy (68) seminar (data not shown). A projector, located by Sensor 27 in Fig. 1, operated whenever the room was occupied, and the lights were always on; the main doors were also closed. A CPC 3007 (TSI Inc.) was used to identify any particle hotspots within the unoccupied auditorium. The projector and lights were switched on and multiple continuous measurements were collected. Mean concentrations were approximately 579 cm^{-3} (SD 21.8 cm^{-3}) and 535 cm^{-3} (SD 20.1 cm^{-3}) at the front and back of the auditorium, respectively. Further measurements were made 90 min later, thus allowing the projector to warm up, at different locations in the room and by the projector. Mean concentrations next to the projector increased slightly to 712 cm^{-3} (SD 76.1 cm^{-3}); similar concentrations were measured around the room. Next, the 2 main doors of the room were closed and further measurements were collected 30 min later. Mean concentrations increased to 895 cm^{-3} (SD 34.6 cm^{-3}) (by the projector) to 916 cm^{-3} (SD 25.5 cm^{-3}) (at the front of the room where the CPC 3022A had been positioned). While a slight increase in particle concentrations was observed when the projector was operating, concentrations did not increase to the levels observed during times of occupancy. A slight increase in particles was also observed when the main doors were closed. This is likely due to the reduced airflow into and out of the room. Again, the projector does not seem the likely source of such high levels of particles observed during occupancy. Another activity that frequently occurred whilst the auditorium was occupied was the consumption of food and drink, both hot and cold. Pizza and coffee was served on occasion, but by no means every time. Hot food has been identified as a source of particles [33,34]; however most studies focus on the particles generated during the cooking process and few have reported particle concentrations from standing cooked food. To summarize: increased particle counts occurred under high-occupancy events, either from the occupants themselves or their activities, and when the HVAC switched between modes; routine maintenance and cleaning of the room may have been another potential source. No other sources from nearby rooms were observed.

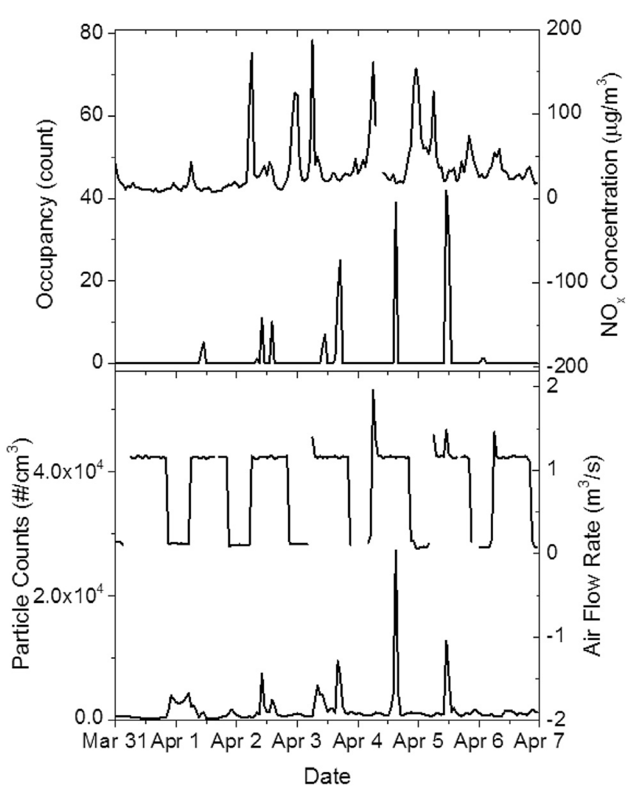

Fig. 3. Time-series of particle number counts (cm^{-3}) and airflow (m^3/s) (bottom) and occupancy (counts) and NO_X (μgm^{-3}) (top). Particle number counts coincide with the following events: 1) the HVAC switching to off-mode; 2) a class of 5 people; 3) HVAC switching to off-mode; 4) a class of 10 people; 5) a class of 9 people; 6) the HVAC switching to on-mode; 7) a seminar of 25 people with pizza; 8) a seminar of 39 people; 9) a seminar of 42 people; 10) HVAC switching to off-mode; 11) HVAC switching to on-mode. The missing data points observed for NO_X and airflow are due to instrument failure.

While outdoor conditions are indeed important for naturally-ventilated buildings, the auditorium is a windowless subterranean room recently constructed using modern materials. The room, as well as the building, is mechanically ventilated using a modern HVAC system equipped with 2 sets of high-efficiency filters (MERV ratings 10 and 14). The higher the MERV rating, the more efficient these filters are at preventing particle filtration, and efficiencies have been reported by Orch et al. [35] for particles between 0.001 and 10 µm in size. Given these characteristics, it is not surprising that the results of this study indicated minimal outside interference. This finding is also supported by Wang et al. [36] who state that outdoor particle concentrations should not be used to approximate indoor concentrations for commercial buildings equipped with HVAC. However, spikes in particle concentrations frequently coincided with times the HVAC switched between modes. Studies have reported various HVAC components as successful particle deposition sites due to impaction and gravitational settling, for example on the heat exchangers [37], on the ceiling, walls and floor of ducts [38,39], on the filters [40], and as a surface for microbial deposition and growth [39,41]. Although HVAC is successful at removing particles from the outdoor air, especially with the installation of high-efficiency filters [42], Jeong et al. [38] determined that a large fraction of inhalable particles may enter a building room if the HVAC system is of moderate length with few fittings. Their study also demonstrated that particles that have deposited in the HVAC system, but have low adhesion, may be resuspended during the initiation of airflow, for example when an HVAC system switches from off-to on-mode, and that the degree of resuspension depends on the particle surface loading. Bonetta et al. [41] attributed the daily spike in indoor fungal and bacterial counts to the HVAC system switching between modes. They speculated that microorganisms proliferate on the filter and in the ducts during nighttime off-mode then enter the room air as airflow increases. This may explain the 6:00AM spikes observed in this study, when the HVAC switched to on-mode. Another spike in particle concentrations was frequently observed when the HVAC switched to off-mode. Although fewer studies have examined this, it is plausible that as the HVAC enters off-mode and exfiltration slows, particles are no longer being removed and so increased concentrations are detected by the CPC. In addition to the HVAC system, other particle sources included certain chemicals and paints, hot food, cleaning (both from the product used and the actual physical activity), and people/occupants. In fact, people are important in terms of both generating particles, for example bioaerosols [41], and resuspending them, from mechanical and thermal disturbances [16]. Secondary organic aerosol (SOA) formation, including UFP, can occur when condensing ozone-reactive chemicals, emitted by indoor furnishings, building materials and even people, either nucleate or partition onto already-present particles [43]. HVAC can influence SOA formation by modifying ventilation rates and thus the concentration of pre-existing particles within the room; the temperature of the room, the HVAC filter efficiency and whether the filter removes ozone also influence SOA formation [44].

3.3. Temperature variability

This section assesses the thermal environment of the auditorium. Two HVAC-embedded thermostats located on either side at the front of the auditorium are used to control the temperature of the auditorium by controlling the HVAC SAF. However, this limited number of sensors may not adequately capture temperature variation, which in a large open space like the auditorium, may be significant. Data traces from these thermostats as well as from 25 wireless temperature sensors deployed around the room were analyzed and mapped, so that the temperature variability could be assessed and the optimal number and location of sensors needed to represent the thermal distribution across the entire room could be identified. Mean temperature concentrations recorded by the HVAC-embedded thermostats differed depending on whether the HVAC was operating under on- or off-mode, and whether it was occupied or not. When the room was not being occupied, mean temperatures were 21.2 °C (SD 1.12) and 20.1 °C (SD 0.53) for off- and on-modes respectively. Temperatures increased with higher occupancy and are discussed later. Fig. 4 depicts the thermal profile of the auditorium when occupied by 60 persons during a typical workday. A significant variation of approximately 2 °C can be observed between the warmest (Sensor 27) and coolest (HVAC thermostats, Sensors 40 and 41) locations. This indicates that the HVAC-embedded sensors do not effectively represent the temperature distribution across the whole auditorium, and a more representative sensor could be selected to inform HVAC control. While a dense wireless network provides a more comprehensive thermal profile of the room, it is also expensive to deploy and maintain. However, accurately grouping the sensors and selecting just one strategically placed sensor from each group should adequately represent the thermal profile of the auditorium and permit better HVAC control without the expense of a dense network.

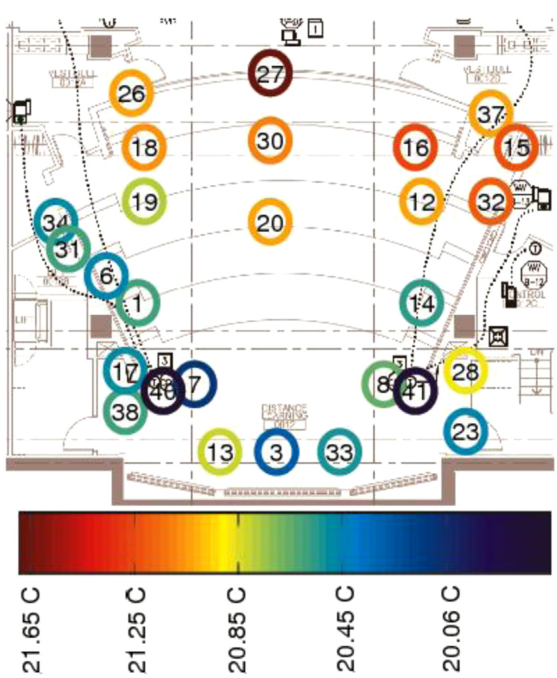

Fig. 4. Measured temperature by wireless sensors and thermostats (Sensors 40 and 41) during a typical workweek when the auditorium was occupied by 59 individuals. The color bar (below) indicates the corresponding temperature of each sensor. Data was averaged for the entire hour that the seminar ran.

3.4. Clustering

In order to determine which sensor(s) best represent(s) the spatial distribution of the auditorium a clustering approach is proposed in which sensors are categorized according to either shared temperatures, or shared temperature trends. Spectral clustering was chosen to perform this analysis. Compared to other clustering algorithms such as k-means or single linkage, spectral clustering – the details of which can be found in Luxburg et al. [45], can derive higher quality results and more importantly, be implemented and solved more efficiently using standard linear algebra computation. The first method, Euclidean distance, is a value-based approach in which 'closer' sensors are grouped together in a cluster, although no specific temperature range is defined per cluster. The second approach, Correlation, plots the temperature trends of each sensor, and groups them into clusters according to the degree of correlation in each trend (−1 to 1). If the correlation is 0, then there is no correlation between sensor trends. The user can choose to define the number of clusters, or not. The more clusters generated, the smaller the temperature range within each cluster, and the smaller the temperature differences between clusters, but the more sensors will be needed to represent the temperature profile. After the clusters have been defined, the temperature range and differences can be measured. Once the sensors have been assigned to clusters, one sensor (or however many sensors per cluster is desired) is selected. This selection can be made either randomly, or by selecting the sensor that is closest to the mean of the cluster. Further description of these clustering algorithms can be found in Fu et al. [46].

Data used to generate the clusters were collected when the HVAC was in on-mode and the auditorium occupied. The dataset was split into two halves. The first half was used to generate the clusters, while the second half was used to validate the robustness of the methodology. The clustering results from the spectral clustering algorithms based on Euclidean distance and Correlation are shown in Fig. 5. Three clusters are derived from the Euclidean-based clustering algorithm and two clusters from the Correlation-based algorithm. The results from Euclidean-based clustering indicate that the majority of sensors with low average temperatures are located at the front of the auditorium, Cluster 1, while those with high temperatures are located at the back of the auditorium, Cluster 2. The sensors in Cluster 3 did not exhibit any consistent geographical patterns, making it harder to determine the thermal distribution of the auditorium. For the correlation-based clustering, the sensors can be classified into two distinct groups. Similar to the results of Euclidean-based clustering, Cluster 2 consists of sensors located at the front of the auditorium (lower average temperature) while Cluster 1 comprises sensors at the back of the auditorium (higher average temperature). While the location of Sensor 1 is geographically closer to Cluster 2, it actually belongs to Cluster 1. This may be because Sensor 1 is located next to a corridor and thus affected by unstable airflow patterns from human movements and walls. Of the two different approaches, Correlation-based clustering proved to be the most robust.

In the second stage of analysis, the data were re-analyzed this time incorporating the HVAC-embedded sensors. Both thermostats were assigned to Cluster 2 indicating that: 1) only one is necessary and the other can be removed, and 2) the thermostats may not adequately measure the thermal environment of the auditorium. Both thermostats remain assigned to Cluster 2 until $k = 5$. It is important to note that in this case, the temperature differences are

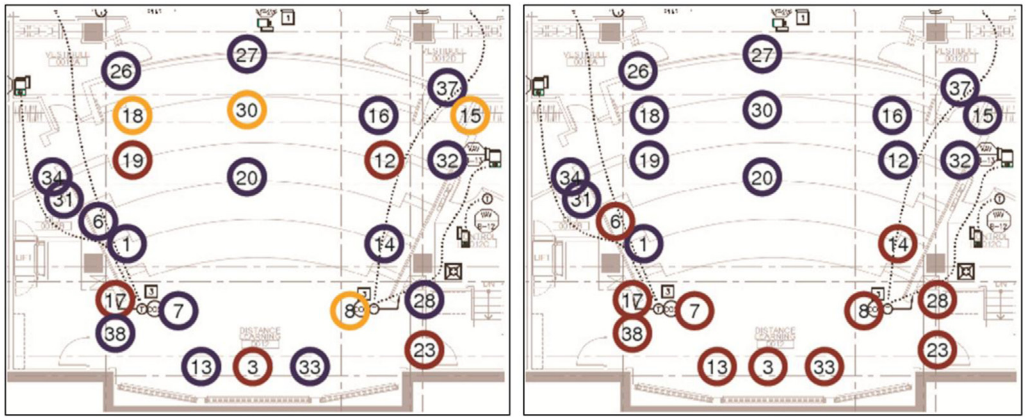

Fig. 5. Clustering sensors based on Euclidean distance (left) and Correlation (right). Circles indicate the location of sensors while the colors represent clusters.

small (<1 °C). This may be because all occupancy scenarios were analyzed together and larger differences may be apparent if the different occupancies were analyzed separately. At any rate the methodology outlined here may be useful when applied to other scenarios.

These results raise several issues: firstly, when occupied, air in the auditorium is warmer at the back than at the front. This implies that the HVAC may be cooling the front of the auditorium more effectively than the back, and hence that HVAC may not be distributing the air efficiently. However, other factors could be causing this disparity. For example, the data used to generate the clusters included all levels of occupancy. When occupancy was low to moderate, the back of the room tended to fill up before the front, therefore localized warming could have been occurring. However, the initial temperature variability data presented in Fig. 4, when the auditorium was fully occupied (+60), showed warmer temperatures toward the back of the room. This could be explained by the projector, which emitted a significant amount of heat and will influence some of the surrounding sensors, for example Sensor 27 in Fig. 4. Lights were another source of heat, and while they were evenly distributed throughout the room, the distance between the ceiling lights and the sensors decrease towards the back of the room as the floor slopes upwards. In fact, the distance between the ceiling lights and the sensors (located on the desks) at the very back of the room is approximately 3 m compared to 5 m at the front of the room. This is compounded by the fact that heat rises and the sensors at the back of the room are 1 m higher than those at the front. The front of the room is next to an external wall and may have been impacted more by the winter temperatures, whereas the back of the room faces an internal corridor. All of these factors may explain the temperature disparity. Finally, the question arises of whose comfort should be prioritized. The speaker stands at the podium at the front of the auditorium, close to the HVAC-embedded thermostats. If the speaker's comfort is the objective, then the current setup may be optimal as it prioritizes their comfort. And the fact that the room is cooler at the front may benefit the speaker, who will be more animated than the other occupants, likely moving around and gesturing, and thus more likely to enjoy a cooler room. However, the majority of people in the room would be better represented by an alternative sensor location. As Salma et al. [16] state, comfort is important for the students so that they can concentrate on the lectures.

To summarize, sensor location is important for reliably informing HVAC operation. Some locations for sensor placement may be better than others, depending on whose comfort is prioritized. Although in this particular case the variability between different temperature sensors was low, the same methodology may be applied to other buildings/rooms, perhaps with more of an impact.

3.5. Predicting occupancy times

The current static operation protocol for the HVAC is on-mode daily 6:00AM to 9:00PM. Although this set-up can maintain indoor temperature set points and CO_2 levels effectively, it does not consider the dynamic occupancy patterns of the auditorium, nor the fact that the auditorium is largely unoccupied during the weekend. Using a simple energy balance expression, the energy consumed per unit time by HVAC during both on- and off-mode can be calculated by equating it to the cooling/heating load:

$$\dot{E} = \rho \cdot Q \cdot C_p \cdot \Delta T = 1.206 \cdot Q \cdot \Delta T \tag{1}$$

where $\dot{E}$ is the energy consumed (kW), ρ is the density of air (kg/m^3), C_p is the specific heat at constant pressure (KJ/kg K), Q is the volumetric flow rate of air (m^3/s), ΔT is T_1 (the air temperature entering the auditorium in °C) − T_0 (the air temperature entering the Air Handler Unit in °C); the product of = $\rho \cdot C_p$ is approximately 1.206 for normal pressure and temperature (1 atm, 25 °C).

When the auditorium was occupied with approximately 25 people, the average energy consumption over one hour was 7.36 kWh compared to 1.81 kWh when it was empty. Therefore instead of time-based scheduling, a more focused protocol in which HVAC operates only during times of occupancy would result in significant energy and financial savings. In Missouri, the price of commercial electricity at the end of 2013 was 0.103USD/kWh. The fact that 80% of its production came from coal [2], further highlights the importance of energy efficiency for environmental reasons.

3.5.1. Calendar-based HVAC control

In this section a calendar-based HVAC control is proposed and the projected energy use is calculated based on occupancy (scheduled classes). The difference between these estimated values and the actual energy used under current HVAC operation was then calculated to determine savings.

Reservations to use the auditorium are required via a central calendar. Between January 31st, and April 13th 2013, 46 reservations were made. For quality control purposes, the start and end times of these 46 scheduled events were compared with the corresponding images captured by the webcam. The room was correctly reserved 98% of the time, thus the calendar can be used to reliably predict occupancy times. An important part of calendar-

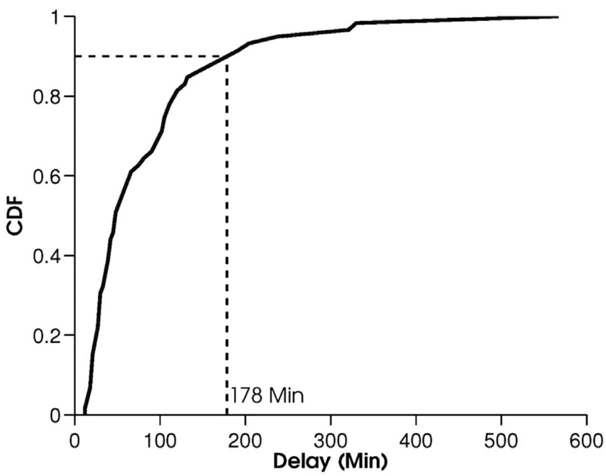

Fig. 6. A cumulative density function depicting the time it takes for temperatures to stabilize in the comfort zone.

based HVAC scheduling is understanding the time required to precondition, i.e. turn-on the HVAC so that the room is at a comfortable temperature before individuals enter. If HVAC starts preconditioning too early, energy may be wasted providing thermal comfort to an empty room. Conversely, if preconditioning begins too late occupants may experience discomfort, which compromises the basic objective of the HVAC system. In order to ascertain an appropriate way of manipulating the HVAC between modes, a preconditioning time of (*tp*) was identified from data recorded by the HVAC-embedded thermostats, so that the HVAC would operate *tp* prior to auditorium occupancy. The preconditioning time was defined as the time it takes for temperatures to stabilize in the comfort range 21 $\pm$ 1 °C. When the HVAC switched to on-mode at 6:00AM, the temperature in the auditorium fluctuated in and out of this comfort range. Using the daily temperature dataset, the time it took for the temperature to reach the occupancy comfort range and remain there without variation was recorded. The results are presented as a distribution in Fig. 6, demonstrating that 90% of the time it takes 178 min for the temperature to stabilize in the occupancy comfort range. Therefore the HVAC should switch to on-mode approximately 178 min prior to an event.

The next consideration was when to return the HVAC to off-mode. The most efficient route is selecting the end time of the event, providing the interval before the next scheduled event is longer that *tp*. The calendar-based scheduling of HVAC includes the following energy saving rules:

1) The HVAC should switch to on-mode at *tp* prior to the occupancy event.
2) The HVAC should switch to off-mode immediately after the event. If multiple events are scheduled, apply Rule 3.
3) The HVAC should only remain in on-mode if the interval between events is shorter than *tp* to avoid oscillation (the frequent switching between modes).
4) The HVAC should be set to off-mode during the weekend, unless an event is scheduled.

Potential energy savings were calculated using data that had been collected between February 10th and February 17th, representing a typical working week in the auditorium. Actual energy usage during that week was compared to what the energy usage would be if these energy saving rules were implemented. Seven events occurred between Monday and Friday, and occupancies ranged from approximately 10 to 70 people. By applying Rules 1) and 2), HVAC turns on at *tp* (178 min) before the event to precondition the auditorium and turns off immediately after the event. On Friday there were two events separated by a time interval of 150 min, which is shorter than *tp*. Thus Rule 3) is applied and the HVAC remains on for the 150 min between the two events. Rule 4) is applied for the weekend, and the HVAC is switched off completely. Fig. 7 presents the energy saved when each of these rules are applied. Employing Rule 1 produced an 8% reduction in energy consumption; Rule 2 and a 37% reduction was observed. No energy savings were garnered by applying Rule 3, as the HVAC operated as it would in its current operation. Rule 4 saved 34% of energy and would be easily implemented. If all rules were applied, the total energy savings would be 79%.

Most events in the auditorium finished before 4:00PM, after which, according to Rule 2), the HVAC may return to off-mode, 5 h earlier than the current protocol. Increased energy savings can be made by scheduling events close together. That way the HVAC can remain in on-mode for a shorter total period of time and expending energy to precondition is limited. If the calendar is consistent throughout the weeks, an algorithm may be written so that HVAC operation becomes automated and limited additional man-power is needed. In Missouri, more than 80% of the electricity generated comes from coal, a reliance that has been increasing over the years [1]. Hence reducing HVAC energy consumption can directly reduce CO_2 emissions.

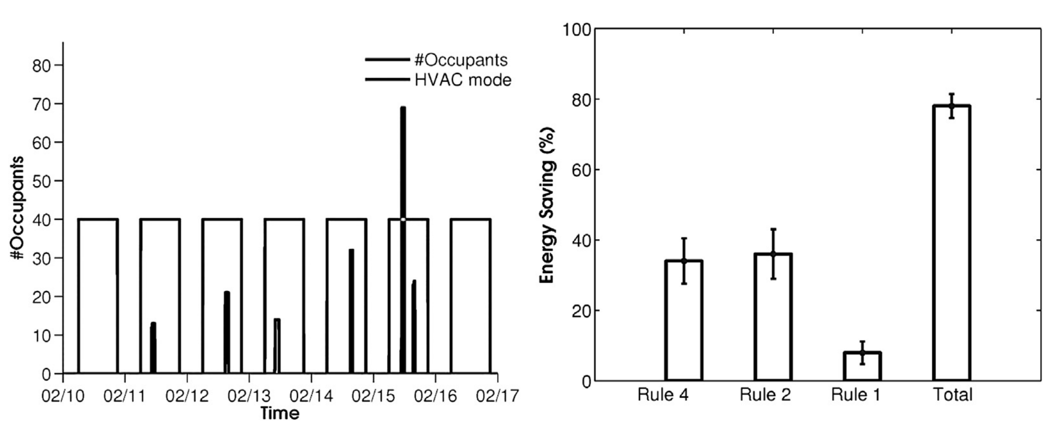

Fig. 7. Comparing the on-mode operation of the HVAC for the current scenario with that of calendar-based scheduling (left); the columns represent the times during which the HVAC is operating in on-mode. (Right): the energy savings garnered by implementing each of the energy saving rules. The columns depict the mean energy savings across the week, and the error bars represent the variation between these days.

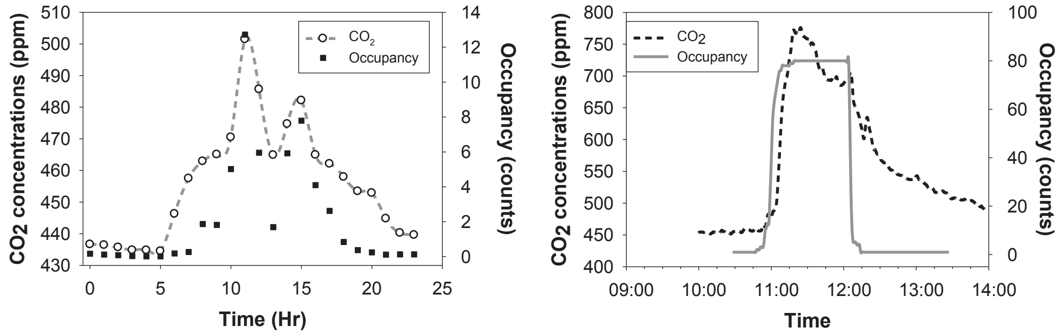

Fig. 8. Weekday hourly average CO_2 concentrations and occupancy counts (secondary axis) (left); and one-minute CO_2 concentrations and occupancy counts (right). Occupancy counts include times when the auditorium was not occupied.

3.5.2. Proxies of occupancy

The previous section demonstrated how calendar-based HVAC control could significantly reduce energy consumption, and a weekly energy savings of up to 79% was calculated using the projected energy usage that would result if the HVAC operated only during occupancy and according to the energy saving rules. However, pre-scheduling HVAC operation based on an occupancy calendar is somewhat cumbersome and does not incorporate impromptu or unscheduled events. This section will assess 1) the reliability of the current setup, in which CO_2 and temperature are used as both indicators of air quality and proxies of occupancy to inform HVAC when additional SAF is needed, and 2) whether incorporating a newly selected temperature sensor from the clustering results as well as a particle number metric, could improve HVAC performance.

The presence of people in the auditorium caused CO_2, temperature and particle numbers to increase. When CO_2 and temperature exceeded a predetermined set point, then the supply air flowrate was increased, and CO_2, temperature and particle numbers should then begin to decrease. Of these metrics, CO_2 demonstrated by far the strongest correlation with occupancy ($B = 0.17$, SE < 0.01) with an R^2 of 0.62 ($p < 0.001$) during simple regression analysis. The correlation is also highlighted in Fig. 8a which presents a 24-h time-series of weekday hourly average CO_2 concentrations along with hourly average occupancy counts (secondary axis). A similar trend is observed with corresponding peaks at 11AM and 3PM, the time at which the auditorium is most frequently used. Fig. 8b) depicts the association between CO_2 and occupancy at a higher (1-min) resolution and illustrates that CO_2 levels increase when the room is occupied, and begin to decrease with the increase in SAF from the HVAC. Particle numbers demonstrated a moderate correlation with an R^2 of 0.28 ($B = 0.002$, SE $= <0.01$), while temperature and airflow each demonstrated an R^2 of below 0.05. Finally, multivariate regression was performed on continuous data, to assess the correlation between occupancy counts and CO_2, particle numbers and the new temperature sensor. These variables were together able to explain 67% of the variability in occupancy ($P < 0.001$), although this is only marginally better than using CO_2 alone. Some loss in explanatory power may be due to the addition of SAF that occurs at high occupancy, which reduce the pollutant concentrations and temperature, while occupancy remains elevated. Incorporating the new optimal temperature sensor from cluster analysis could not explain more of the variance in occupancy counts than the HVAC-embedded temperature sensor. Although there is some evidence of multicollinearity between predictor variables, the variance inflation factor (VIF) was <2, and hence any multicollinearity present is not strong enough to warrant the removal of a predictor variable.

Although these air quality indicators may reliably represent periods of occupancy and may thus be used to inform HVAC operation, one obvious disadvantage is that preconditioning will not occur prior to the event, hence the room may fall outside of the comfort range. One solution would be to incorporate historical data to infer/estimate preconditioning. Even if this resulted in the HVAC operating at on-mode more frequently, this would still be an improvement on the current setup. It is important to note that given the auditorium was unoccupied when the HVAC was in off-mode, how these trends would change during off-mode is unclear. What is more, it is not clear whether keeping the HVAC in off-mode for longer periods of time during the day would cause diminished air quality due to increased particle concentrations.

4. Conclusions

A wireless network consisting of a retrofitted CPC, 25 temperature sensors, 2 HVAC-embedded temperature and CO_2 sensors and a webcam were successfully installed in the basement auditorium of a university building so that the temperature profile and air quality of the room could be recorded remotely. The presence of people and their activities, and the HVAC switching between modes were important sources of particle number concentrations. Outdoor sources were negligible. The wireless temperature network was able to capture the spatio-temporal dynamics of the room, permitting increasingly accurate temperature profiling and better data with which to control and monitor the effectiveness of the HVAC. The temperature of the room varied only slightly; however the back of the room tended to be warmer than the front of the room during occupied periods. The HVAC-embedded temperature sensors reported the coldest temperatures, while Correlation-based clustering analysis identified 2 clusters from which 2 sensors, other than the HVAC-embedded temperature sensors, may be selected for HVAC control. However, the choice of sensor with which to control the HVAC depends on whose comfort should be prioritized, for example in this study should it be the majority, who are stationary and concentrating on a class or seminar, or the speaker − who is often more active and gesturing, trying to retain the attention of the audience. Or perhaps a sensor from the cluster that represents the largest area of the room should be selected.

The financial cost of implementing a dense wireless temperature network is recognized, both in terms of installing and maintaining the system, and validating the related data. It is unlikely that the personnel currently charged with HVAC control will have the time or the incentive to devote to further monitoring. While it is unlikely to be a realistic long-term option, the advantage of wireless technology is that the network of temperature sensors can be easily and quickly installed, and ready to collect data almost immediately. This data can be accessed remotely, without an individual having to spend time physically going to the room to obtain the data. It causes no disturbance to the occupants of that room, as there is no wiring to distract or cause health and safety concerns. It is therefore a feasible short-term study, especially in a university setting where there is always interest in new projects, from which the thermal profile of a room and the effectiveness of the current HVAC operation can be assessed. Similar to this study, clustering analysis may be performed to help identify an optimal location for temperature sensor, increasing the efficacy of the HVAC system. Given that HVAC is a huge consumer of energy, improving its function and potentially reducing the amount of time it needs to run, can result in large energy and financial savings. It would be even more advantageous if clustering analysis and sensor selection could be performed without having to install a dense wireless temperature network, but it is unclear at this time how this would be achieved.

In this study, experimental data demonstrated that operating the HVAC according to a calendar-based rather that a time-based schedule resulted in significant energy savings of up to 79%, depending on which energy saving rules were applied, and especially if occupancy events were scheduled close together. This should be considered when future class and seminar timetabling is conducted. Finally, CO_2 was observed to be a reliable indicator of occupancy, demonstrating the strongest correlation with occupancy counts of the different metrics assessed; however particle number concentrations and either the HVAC-embedded or optimally-located temperature sensors may supplement CO_2 in predicting times of occupancy for a more efficient and effective HVAC control. Incorporating a particle metric can also identify filter efficiency and improve the air quality of the room.

While the focus of this study was occupancy comfort, and only those sensors deemed most likely to affect comfort were included for analysis, future work will incorporate the remainder of the sensors to assess the thermal profile and temperature dynamics of the auditorium as a whole, and to track more precisely how air moves through the room. In addition, given the strong temperature fluctuations that occur in continental climates like Missouri, the outdoor air temperature should be a factor when considering any alterations to a time-based approach for HVAC operation, and this will also be considered in future work.

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Nomenclature

CO_2	carbon dioxide
CPC	condensation particle counter
HVAC	heating ventilation and air conditioning
MERV	minimum efficiency reporting value
NO_X	nitrogen oxides
SAF	supply airflow
SOA	secondary organic aerosol
UFP	ultrafine particles
VAV	variable air volume
VOCs	volatile organic compounds

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