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Energy Conservation through Flexible HVAC Management in Large Spaces: An IPS-based Demand-driven Control (IDC) System

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ABSTRACT:

Buildings consume substantial amounts of energy and require sophisticated control strategies to fulfill occupants' comfort requirements. In large spaces, various occupancy patterns result in uneven load distributions, requiring high-resolution occupancy information for sufficient system control. In recent years, the development of indoor positioning systems (IPS) enabled the possibility of more scientific and precise occupancy detection systems, leading to better operation of buildings' HVAC systems. This paper proposes a demand-driven control system for air conditioner control in large spaces based on IPS. The proposed system focuses on optimizing the ventilation rate based on number of occupants and their spatial distribution in an experimental space. A dual-network (Wi-Fi network and BLE network) indoor positioning system is installed to collect the occupancy data and guide the operation of Variable-Air-Volume (VAV) boxes. The energy-saving potential of the proposed system is examined with a computational fluid dynamics (CFD) model in terms of temperature distribution and energy consumption. This study also explores the interrelationship between cooling load variation and occupancy pattern under different control mechanisms. The final results show the proposed system has significant energy-saving potential by avoiding over-cooling in unevenly distributed occupancy conditions.

Key words: Energy efficiency, Demand-driven control, Occupancy, Indoor positioning system, Energy conservation

Nomenclature

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Nomenclature

$RSSI$	The received signal strength indicator
α	A constant value when determining $RSSI$
d	The distance between the transmitter and the receiver
R	The Gaussian random error with zero mean
$RSSR_{si}$	The received signal strength of reference points
s	The index of the signal source
i	The index of the reference point
p	The order of distance
θ	The shape factor of the distribution
r	The rank of the reference point
P_i	The probability of the occupant being located close to reference point i
t, τ	The index of time
$w(t)$	The time development of the probability density function after several time steps
x_t, x_τ	The vertical zone index at time t , τ
y_t, y_τ	The horizontal zone index at time t , τ
x_i, y_i	The vertical and horizontal zone index of reference point i
$x_{\tau,i}, y_{\tau,i}$	The vertical and horizontal zone index of reference point i at time τ
$W_\tau(x_\tau, y_\tau)$	The transition function of random process
η	The constant value of probability that occupant remains at the same zone
T_S	The temperature of supplied air from VAV box
T_{OUT}	The ambient air temperature
T_{IN}	The indoor temperature in a zone
T_V	The air temperature of ventilation
m_I	The mass flow rate of infiltration air in a zone
m_V	The mass flow rate of ventilation air in a zone
M_k	The mass flow rate of air provided by VAV box k
Q	The total heat flux in a room
z	The index of zone
Q_z	The total heat flux in a zone z
Q_I	The heat gain to zone due to infiltration
Q_V	The heat gain to zone due to ventilation
Q_G	The internal heat gain to zone by occupant, equipment, etc.
Q_{ADJ}	The heat gain to zone due to air flow from adjacent zone, etc.
Q_S	The heat gain to zone from all surfaces
N_O	The number of occupants in the zone
N_C	The number of computers in the zone
N_L	The number of lamps in the zone
W_O	The total fixed heat power of one occupant per hour
W_C	The total fixed heat power of one computer per hour
W_L	The total fixed heat power of one lamp per hour
W_z	The total fixed heat power in a zone z
n_1	The ballast consumption coefficient
n_2	The illumination shade insulation coefficient
C_{Air}	The specific heat capacity of the air

1. INTRODUCTION

In recent years, energy conservation has become a major objective in every country's sustainability efforts. Buildings have been reported as the largest energy consumers in cities [1], such that the building sector accounts for about 40% of energy use in Europe [2], 28% in China [3], and about 39% in the UK [4]. Among commercial buildings, HVAC systems consume the largest portion of energy from the grid and account for 48%, 55%, and 52% of energy usage in the US, the UK, and Spain, respectively [4]. The US Department of Energy (DOE) also highlights HVAC systems as the major target of building energy efficiency measurements [5]. Therefore, the energy performance of HVAC systems is the key to improving efficiency in buildings [6]. In commercial buildings, it is common to find large spaces partially occupied or unoccupied with the HVAC system running at full capacity for significant periods during the course of a typical business day [7]. It is frequently observed that some parts of a building's space are densely occupied, while other parts are empty. Because of the uneven distribution of occupants, it is common to find that some zones are over-cooled, while other zones are insufficiently cooled, causing occupants thermal discomfort. Under these conditions, energy can be significantly wasted, especially within unoccupied zones. Therefore, it is necessary to implement a more efficient and smarter operating mode for HVAC systems [8]. Recent studies suggest a lack of accurate occupancy information is the major source of uncertainty hindering effective HVAC control [9]. Many existing positioning technologies, such as Radio Frequency Identification (RFID) [10], Ultra-wideband (UWB) [11]. and Inertia Measurement Units (IMUs) [12,13], count and track occupants inside buildings for higher positioning accuracy, but these technologies require large initial capital investments, new infrastructures, and suitable control mechanisms [14]. Normally, the detected occupants' location cannot be directly coordinated in HVAC systems due to thermal zone-based control designs [15]. Therefore, it is necessary to investigate a proper control mechanism for a suitable occupancy detection system that can identify uneven occupancy in large spaces. Such a control mechanism would result in sufficient thermal comfort, eliminate energy waste, and promote HVAC operational efficiency. To bridge such a research gap, this paper proposes a demand-driven control method based on the spatial distribution of occupants. The spatial distribution of occupants is captured with a novel IPS that reports the occupied meshes in a continuous large space through coupled Wi-Fi and Bluetooth Low Energy (BLE) networks. With a demand-based control mechanism, the Variable Air Volume (VAV) HVAC system can adjust its energy consumption based on real demand

and avoid unnecessary energy waste.

2. BACKGROUND

2.1 Variable-Air-Volume HVAC System and Demand-Driven Control

Different from conventional Constant Air Volume (CAV) systems, which supply a fixed airflow rate for given temperatures, a VAV system has multiple VAV boxes that can supply varied airflow rates at a constant temperature. One major advantage of the VAV system is its precise temperature control to meet load demand and avoid waste with more flexible air supply amounts. Because of this, most office buildings are equipped with VAV systems. A VAV terminal unit, also called a VAV box, is the zone-level flow-control device equipped with a calibrated air damper and an automatic actuator. The VAV terminal unit normally connects to a local or a centrally controlled system. Traditionally, the air temperature in a return air duct works as a control signal to adjust air flow into the room by controlling VAV boxes based on the differential between the measured temperature at the return duct and the room temperature set point. For large spaces, such as lecture halls, movie theaters or conference rooms, they normally install multiple, centrally-controlled VAV terminal units. It is very common to find these large-scale spaces partially occupied or even unoccupied with the HVAC system at full capacity during a typical business day. Therefore, the reasonable operation and coordination between VAV terminal units is extremely important for large spaces due to their high ceilings, spacious floor areas, and large number of occupants.

In order to enhance and optimize HVAC performance and control, many publications propose and discuss several control strategies without considering occupancy distribution information [16][8][17][10], which may or may not avoid a redundant cooling/heating supply or ignore places in demand by bypassing actual occupancy patterns. Demand-driven control is a demand-side management tool to enable the proper operation of HVAC systems [18]. Some simulation-based research studies show potential energy savings from demand-driven HVAC operations vary from 10% to 60% [19]. This control mechanism aims to use the actual energy load information to improve control accuracy and eliminate unnecessary waste. For example, the demand-driven control system determines the volume of conditioned air in a thermal zone based on occupancy information (such as the number of occupants) and environmental information (such as temperature and humidity), rather than fixed operating schedules. Therefore, applying demand-driven control systems to multi-zone VAV controls in large-scale rooms shows great potential for optimizing HVAC operation. Lin and Claridge proposed a temperature-based Days Exceeding Threshold-Toa (DET-Toa) method to detect persistent small increases or decreases in the normal building energy consumption [20]. Zeng et al. developed a predictive model of HVAC energy consumption and a data-driven approach to optimize the temperature and air static pressure setting point [21]. In a more recent study, Zhou et al. proposed a supervisory demand-based temperature control system. In this research, the primary VAV box and secondary VAV box differentiate the occupied and unoccupied zones based on the temperature measured at the breathing level [17].

The conventional demand-control systems include occupancy-driven demand control [22], temperature-based demand control [17][20], and CO2-based demand control (mostly in DCV systems) [23]. Each control mechanism is subject to limitations. A temperature-based demand control mechanism adjusts the supplied airflow rate based on nominal temperature or the temperature difference between the supply air and setting values. However, occupancy derived from temperature fluctuations may not be accurate because temperature fluctuations are not necessarily caused by occupants; therefore, such a system yields huge potential for errors in unoccupied zones. CO2-based demand control compares CO2 concentrations between supply and return ducts to determine the number of occupants in a space. Many demand-driven strategies are based on coarse occupancy detection by balancing the CO2 concentrations of supply air, return air, and outdoor air, although it is costly and difficult to accurately estimate the actual occupancy pattern [23][24]. However, similar to temperature-based methodology, CO2 concentration is an indirect reflection of occupancy. Due to the time delay of CO2 reaching its equilibrium and a nonlinear relationship with the number of occupants, CO2 is a dubious occupancy indicator. Therefore, this research develops a fine-grained occupancy detection approach based on an Indoor Positioning System (IPS) to collect occupants' spatial distribution to enable the proposed IPS-based demand-driven control (IDC) approach and study its energy-saving potential. The IDC HVAC control mechanism is built on the new occupancy measurement framework that represents large spaces as small, occupied patches based on data collected from the IPS. The operation of VAV boxes is determined by the distribution of occupied patches. Temperature sensors are also installed at the breathing level, instead of the return ducts, to measure the temperature around occupants. Only occupied zones will receive cooling air until they reach a sufficient thermal comfort level. Therefore, accurate occupancy detection is the premise of proper demand-driven system control. The ASHRAE Guide 14 suggests ideal occupancy identification for a building model should have an hourly Mean Bias Error fall within ±10% and an hourly Cumulative Variation of Root Mean Square Error fall below 30% [25,26]. In a CO2-based occupancy prediction model, a 3 or 4-tolerance (10%-13% for about 30 occupants) away from actual occupancy could be acceptable if over 80% of accuracy for occupancy detection guaranteed [27].

2.2 Building Occupancy and Indoor Positioning Systems

Occupancy information can serve as inputs for energy simulations and assist facility managers in optimizing HVAC system operation to provide sufficient thermal comfort. Therefore, accurate building occupancy detection is the premise of efficient HVAC system control and design [28]. Building occupancy detection requires retrieving information at various resolution levels. Christensen et al. defined "occupancy resolution" as a three-dimensional system (i.e., temporal resolution, spatial resolution, and occupant resolution) [29]. Other researchers have summarized occupancy resolution using different scales, such as present, count, location, track, identity, and behavior [30]. Higher data resolution and accuracy enables more sophisticated building energy management strategies.

Many researchers have proposed studies on schemes to determine occupancy profiles, and most studies still obtain building occupancy schedules based on assumptions or experience with occupancy models. The American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) standard 90.1-2007 [31] recommends approximate occupancy diversity factors for different building types or zones by hourly occupant distribution within different day types in order to standardize building simulation and analysis when actual data is unknown. It has been observed that the difference between actual occupancy and standardized occupancy schedules recommended in the ASHRAE can be as high as 40% when comparing occupancy schedules in terms of days, weeks, months, and holidays [32]. This discrepancy might cause mismatching between actual energy costs and simulated energy costs in buildings. Therefore, researchers have proposed many approaches to collect reliable occupancy information. These approaches fall into two categories: (1) simulation-based occupancy models and (2) direct monitoring through sensors. Simulation-based occupancy models, such as the agent-based model and Markov models, estimate or predict occupancy based on historical data and analytical analysis; however, their accuracy relies significantly on abundant historical data collections and data mining processes and normally provides low-resolution information, such as the number of occupants and a rough estimate of the duration of the occupants' stay in certain spaces [33][34][35]. Although these model-based and data-mining process methodologies provide insight to facilitate analysis and prediction of occupancy profiles, their outcomes are seldom used for building facility operations. On the other hand, many researchers utilized ambient sensor systems to directly monitor occupancy, such as CO2-based detection systems [36][37], infrared sensors [38], and RFID [10]. Among those systems, occupancy sensors are widely used for detection in lighting and HVAC systems because they are suitable in cases when only the on/off (occupied or unoccupied) status needs to be detected, potentially leading to inaccessibility of the number of occupants with a timestamp. Another popular methodology is CO2-based detection systems, which are widely applied in building ventilation control systems and show good results in occupant number prediction for whole buildings. CO2-based detection determines the ventilation demand using a balance equation between CO2 concentration of supply air and return air duct [19,23,39]. A study conducted by Jiang et al. [27] suggests the estimation accuracy of CO2 concentration is often less than 50%. This approach is bound with limitations like time delays, high costs, and inaccuracy due to indirect detection [40]. Also, several researchers use lighting sensors or light switch on/off actions to report the duration of time an occupant spends in one room, or they use building envelope actions (window shades) and building electricity use variance to reversely ratiocinate occupancy [41], possibly causing very low-resolution results [42]. Several researchers combined CO2 sensors with temperature, humidity, lighting, and sound sensors and reported accuracy ranging from 75 to 84.5% [43,44]. Infrared sensors and motion sensors are often utilized to detect the events of "occupied to vacant" or " vacant to occupied" in single-person office rooms without detecting the number of occupants at an accuracy of 46% [38,45]. RFID technologies were reported with a higher detection accuracy of 88% for stationary occupants and 62% for mobile occupants [10].

A fully functional IPS can retrieve real-time locations and identify objects in indoor areas. Many researchers have introduced similar systems for the study of built environments [10][46][47] and focus on the building occupancy presence, number of occupants, and building energy variances. However, it is extremely challenging to capture occupancy distribution in real time and identify unique identities of occupants. In previous research, Wi-Fi and BLE positioning networks show great potential for commercial application [18][48][49] at low cost. Given their popularity, Wi-Fi infrastructures installed in most buildings become the most effective existing signal network with the promise of minimum cost [14]. However, Wi-Fi signals have significant issues in terms of stability when close to obstacles, metals, and building separations. It is impractical to merely rely on a Wi-Fi network for reliable positioning data. Therefore, we introduced another layer in the form of a Bluetooth Low Energy (BLE) network to cross reference the signal fingerprints of Wi-Fi networks. BLE technology is a cheap (less than 20 USD per beacon station and a cell phone can be the tag), portable, and controllable signal network applicable in indoor location acquisition and information broadcasting with location tags. This research intends to improve the operation of HVAC systems based on a new IPS-based occupancy acquisition approach. Therefore, we chose both Wi-Fi and BLE networks to construct the indoor positioning coordination and draw the occupancy distribution. Since most HVAC systems are controlled using thermal zones and VAV box affect areas, it is not necessary to have high positioning precision to enable demand-driven control based on occupants' spatial distribution. More specifically, we utilized the dual network IPS to locate occupants in space meshes and use these meshes to quantify the spatial distribution of occupants. With such information, we can optimize the HVAC operation and minimize energy waste.

3. METHODOLOGY

3.1 Positioning System and Space Meshing

In a large space with Wi-Fi and BLE networks installed, each location inside the space has a unique combination of received signal patterns from the Wi-Fi and BLE networks. Given this property, the k-nearest neighbors (kNN) algorithm is adopted to estimate the most likely location based on signal strength. Since the movements of occupants are continuous, the future location of an occupant is based on his or her current position. Therefore, a random walk algorithm is also embedded in the proposed positioning system. The system assumes occupants can only move to an adjacent zone close to the current location. Figure 1 shows the proposed positioning system that integrates both the kNN and random walk algorithms.

Insert Figure 1 about here

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(1) Signal Measurement of kNN algorithm

A signal receiver can sense radio signals in the surrounding environment. Since the source of signals could vary in frequency or voltage, received signal strength indicators (RSSIs) are typically used as a quantitative representation of signal strength. $RSSI$ is an integer value measurement of a received radio signal that complies with the IEEE 802.11 standard. Based on this protocol, BLE and Wi-Fi networks can adopt the distance estimation metric proposed by Texas Instruments of 2.4 GHz radio signal as

$$RSSI = \alpha - 10 \cdot n \cdot \log_{10}(d) + R \tag{1}$$

where power level is measured by $RSSI$ in dBm; d is the distance between the transmitter and the receiver; the term R denotes a Gaussian random error with a zero mean caused by shadowing; α is a constant that depends on several factors, such as averaged fast and slow fading as well as transmitted power (α can often be determined beforehand); and n is the signal propagation constant reported in the device manual.

The k-Nearest Neighbors (kNN) algorithm is a non-parametric pattern recognition approach for classification purposes. The algorithm compares the "distances" between received signal strengths and all reference points to determine the closest reference point as the rough location of the receiver. There are many measurement metrics that can represent the "distance" between the reference points and receivers. To generalize the estimation, this research adopts the Minkowski metric (or p norm) as the measurement tool. The Minkowski distance can be calculated using the following equation:

$$Dis(RSSI, RSSR_{si}) = \sqrt[p]{\sum_{s=1}^{S} (RSSI - RSSR_{si})^{p}} = \|RSSI - RSSR_{si}\|_{p} \tag{2}$$

where $RSSI$ is the received signal strength of the receiver, $RSSR_{si}$ is the received signal strength of reference points, s is the index of the source, i is index of reference points, and p is the order of distance.

Once all the distances are calculated, the kNN algorithm ranks the distances in increasing order. Shorter distances, or a higher rank, mean the receivers are closer to the given reference point. In our model, $k = 10$, which means the top ten reference points with the shortest distances will be selected as potential location candidates. Then, the probability of a receiver at the location of certain reference points is assigned based on the kNN rank, which follows a geometric distribution, where r is the rank of that reference point and θ is the shape factor of the distribution in our algorithm $\theta = 0.5$.

$$P_i(r) = (1 - \theta)^r \cdot \theta \tag{3}$$

P_i is the probability of the occupant being located close to reference point i. Then $P_r(x, y)$, the probability of an occupant located in a zone, is calculated by averaging all P_i's in that zone. The row and column indices of a zone are x and y. For example, the probability of an occupant's location being in zone 2, or $P_r(1,2)$, is averaged from the P_i's of reference points R2, R3, R9, R15, and R16.

(2) Space Meshing and Random Walk

In commercial buildings, large rooms are normally divided into multiple thermal zones for the ease of HVAC system operation and interference. Each thermal zone has multiple independent VAV boxes or other air conditioning devices to enable flexible operations. The separation of thermal zones and corresponding subsystems allows facility managers to provide different levels of thermal comfort in regards to space occupancy status. This study takes the conditioned air supply in a large office room as an example to explore the possibility of implementing a demand-driven control mechanism based on high-resolution occupant distribution. This type of occupancy information is collected from the proposed IPS and reflects uneven spatial cooling demands. Therefore, instead of coordination, the proposed IPSs are specially designed for space patches/meshes. All inner space is meshed into small space patches for three major benefits: (1) ease in HVAC operation, (2) high detection accuracy tolerance, and (3) a simpler positioning algorithm. Once the spaces are meshed, an occupant's movement is modeled as a random walk on a 2D lattice.

In any enclosed space, occupants enter from specific entrances and walk toward their targets. Although their destinations are unclear, their movements are continuous, and the next location of their movements must be close to their current location. This fact enables us to exclude the possibility of zones far away from the current zone when predicting in which zone an occupant will be located at the next time step. Therefore, in addition to the kNN algorithm, the proposed algorithm also introduces a possibility estimation approach to predict the occupant's location based on the random walk theory. For each time step, the occupant will move to another zone or remain in the same zone. The time development of the probability density function $w(t)$ after several time steps from 0 is given by

$$w_t(\tau) = W(x_t \to x_\tau, y_t \to y_\tau) \cdot w_t(t) \tag{4}$$

where $W_\tau(x_\tau, y_\tau)$ is the transition function of the random process.

The equation represents the discretized time-development of one step as

$$w_t(\tau) = W_\tau(x_\tau, y_\tau) \cdot w_t(\tau - 1) \quad (5).$$

This random process has a transition functions as

$$W_\tau(x_\tau, y_\tau) = \begin{cases} \dfrac{1-\eta}{\sum_i(|x_{\tau,i} - x_i| + |y_{\tau,i} - y_i|)}, & if\ |x_{\tau,i} - x_i| - |y_{\tau,i} - y_i| = 1 \\ \eta, & if\ x_i = x_{\tau,i} \cap y_i = y_{\tau,i} \\ 0, & else \end{cases} \tag{6}$$

where x_τ and y_τ are the vertical and horizontal zone indices at time τ, and η is a constant that suggests the probability that the occupant remains at the same zone at next time step $\tau + 1$. The final location for the time step τ is determined by maximizing the product of both the kNN probability and the transitional probability.

$$\arg\max_{x \in Z} P_r(x) \cdot W_\tau(x), \quad \forall x \tag{7}$$

3.2 Field Tests and Tracking Accuracy

To investigate whether the proposed occupancy detection approach could effectively obtain highly accurate occupancy data, the research team conducted a field experiment in a signal-covered space inside an institutional building. The selected testbed is an open space without any separations so the possible interference caused by internal walls can be mitigated. The space is part of a public lobby in the AC3 building of City University of Hong Kong. There is no wall or separation inside the space that may cause sudden signal strength depreciation. The testing space was marked and divided into a 6 by 6 grid with 36 zone patches (1 meter by 1 meter) and 85 location nodes (presented as Rxx). Figure 2 shows a picture of the experimental space and the network settings.

Insert Figure 2 about here

In the space, the signals for three access points were detected without knowing their locations. Four iBeacons were installed at nodes R25, R22, R61, and R64 to generate Bluetooth Low Energy (BLE) networks. To construct positioning coordinates, the signal strength of all three access points and the four iBeacons was collected for each node on the grid. These nodes served as reference points (RF) to locate occupants in the future. There was a column at the location of a reference point (R53) in the experiment space, so no signal was collected for R53, R47, and R60. The signal strength of these three reference points was derived by averaging the signal strength of surrounding reference points. Each reference point was measured three times to minimize random error. Three research assistants participated in the preliminary experiment, each equipped with a data logger that recorded the signals from all seven signal emitters. For the accuracy test, all research assistants walked through the space and covered all zones. Each assistant randomly selected a location inside each zone and recorded the signal strength of the APs and iBeacons.

After the preliminary experiment, two groups of data were archived for detection system construction and validation. The first data group (construction group) included the signal strength at the extract location of each reference point. This data was used to train the positioning algorithm and construct a reference grid with coordinates (i.e. the signal “fingerprints”). The second data group (validation group) included experimental data collected by the research assistants. Instead of reference nodes, each assistant collected a set of data at a random location inside each zone. The signal was collected in a manner allowing the determination of the location of the assistant and validation of the positioning accuracy. Figure 3 shows a comparison between the walking path of a sample test and its predicted probability spectrum based on Hamming distance. The top two images of Figure 3 are ground truth of a trail movement; the bottom two images of Figure 3 show the predicted position with probabilities (lighter color suggests higher probability). Our proposed algorithm will select the zone with the highest probability as the predicted location.

Insert Figure 3 about here

To determine the accuracy performance of the proposed IPS system, we summarized its accuracy in Table 1. The accuracy is calculated by the total number of correct predictions in each timestamp divided by the total number of timestamps.

Insert Table 1 about here

Table 1 compares the performance of different distance metrics for the kNN algorithm and shows the chronic accuracy of the model. From the results, the City Block distance and the third order Minkowski distance show the highest accuracy, and the City Block distance is selected for system control algorithm development. At the same time, chronic accuracy shows the error development is constrained to some degree, and the accuracy is converged/stable. These results suggest there is no significant error accumulation in the model, and the algorithm is robust and reliable.

3.3 Control Algorithm

The flow chart in Figure 4 shows the supervised demand-driven control algorithm proposed by this research. The supervised control algorithm executes through three control phases.

(1) In phase I, the indoor positioning system will identify whether the zones or patches are occupied. Once the system finds occupied patches, it will estimate the occupancy distribution for each thermal zone and calculate the necessary air supply amount to be distributed to that zone.

(2) In phase II, the algorithm will determine which VAV boxes should be turned on or off and the flow rate the VAV boxes need to provide to the zones. To quantify the thermal comfort of each zone, the temperature difference $e_{Z,i}$ (tracking error) between the average temperature of temperature sensors in each zone (T_Z) and the room temperature set (T_{SET}) will be used to determine the airflow rate of each VAV box. If the $e_{Z,i}$ fails to meet the condition ($e_{Z,i} = |T_Z - T_{SET}| \leq 0.5°\text{C}$), a temperature-based PID control and feedback mechanism will adjust the airflow rate to reach the setting point. It should be noted that the supply airflow rate of each operating VAV box is adjusted independently for each zone during this phase. Also, the supply airflow rate should be adjusted to create a temperature distribution to match the occupancy distribution. The flow rate of each VAV box can then be estimated or simulated with fluid dynamic theories [50]. In this paper, the flow rates were calculated based on CFD simulation; to simplify the calculation, the flow rate can also be determined by ASHRAE standards. Combined with the mechanical information of VAV boxes, the cooling load and energy consumption can be estimated through integrated efficiency over time. When the temperature tracking error in a corresponding zone is minimized and the corresponding zone is conditioned to the setting point, meaning it meets the thermal comfort level, the VAV box will work at that specific airflow rate. When the VAV box of a target zone operates at full capacity for more than a specified time length (e.g., 5 minutes) and the zone still cannot be cooled to reach the corresponding temperature setting point, the system will proceed to the next execution phase.

Insert Figure 4 about here

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(3) In phase III, the adjacent VAV boxes will work together with one of the target zones to compensate the cooling load when one target zone in phase II cannot reach the expected thermal comfort within 30 minutes. In the control algorithm, occupancy distribution mapped into occupied patches can be acquired by IPS and only occupied areas in zones would be conditioned by VAV boxes. When the target zone's air supply amount provided by a VAV box is not sufficient, the adjacent zone will provide additional cooling power at its full capacity. Figure 5 illustrates how zones are defined. The operation efficiency of a VAV box is determined by the occupancy level of the zone it covers and its adjacent zones. Once the adjacent zone is defined, the target zone and the adjacent zone would be combined as an integral zone. Phase II would be repeated so that the flow rate provided by VAV boxes in two zones is adjusted based on the load in the integral zone and the temperature captured by the sensors located at the thermal comfort level in the two zones. Once occupancy information in the former zone has varied and cooling load estimation is lower than the maximum cooling load, the corresponding zones would be conditioned individually, and control phase III would transition back to phase II.

Insert Figure 5 about here

Compared to a conventional control system, the proposed algorithm treats the HVAC system in a large space as a loosely connected system. Through switching between the zone levels to deduce a room level control basis, the proposed algorithm provides a customized flow rate based on the demand of each zone to avoid waste. The energy-saving potential is realized by matching the demand to capacity and avoiding unnecessary cooling or heating activities in unoccupied zones. Therefore, this proposed system is highly suitable for indoor spaces with uneven load distribution.

3.4 Energy Simulation Model

Since the preliminary experiment only has an IPS installed, to validate the efficiency of the proposed control algorithm, we developed a building simulation model and conducted a computational fluid dynamic (CFD) simulation for a sample office space. Simulation is an economic approach to explore the feasibility of a control algorithm at low cost before the practical system implementation. The outcome of the simulation could provide guidance for future system design. More specifically, the outcome of our CFD simulation includes the temperature distribution and the stable flowrate to maintain that temperature distribution. The flowrate indicates how much energy the system will consume to supply the cooling air amount and maintain the power of the VAV boxes. Therefore, the occupants' thermal comfort is achieved by matching the temperature distribution and occupancy distribution.

In this study, Fluent Airpak was employed to simulate temperature distribution of the airflow pattern under different control strategies. Fluent Airpak is one of the most popular commercial software programs used in the HVAC field to simulate airflow, air quality, and contaminates. It can construct realistic boundary conditions and predict the air spread and penetration in a confined room. The physical test bed is an office room 10 meters in length, 10 meters in width, and 3 meters in height. There are 21 occupants living in the room, and each occupant has one work desk, one computer, and one monitor. To simplify the model, the mixing ventilation type is chosen. Hence, the air in this room is a steady and uncompressible Newtonian fluid with the buoyancy effect of the body face neglected. The default ambient temperature outside the room is set as 35℃, which is a typical summer temperature for most subtropical cities [17], while the indoor air temperature is set to 25℃, also a typical indoor temperature setting point in most commercial buildings. The specifications and physical conditions of the test room are illustrated in Figure 6.

Insert Figure 6 about here

The space also has wireless temperature sensors installed at the human breathing level, which is a height of 1.1m and at least 0.5m away from the nearest occupant [17]. The walls of the room are adiabatic, and the heat flux of the walls is neglected. The turbulence in the room is modeled with two standard $k-\varepsilon$ equations to represent the airflow of the mixing ventilation. More detailed room specifications and CFD model settings are summarized in Table 2. The total cooling load is about 5.3kW when the room temperature is set at 25℃.

Insert Table 2 about here

The transfer function method (TFM) is used to estimate cooling load and identify uneven cooling demand. The TFM can relate an output function at one specific time to the value of one or more input functions at that time or to previous values of output functions [51]. Based on TFM, heat flux to the zone can be expressed using the formula below:

$$Q_i = \mathrm{Q}_I + Q_V + Q_G + Q_{ADJ} + Q_S \tag{8}$$

where Q_{ADJ}, Q_S in equation (8) represents the heat gain due to air flow from the adjacent zone or boundary condition and the heat gain to the zone from all surfaces, respectively. The model constructed in this study represents an inner space not in direct contact with the building envelope or surface, and in this case, the heat transfer between two adjacent zones is neglected.

While the heat gains to a zone due to infiltration Q_I and ventilation Q_V are

$$Q_I = m_I \cdot C_{Air} \cdot (T_{OUT} - T_{IN}) \tag{9}$$

and

$$Q_V = m_V \cdot C_{Air} \cdot (T_V - T_{IN}) \tag{10}$$

ASHRAE standards require a minimum ventilation rate of fresh air for occupants in rooms or whole buildings [52]. That is, heat gains to a zone due to ventilation can be estimated with occupancy information. The heat production, Q_G, usually includes the process of equipment heat dissipation (such as computers in our model, shown in Figure 6), lamp heat dissipation, and human body heat dissipation. Therefore, the energy consumption of occupants can be calculated as

$$Q_G = W_z = \sum_{N_O} W_O + 1000 \cdot n_1 \cdot n_2 \sum_{N_C} W_C + \sum_{N_L} W_L \qquad (11)$$

The values of W_C, W_L could be different based on the device type and size. W_O can also be different according to occupant type (men, women, or children), activity, and garments worn. To maintain a consistent room temperature setting (T_{SET}), VAV boxes in the HVAC system need to provide conditioned air with supply temperature T_{IN} to compensate for the total heat flux illustrated in all heat gain equations. The total heat flux, then, can be calculated as

$$Q = \sum Q_z = C_{Air} \cdot \sum_k M_k \cdot (T_{IN} - T_S)\,. \qquad (12)$$

M_k is the volume of air provided by VAV box k at unit time, which is the control object in this study. The volume of supply air and the ventilation of VAV boxes can be used to calculate the energy consumption of the ventilation system in the test space.

3.5 Infrastructure Coupling for the Simulated Space

Current building service systems in most commercial buildings assume the building occupants have fixed occupancy schedules. The facility managers operate the building facilities based on fixed occupancy schedules or maximum occupancy. Partially occupied and unoccupied conditions are not considered during the day's standard operating periods (e.g., 9am to 6pm) [10]. The chart in Figure 7 illustrates the integrated detection-control system and the interrelationships between the indoor positioning system and the HVAC control system. Through a positioning algorithm and received signal strength of all Wi-Fi access points (APs) and BLE broadcasters (iBeacons), the indoor positioning system can locate all occupants inside the room. The identity of occupants can be acquired through each device's unique MAC address. Location coordination and timestamps can calibrate and synchronize the two systems. Then, the number of occupants and their distribution inside the room is calculated through occupant location coordination. The flowrate of each VAV box is determined by the occupancy status (fully occupied, partially occupied, or unoccupied) of patches in each thermal zone. Under the thermal comfort requirement, we could adjust the status of VAV boxes based on feedback control mechanisms, and the mapping of occupancy and thermal comfort requirements in this integration can provide further insight into the relationship between occupancy distribution and air supply amount at one acceptable thermal comfort requirement. The fluctuations caused by occupant pass-by and short stays will be eliminated to avoid too-frequent adjustments [10].

Insert Figure 7 about here

Figure 7 shows the fundamental infrastructures of the VAV system and the indoor positioning system. Wireless temperature sensors are also installed at the breathing level to measure temperature in the space. The APs and iBeacons generate two radio frequency networks covering the whole experimental space. There are four thermal zones inside the room, and each zone is independently served by a VAV box. The proposed HVAC control mechanism is also able to differentiate the occupied, partially occupied, or fully occupied spatial conditions by coupling with an indoor positioning system. The experiment space is divided into four thermal zones (Zone A, Zone B, Zone C, and Zone D) based on the locations of four VAV boxes. Each zone has wireless temperature sensors installed, and each zone is further divided into smaller patches for higher error tolerance in positioning. The distribution of occupancy in each zone can be reflected in the occupied patches. For example, in Zone A of Figure 8, there are five work stations, but only three are occupied. The temperature of each zone is collected from the wireless temperature sensors to represent the thermal comfort level of occupants. The occupancy pattern and residents' routes in the space are randomly simulated based on the signal samples collected from the preliminary field experiment. All occupants perform as the regular building energy end-users by requiring thermal comfort and controlling the occupancy-schedule related appliances. With occupancy distribution, the building energy load at zone level or building level can be formatted in detailed in occupant-related loads, such as human thermal gains as well as appliances' energy usages in real-time.

Insert Figure 8 about here

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4. RESULTS AND ANALYSIS

4.1 Types of Occupancy Distribution

To validate the efficacy of the proposed control algorithm, 12 scenarios with four zone-level occupancy types (fully occupied, half-occupied, partly-occupied, and unoccupied) were tested in the preliminary experiment. These occupancy types are defined as follows: (1) fully-occupied zones are zones where residents occupy all patches, (2) half-occupied zones have half or more than half of patches occupied, (3) partly-occupied zones have fewer than half of all patches occupied, and (4) unoccupied zones are zones without any occupants. Two types of room-level occupancy distributions are also defined in the preliminary test: (1) even distribution, in which all four zones are occupied at some level (or no zones in the room are unoccupied), and (2) uneven distribution, in which at least one unoccupied zone is observed. Figure 9 illustrates different occupancy distributions.

Insert Figure 9 about here

To investigate the performance of the HVAC system control algorithm developed by this research, CFD Airpak was applied to simulate airflow patterns to assure the required comfort level is achieved. In the CFD simulation, temperature is selected as the thermal comfort level indicator. In the preliminary test, we assumed a thermally comfortable space should have a temperature around 25℃. As a demand-driven control system, the proposed algorithm only guarantees the occupied patches are thermally comfortable. If the temperature of the zone is higher than the threshold, the VAV boxes will switch on and adjust the temperature. Once the target temperature is reached, the

VAV boxes will turn off. The supply air amount for each zone varies with different numbers of occupants in that zone. Table 3 lists the 12 scenarios with different occupancy patterns and supply air amounts, determining the temperature variation. Each zone is conditioned independently with its VAV box at full capacity while no cooling air is provided to an unoccupied zone.

Insert Table 3 about here

4.2 Comparison with Conventional Methods

The most widely selected indicators to estimate the number of occupants are CO_2 concentration and room temperature distribution. In practice, facility management systems use the temperature at return air vents as the control variable of thermal comfort in most commercial buildings. Yet, in this paper, we utilize IPS as a new way to gather more precise occupancy information to estimate actual demands. Therefore, to form a comparison, two conventional control methods, the return air temperature (RAT) control system and the breathing level temperature (BLT) control system, have also been examined in the CFD simulation. In the RAT control system, the temperature sensor is installed inside the return air vent to collect return air temperatures. The VAV boxes operate based on the temperature difference between the setting point and the return air. However, the temperature around a return duct cannot efficiently represent the thermal comfort need of occupants due to thermal stratification and uneven distribution. The BLT control system uses temperatures collected by sensors at the human breathing level to determine when to turn the VAV boxes on or off to maintain a thermal comfort temperature. However, temperature fluctuations at breathing level are not necessarily caused by occupants, so that cannot accurately reflect the occupancy. In the proposed IDC system, VAV boxes are operated based on the zone-level occupancy of the space meshes/patches with the help of IPS tags and feedback adjustments based on temperature sensor nodes at breathing level. To keep the temperature (T_z represents breathing level temperature) at the proper level, cooling air is supplied to the zone in proximity to occupied zones, intentionally avoiding VAV-box operation in unoccupied zones.

Figure 10 shows the comparison between temperature distributions around occupancy level under all three control mechanisms (RAT, BLT, and IDC) in three typical scenarios. In those cases, we assumed the occupancy distributions as illustrated in the figure and that equipment is turned on to distinguish the differences among the three methods.

Insert Figure 10 about here

Temperature contours under the three control systems depicted in Figure 10 show different temperature distributions around occupied patches. In the RAT, the VAV boxes condition all zones with temperature feedback from return ducts without detecting the room occupancy condition. Therefore, all VAV boxes must be adjusted simultaneously with the same setting. In the BLT, the heat radiation of the occupants and computers skews the temperature contour. VAV boxes are adjusted accordingly using the feedback from the breathing-level temperature sensors where occupants are located. Such improvement avoids unnecessary over-cooling and assures all zones are sufficiently conditioned. However, unoccupied zones with a higher temperature are also supplied with cooling air, as in Zone B. Therefore, cooling air supplied by a BLT system in such areas results in energy waste. In the IDC, only occupied zones are conditioned, so the temperatures in unoccupied zones would not be considered. The temperatures of unoccupied zones are normally higher than the typical thermal comfort level. As shown in Figure 10, only occupied zones are conditioned. Comparing the RAT, BLE, and IDC systems, the IDC system conserves the most energy by avoiding interference from unoccupied zones. The temperature-based thermal comfort level is sufficiently satisfied in occupied zones for all three systems, while the IDC system leaves unoccupied zones at a higher temperature. Therefore, the rationale behind the proposed IDC system is mainly based on the temperature distribution of the occupied zones and leaves the unoccupied zones. Therefore, energy can be saved by intentionally avoiding cooling unoccupied zones and leaving their temperatures high.

Insert Figure 11 about here

Figure 11 compares the average temperatures of occupied and unoccupied zones for the above three scenarios. Using Scenario 4 as an example, the proposed IDC system only needs to maintain the temperature of occupied Zone C and Zone D at 25.5℃ and intentionally leave Zone A and Zone B uncooled to be more efficient with the air supply. Since the RAT does not need information on occupancy distribution and merely adjusts VAV boxes based on the temperature at return air ducts, the VAV boxes must be uniformly adjusted for the whole room. For the BLT system, where occupancy detection is also based on temperature, a fluctuation in temperature caused by equipment can be easily misinterpreted as occupancy. With the help of the CFD simulation, we can examine the necessary supply air amount for all three systems. Table 4 compares the amount of conditioned air supplied in the above three different scenarios. Under conventional control systems, the required supply airflow rate is 1350 m3/h for the RAT system and 1087 m3/h for the BLT system. Compared to the RAT system, the IDC system will save 30.4% of air supply, dramatically reducing the energy consumed to power the electrical fans and cooling system. It can also be observed that more detection of unoccupied zones by the IDC means more energy can be saved using the proposed IDC systems.

Insert Table 4 about here

Figure 12 shows the required air supply amount of all 11 scenarios (S12 is the unoccupied scenario). The IDC system is the most energy-efficient mechanism that needs the least air supply to maintain the occupants' thermal comfort. It is also important to note that in the condition of even distribution of room-level occupancy, the BLT and IDC systems require the same amount of cooling air.

Insert Figure 12 about here

4.3 A Case Study on the Daily Energy Saving of the IDC System

This case study adopts a sample occupancy schedule to examine the energy-saving potential of the proposed control system. An occupancy of 21 total occupants in the preliminary experiment is scaled to an ASHRAE-recommended occupancy schedule. According to ASHRAE standard 90.1 [31], the hourly schedule has been mapped into the three occupancy scenarios we previously discussed: (1) from 09:00 to 10:00 and 18:00 to 19:00 in Scenario 6, (2) from 10:00 to 12:00 and from 14:00 to 18:00 in Scenario 1, and (3) from 12:00 to 14:00 in Scenario 4. We assume the HVAC system for the whole building is turned off from 20:00 to 08:00. Therefore, in this study, we divided the occupancy schedule into three scenarios. Based on the results in the previous section, occupancy distributions of those scenarios were acquired and air supply amounts were determined at a certain comfort level. To illustrate energy consumption, Figure 13 shows the proposed occupancy schedules with specifications for the four thermal zones. We also assumed computers are still running when occupants leave the room during working hours or lunchtime, and all three control systems update the VAV box settings every hour.

Insert Figure 13 about here

Figure 14 shows the cooling load estimated for all three systems and IDC's energy-saving potential during a typical work day. The cooling load was calculated with the supply air amount in Table 3 and the duration of occupancy. Then, the energy consumption of the room was estimated based on the calculated cooling load. As shown in Figure 14, a significant load reduction can be realized when IDC control systems are substituted for the traditional RAT control systems. As observed in Figure 14, an IDC system has a higher chance of saving more energy when more load variation exists. For example, when occupants leave the office during lunchtime, some of the VAV boxes can be turned off. Since we assume all occupants are present during the day and only leave for a short period at lunch, there is a relatively small energy-saving potential with the IDC system compared to the BLT system. Similarly, in some seldom-used rooms designed for special purposes —such as the conference room, kitchen, or restrooms—the IDC system has a higher energy-saving potential. Compared to the RAT system, the energy-saving potential of the IDC system during the entire day can reach around 8.99 kWh, which is 22.77% of the total daily energy consumption. Compared to the BLT system, the IDC system can achieve a 0.74kWh (2.36%) reduction in energy use during a two-hour lunchtime. The difference between the IDC and BLT is not large since the room was almost fully occupied by the residents throughout the whole day. It also can be observed from Figure 14, the majority of energy saving comes from the discrepancy between the IDC and BLT during lunch time. Given the IDC and RAT evenly provide conditioned air to all zones due to the lack of occupancy distribution information, the BLT has the advantage in providing unbalanced service to different zones. Therefore, the more unevenly distributed occupants are within the large space, the more energy can be saved with the BLT.

Insert Figure 14 about here

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5. DISCUSSION

5.1 Implication of the Findings

In this study, a cooling load estimation model is employed to assess the primary cooling air amount. Such a temperature-based estimation system is the most widely used control method in most buildings. However, the two major drawbacks of temperature-based systems are (1) all conditioned air supplies must be uniformly controlled, and (2) there is no feasible solution for unoccupied zone detection. Demand-driven control can resolve both limitations by adjusting the supply airflow rate based on accurate occupancy [19] and leave high temperatures in unoccupied areas un-ameliorated [53]. Therefore, the proposed IDC control system provides significant energy-saving potential by avoiding unnecessary zone-level energy consumption. As shown in Figure 6, through intentionally avoiding interfering with the temperature in unoccupied zones and leaving them as hot spots, the total conditioned air supply can be reduced. This principle can also be extended to other building service systems, such as lighting and ventilation systems. Building upon occupant distribution detection, engineers will be able to design and construct more sustainable and smarter systems that can be automatically controlled.

The IDC system also provides a low-cost pervasive sensing network solution for building monitoring and indoor occupancy acquisition. If the complete installation of an indoor positioning system is not feasible for some buildings, a portable system could be used to detect the occupancy pattern from room to room. Since many existing buildings are manually and periodically controlled, using occupancy patterns would be helpful to guide the system settings in different thermal zones [54]. Long-term occupancy pattern recognition can assess the utilization of space and identify mostly unoccupied zones. Such information can not only help optimize the HVAC operation schedule, but also enable unoccupied space reassignment [16]. It is also feasible to provide a better indoor environment and thermal comfort for frequently used spaces and preferred spaces [55]. In the IDC system, the integrated facility operating system and indoor positioning system record the occupancy, timestamp, and system operation information of each space. Historical data logs of these systems provide a rich source for further data mining and processing, especially for profiling energy-consumption patterns through a machine-learning process by associating energy needs with spatial locations [56]. A large number of local energy management strategies require such types of information, including demand response (DR) and demand-side management (DSM) [57] [58].

5.2 Limitations and Future Work

In this research, we would like to couple the Wi-Fi and BLE networks to obtain occupancy distribution for demand-driven control with the purpose of improving building energy efficiency. Although the proposed system advances current energy management in buildings, this study also yields several limitations we intend to resolve in future research. First, the room-level cooling load in this research is estimated by linear addition of all subzones. In practical operation, the supplied flows from multiple air vents will interfere with each other through a nonlinear heat transfer process. Therefore, future research should adopt more sophisticated fluid-dynamic models that consider such superimposed effects. Second, obstacles in the positioning networks could result in inaccuracy in the location detection. The current experiment test bed is a continuous space without large separators, such as structural columns or walls. Also, the space boundaries in direct contact with the building envelope and surface could significantly change the simulation results since the outside environment is more dynamic and complicated. These building surfaces and components could also potentially disturb the stability and accessibility of received signals [59]. Therefore, more complicated indoor geometry needs to be examined to identify potential problems and develop future improvements to positioning accuracy. Third, the indoor positioning system would collect the MAC address or UUID information of occupants' devices, but for the occupants' privacy, this tagging might be impermissible and should be improved and protected. This issue could not be avoided during the research on location tasks. To protect privacy, future work must enable new tagging techniques. Fourth, this study ignored the positions of those occupants who occupied one room just for one short-term duration and could be defined as temporary occupants. In this positioning work, we did not figure out a method to filter the temporary occupants from the permanent occupants. In the next study, we would like to focus on this issue and illustrate a schedule of permanent occupants to provide a more detailed control basis for HVAC systems. Fifth, the frequency of adjustment must be determined for practical application. The positioning system can stream real-time occupancy data to the building management system, but the response of the facility control system is subject to lag and instability. A too-frequent adjustment could result in error accumulation and system instability. Therefore, for automatic centrally-controlled systems, it is essential to investigate the best system adjustment frequency to find a compromise between system uncertainty and energy-saving potential. Sixth, another significant issue is related to privacy: no matter which IPS is used, it always requires the occupants to carry sensing tags (in our system these tags were personal cellphones). More studies are necessary to develop safer technologies to provide occupant privacy. The last and most important limitation of our research is the control system actuation is based on simulation. More validity must be provided through field experimentation to verify how much energy can be saved by the proposed system. Current energy consumption is derived from CFD temperature simulation. It is strongly suggested that future studies create a complete control loop with physical actuators and carefully monitor their energy consumption.

5.3 Contributions

Efficient HVAC system control depends on reliable occupancy information. The direct observation of indoor positioning systems enables accurate load estimation and flexible control. In this study, the proposed control mechanism relies on high-resolution occupancy information collected from a dual Wi-Fi and BLE network. Both networks are convenient to install and apply, especially Wi-Fi access points which are normally pre-installed in most buildings. In current popular applications, BLE technology is convenient for broadcasting and integrating signals with location information. To eliminate the weakness of Wi-Fi technology in providing more accurate location tags, this study coupled BLE technology into the dual networks. Integrating the indoor positioning system with an energy management system could allow for more efficient energy use in buildings. In conventional control systems, occupancy information is approximated from historical or indirect data. Such approximation not only lacks accuracy, but also sacrifices resolution [60]. The major improvement in the proposed system is controlling the building facility by relying on zone-level occupant distribution. Using current control mechanisms, the setting point of a building's facilities, such as an HVAC system or lighting system, is determined by the rough estimation of room-level occupant counts. With the help of the IPS, the proposed control system can not only detect the number of occupants, but locate their accurate spatial distribution in the form of space meshes. With meshed occupancy patches enabled by the dual layer positioning network, the VAV boxes of HVAC systems can be adjusted accordingly with higher positioning accuracy tolerance and compatibility with system design. In addition, the zone-level and room-level occupancy patterns can be recognized and used to guide facility operation. For example, the occupancy pattern has been categorized into unoccupied, partly-occupied, half-occupied, and fully-occupied to estimate the necessary air supply amounts and adjust the system settings. Such differentiation avoids over-cooling caused by uniform control of multiple zones with different occupancy levels. In summary, the major contribution of our proposed system is it develops a specifically designed algorithm, which combines both kNN and random walk model, for the dual layer positing system, and it integrates the demand-driven HVAC control principle with meshed spatial occupancy distribution detected by the proposed IPS. Given that the HVAC system is designed to control thermal zones, the spatial occupancy distribution is ready for direct implementation. At the same time, given that the IPS system we proposed is not intended to capture exact location coordinates, it has much higher tolerance in positioning inaccuracy. Moreover, meshes/patches work like a 2D lattice, which is much simpler compared to a continuous space. This allows simple control algorithm design as well as higher processing and control speed.

6. CONCLUSION

Among the HVAC control modes, occupancy behaviors are the key to assessing whether the occupants' thermal comfort has been sufficiently satisfied. The proposed demand-driven control system implements an indoor positioning system to collect occupancy information with higher resolution and accuracy. Wi-Fi and BLE technologies are utilized in the indoor positioning equipment, and in this research, occupancy distribution data acquired by dual networks is generated as a demand-driven signal. Based on such information, the service space can be monitored and controlled by actual demand rather than rough estimations of temperature and the number of occupants. In the zone temperature distribution simulation, different control methods were compared and the results showed higher-accuracy occupancy acquisition can better conserve cooling air amounts. Integrated with the accuracy of IPS, daily energy performance analysis was conducted comparing IDC, BLT, and RAT systems. The results of this study show the proposed system has significant energy-saving potential for demand-driven HVAC operation in large-scale rooms by avoiding over-cooling and uniform cooling.

Although the core of this research focuses on determining occupancy distribution and then controlling air supply modes in VAV systems, such demand-driven control systems can also be extended to other building service systems and may enable more sophisticated control design, making the potential applications far more extensive. In the coupled IPS and HVAC system, we postulate the functional harmony in the integration of two systems and the ability to provide more useful information for future improvements. As the technologies and algorithms in IPS evolve and mature, the accuracy of IPS can be improved and provide greater benefits to occupancy information schemes.

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Table 1 Accuracy of Each Measurement Metric and Its Chronic Development

	Route 1				**Route 2**			
Timestamps	EU	CB	HM	M3	EU	CB	HM	M3
1-200	0.7605	0.7939	0.5842	0.7674	0.8062	0.8276	0.5240	0.8416
201-400	0.6707	0.7197	0.5552	0.6800	0.7017	0.7952	0.5217	0.7598
401-600	0.6400	0.7145	0.5481	0.7258	0.6922	0.7750	0.5123	0.7602
601-800	0.6378	0.7140	0.5512	0.7072	0.7022	0.7813	0.5109	0.7707
801-1000	0.6707	0.7197	0.5552	0.6800	0.7017	0.7952	0.5217	0.7598
Over all	0.6759	0.7323	0.5587	0.7120	0.7208	0.7948	0.5181	0.7784

*Note: EU – Euclidean; CB – City Block; HM – Hamming; M3 – Minkowski 3;
The value in each cell is the positioning accuracy.

Table 2 Room Specifications and Model Settings

Ventilation type	Mixing ventilation
Geometry	10m x 10m x 3m
Diffuser type	Square ceiling diffuser
The dimension and quantity of fresh air diffusors	0.4m x 0.4m, 4
The dimension and quantity of exhaust air vents	0.4m x 0.4m, 4
Heat sources	Occupant 21x75W Computer 21x150W Lamp 16x35W
Total cooling load	5.285kW
Air supply temperature	18℃
Room temperature set	25 ±0.5℃
Turbulence model	Standard equations

Table 3 Supply Air Amount of Different Occupancy Distributions in a Sample Space

Scenario Index	**Occupancy**	M_A	M_B	M_C **(m3/h)**	M_D	M	**Zone Occupancy**	**Room Occupancy**
1	(5,4,6,6)	353	265	382	382	1382	(FO,FO,FO,FO)	Even Distribution
2	(5,0,6,6)	353	0	382	382	1117	(FO,UO,FO,FO)	Uneven Distribution
3	(5,4,6,0)	353	265	382	0	1000	(FO,HO,FO,UO)	Uneven Distribution
4	(0,0,6,6)	0	0	382	382	764	(UO,UO,FO,FO)	Uneven Distribution
5	(5,4,0,0)	294	206	0	0	500	(FO,FO,UO,UO)	Uneven Distribution
6	(0,0,6,0)	0	0	265	0	265	(UO,UO,FO,UO)	Uneven Distribution
7	(5,2,6,2)	353	118	382	118	971	(FO,PO,FO,PO)	Even Distribution
8	(2,3,2,5)	118	176	118	353	765	(PO,HO,PO,HO)	Even Distribution
9	(1,1,3,5)	59	59	206	353	667	(PO,PO,HO,HO)	Even Distribution
10	(4,3,3,5)	280	206	206	280	972	(HO,HO,HO,HO)	Even Distribution
11	(3,0,4,3)	206	0	265	206	667	(HO,UO,HO,HO)	Uneven Distribution
12	(0,0,0,0)	0	0	0	0	0	(UO,UO,UO,UO)	Even Distribution

*Note: The column of "Occupancy" shows the number of occupants at Zone A, B, C, and D;
Ms' show the amount of conditioned air that needs to be supplied to that zone to meet comfort level:
FO – fully-occupied, HO – half-occupied, PO – partly-occupied, UO – unoccupied.

Table 4 Comparison of Supply Air Amount among Three Control Systems

Scenario Index	Occupancy	Room Occupancy	Supply Air Amount (m3/h)			Percentage Reduction	
			RAT	BLT	IDC	RAT-IDC	BLT-IDC
4	(0,0,6,6) (UO,UO,FO,FO)	Uneven Distribution	1350	1087	940	30.4%	13.5%
1	(5,4,6,6) (FO,FO,FO,FO)	Even Distribution	1704	1381	1381	19%	0%
11	(3,0,4,3) (HO,UO,HO,HO)	Uneven Distribution	1250	1116	1014	18.9%	9.1%
6	(0,0,6,0) (UO,UO,FO,UO)	Uneven Distribution	1071	881	650	39.3%	26.3%

*Note: The column of "Occupancy" shows the number of occupants at Zone A, B, C, and D;
FO – fully-occupied, HO – half-occupied, PO – partly-occupied, UO – unoccupied;
The column of "Percentage Reduction" compares the amount of supplied air between the proposed control system and the conventional systems.