Automation in Construction 24 (2012) 89–99

Contents lists available at SciVerse ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations

Nan Li, Gulben Calis *, Burcin Becerik-Gerber

Sonny Astani Department of Civil and Environmental Engineering, University of Southern California. 3620 S Vermont Ave., Los Angeles, CA, 90089, USA

ARTICLE INFO

Article history:
Accepted 16 February 2012
Available online 15 March 2012

Keywords:
RFID
Occupancy detection
Stationary and mobile occupant
HVAC operations
Energy management

ABSTRACT

Building energy management and the necessity to reduce overall energy consumption is becoming an increasingly important topic. Especially in dynamic environments, where the setting and occupancy keep changing, knowing occupancy information, including the number and identities of the occupants and where they are located, can be beneficial in energy management as well as other application areas including safety, security and emergency response. In particular, occupancy information has a direct impact on various aspects of heating, ventilation, and air conditioning (HVAC) systems, such as heat loads, system running time, required heating, cooling and distribution of conditioned air, and preferred temperature set points. Energy-saving strategies can be carried out in response to real-time occupancy changes. In this paper, an RFID based occupancy detection system is proposed to support demand-driven HVAC operations by detecting and tracking multiple stationary and mobile occupants in multiple spaces simultaneously. The proposed system estimates the thermal zone where each occupant is located, and reports the number of occupants for each thermal zone in real time. The field tests yielded an average zone level detection accuracy of 88% for stationary occupants and 62% for mobile occupants. For scattering analysis, averages distances to corresponding centroids were 1.45 m and 3.24 m for stationary and mobile occupants, respectively. In order to explore the benefits of demand-driven HVAC operations, current HVAC work procedures are examined, major energy consumers in HVAC systems are identified and quantified, and energy-saving strategies are presented. This study aims to support reducing the consumption of the HVAC systems by integration of the occupancy detection system and the demand-driven HVAC operation strategies.

1. Introduction

Energy management is becoming an increasingly important topic due to the global climate change, a growing population, decreasing availability of fossil fuels and increasing environmental and economic concerns. These issues have resulted in a consensus that more sustainable ways of addressing energy needs is crucial. In the U.S., 40% of energy consumption is from buildings, approximately 48% of which is consumed by heating, ventilation, and air conditioning (HVAC) systems [1]. Considering the fact that in the U.S., existing facilities represent over 97% of the existing building stock in any given year [2] and that buildings are generally in operation for 30 to 50 years. One of the opportunities for reducing building energy consumption is through improved operations of existing HVAC systems (Table 1).

A close examination of the work procedure of a typical HVAC system helps to identify the main energy consumers, and provide hints on how energy conservation can potentially be achieved. In a typical HVAC system, chillers and boilers that serve one or multiple buildings generate chilled or heated water. Air handler units (AHUs) that serve the whole or part of a building take in outside air, mix it with air flows that return from all thermal zones, and cool or heat the mixed air to a set point with chilled or heated water. A thermal zone is an individual indoor space or group of neighboring spaces with similar thermal loads, and typically served by a dedicated HVAC subsystem. The conditioned air is then distributed by fans and duct systems to all thermal zones. The demand for the volume of conditioned air of a thermal zone is determined by the volume of the zone and the difference between the zone's actual temperature and the set point, and is regulated by a variable air volume (VAV) box that serves this zone. The VAV box can reheat the air with heated water, if necessary, before it pushes the air into the room. There are two major energy consumers in this procedure: (1) cooling or heating and distribution of air by AHUs at the building level, and (2) heating of air by VAV boxes at the thermal zone level.

In reducing the above two energy consumption areas, occupancy information plays an important role as it is used for determining the heating and cooling loads. Occupancy information is defined as the number and identities of occupants in a thermal zone and the resulting activities from occupant being present (i.e. associated plug,

* Corresponding author.
E-mail address: becerik@usc.edu (B. Becerik-Gerber).

0926-5805/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
doi:10.1016/j.autcon.2012.02.013

Table 1
Nomenclature table.

Symbol	Explanation	Unit	Symbol	Explanation	Unit
A_r	Area of room r	*sf*	O_r	Minimum volume of outside air required for ventilation	*cfm*
C_r	Current temperature in the room r	^oF	P_r	Number of occupants in room r	
D_r	Temperature set point in room r	^oF	Q_r	Heat production in the room	Btu / h
E_A	Energy consumption by AHUs	Btu / h	T_A	Temperature of air supplied by AHU	^oF
E_T	Total energy consumption by the HVAC system	Btu / h	T_{out}	Temperature of outside air	^oF
E_V	Energy consumption by VAV boxes	Btu / h	T_R	Temperature of return air	^oF
F_A	Volume of air supplied by AHU	*cfm*	T_v	Temperature of air supplied by VAV box v	^oF
F_V	Volume of air supplied by the VAV box v	*cfm*	μ	Fraction of the return air in the air supplied by AHU	
F_v^{max}	Maximum volume of air that can be pushed through VAV box$v$	*cfm*	ν	Energy required for changing temperature of unit air by 1 ^oF	$Btu / (h^* {}^oF^* cfm)$
F_{Vr}	Volume of air from VAV box v to room r		η_A^F	Energy required to distribute unit air from AHU to rooms	$Btu / (h^* cfm)$
f_{Vr}	Fraction of air from VAV box v to room r	*cfm*	η_A^t	Energy required to cool the unit air by 1 ^oF by AHU	$Btu / (h^* {}^oF^* cfm)$
N_r	Sum of heat transfer and	Btu / h	η_v^t	Energy required to heat unit air by 1 ^oF by VAV	$Btu / (h^{*o}F^* cfm)$

lighting and HVAC loads). Ideally, building operations automatically should respond to dynamic occupancy loads. However, lacking the capability of knowing accurate and real-time occupancy information, current facility management practices usually rely on assumptions to operate HVAC systems, leading to more energy consumption than needed. With timely access to occupancy information, energy-saving adjustments, such as redirecting air flow and reducing system running time, can be carried out in response to either real-time occupancy loads, or predicted loads based on historical data [3,4]. Previous simulation-based research results show that estimated energy savings from demand driven HVAC operations vary between 10% and 60% [3,5–8].

Radio frequency identification (RFID) is an effective technology for indoor localization and has the following advantages compared with competing technologies such as motion sensors, ultra wide band (UWB), and wireless local area network (WLAN): RFID technology can provide adequate accuracy [9]; it is cost efficient [10]; it does not require line of sight conditions [11]; it has on-board data storage capacity that can be used for another purpose such as building asset management [12]; and it is widely used by the construction industry so that hardware can be shared by multiple tasks [13]. This study proposes an RFID based occupancy detection system that can (1) detect multiple stationary and mobile occupants, which can be in close proximity to each other, simultaneously in multiple spaces, (2) estimate the identities of occupants and their coordinates, (3) report the number of occupants for each thermal zone in real time, and (4) estimate the occupants' activities at a high level. The following sections of the paper examine the impact of occupancy information on HVAC energy consumption, and present a series of demand-driven operation strategies. Then, an RFID based occupancy detection system is proposed, including the methodology, test setup, findings, and discussions. The last section concludes the paper.

2. Importance of occupancy information for HVAC operations

Current HVAC systems generally operate according to fixed schedules and maximum occupancy assumptions. Typically, operational settings are dictated according to assumed occupied and unoccupied periods of the day (e.g., 9 am to 6 pm) and do not consider when buildings are partially occupied. Observations of actual building occupancy have found average occupancy in office buildings to represent at most a third of their design occupancy, even at peak times of day [14]. If real-time occupancy information is known, then HVAC operations can be adjusted accordingly, which will result in energy savings. In this section, the energy consumption by HVAC systems is analyzed, the impact of real-time occupancy information on the energy consumption is illustrated, and demand-driven HVAC operation strategies are presented.

The two main energy consumers in HVAC systems are (1) cooling or heating and distribution of air by AHUs E_A, and (2) heating of air by VAV boxes E_V. The objective is to minimize the total energy consumption E_T:

$$\min(E_T = E_A + E_V) \tag{1}$$

Considering energy required to heat unit air by $1^o F$ at AHU is the same as that to cool the unit air by 1^oF:

$$E_A = \eta_A^T {}^* F_A {}^* abs(\mu^* T_R + (1-\mu)^* T_{out} - T_A) + \eta_A^F {}^* F_A \tag{2}$$

$$E_V = \sum_v \eta_v^T {}^* F_v {}^* (T_v - T_A) \tag{3}$$

For calculating the minimum energy consumption, there are certain constraints in current HVAC operations that are related to the way the HVAC equipment works or applicable building codes and standards. These include:

- *At the building level*, the temperature of the return air is the average of the temperature of the air returning from all rooms, therefore:

$$T_R {}^* F_A = \sum_{v,r} F_{vr} {}^* C_r \tag{4}$$

- *At the zone level*, the amount of air that AHUs supply equals to the total amount of air that is received by all VAV boxes, and VAV boxes only heat the air. Therefore, the constraints at this level include:

$$F_A = \sum_v F_v \tag{5}$$

and

$$\forall v, T_v \geq T_A \tag{6}$$

In addition, there are constraints by variable definitions:

$$\sum_r f_{vr} = 1 \tag{7}$$

$$F_v \leq F_v^{\max} \tag{8}$$

- *At the room level*, ASHRAE (American Society of Heating, Refrigerating and Air-conditioning Engineers) standards require a minimum ventilation rate of 20*cfm* per person, or 0.05*cfm* per square foot, whichever is larger:

$$O_r = \max(20P_r, 0.05A_r) \tag{9}$$

From the whole building perspective, the following is required:

$$\sum_{v,r} F_{vr} * (1-\mu) \geq \sum_r O_r \tag{10}$$

Assuming room r is already at its temperature set point D_r, the HVAC system needs to maintain D_r by providing conditioned air to compensate for the total of heat transfer and solar heat gain N_r(positive for net gain, negative for net loss), and heat production Q_r, which consists of total heat load from occupants, lighting, and appliances such as computers. For example, typical heat loads as defined by the ASHRAE handbook [15] are: 75 Btu/h for a human, 150 Btu/h for a desktop, 50 Btu/h for a laptop, and 128 Btu/h for overhead lighting in a typical office. The required amount of conditioned air is determined by:

$$Q_r + N_r = \nu * \sum_v F_{vr} * (D_r - T_v) \tag{11}$$

where ν is the product of the weight of air ($0.75 lb/ft^3$), the specific heat capacity of dry air ($0.24 Btu/(lb * {}^oF)$), and a conversion factor of $60 \min/h$.

If real-time occupancy information is available, room and building level heat loads caused by human thermal radiation as well as associated lighting and appliances usage can be calculated without any delay. With this information, and the objective function in Eq. (1), the following parameters can be calculated: the temperature of air supplied by AHUs (Eqs. (2), (3), (6)), the air volume provided to each zone (Eqs. (5), (7), (8), (11)), and the air volume provided to each room (Eqs. (4), (11)). With the occupancy information, the minimum ventilation rates for each room (Eq. (9)) and the whole building (Eq. (10)) can also be calculated, based on which the outside air volume can be adjusted. It needs to be noted that occupants passing by a room or staying for only a short time (e.g. 10 min) should not be considered to avoid too frequent adjustment of the HVAC system. However, this information is also needed and essential for understanding the patterns of occupancy, which is used to develop occupancy prediction models. Moreover, as the occupants' activities and identities are recognized, more accurate heat loads can be estimated and zone level occupant preferences can be used to determine the temperature set points, which will help further save energy consumption and increase the occupant thermal comfort.

With the availability of occupancy information, the following demand-driven HVAC operation strategies can be implemented to optimize the parameters such as temperature set points and airflow volumes, and to achieve energy savings:

- *Maintaining higher temperatures in unoccupied areas*. Agarwal et al. [16] proposed maintaining the temperature of a room lower than what is specified by ASHRAE standards when the room was occupied. Whenever the room was not occupied, then the HVAC system was throttled back. In the simulation, temperature was maintained at 22.9 °C and 26.1 °C for occupied and unoccupied rooms, respectively. The authors reported a 15% reduction of energy consumption.
- *Maintaining lower ventilation rates in unoccupied areas.* Pavlovas [17] proposed a dichotomy strategy at the building level, where the ventilation rate was kept at the maximum value when the building was occupied; otherwise it was kept at a minimum value. Up to 20% of ventilation energy was saved in simulation.
- *Supplying airflow based on occupancy:* After estimating the occupancy by using indoor CO_2 concentrations, Yang et al. [18] proposed to provide minimum supply airflow rates per ASHRAE standards for each room based on the occupancy loads. This strategy was applied to an office environment, and yielded over 15% energy savings in ventilation. A similar strategy was used by Sun et al. [8], which reported approximately 56% annual energy savings when they implemented this strategy on one floor of a high-rise building.
- *Adjusting outside air volume based on occupancy.* Erickson et al. [7] argued that the outside air volume can be controlled according to the occupancy information in each room, and instead of being based on the maximum design occupancy, the air volume can be dynamically controlled to meet the minimum demand for the detected occupancy. Fourteen percent reduction in HVAC energy consumption was reported.
- *Responding to dynamic heat loads on a timely manner*. If a change of occupancy is detected in real time, associated changes of heat loads can be calculated, and HVAC systems can respond to these changes immediately, before the temperature varies to an extent that is detectable by thermostats. Tachwali et al. [3] classified the cooling airflow rate into three levels – low, medium and high – and determined the rate applied to each room based on the room's real-time occupancy. Simulations reported energy savings of up to 50%.
- *Operating HVAC systems based on occupant preferences.* If identities of occupants in a room can be known and their preferences can be recorded in advance, HVAC systems can adjust and maintain set points to ensure occupant comfort. Klein et al. [19] proposed a multi-agent system, which simulated the heating/cooling and ventilation of rooms based on detected occupants and their preferences. In their system, when a zone was unoccupied during an "occupied period," the heating and cooling was turned off and the ventilation was set for minimum; otherwise it was adjusted based on occupants preferences. The study reported up to 13.6% of energy savings.
- *Learning energy consumption patterns.* If the system can profile the pattern of an occupant or a room, and learn the trend of occupancy and associated energy needs, it can proactively operate for optimum energy consumption. Erickson and Cerpa [6] examined the occupancy prediction based on logged occupancy information, and in the simulation, HVAC systems started to condition a room to a comfortable temperature only when the room was predicted to be occupied for 10 min or longer. If the room was predicted to be occupied for less than 10 minutes or unoccupied, a higher temperature allowed by applicable standards was used until midnight, when the HVAC system was entirely shut off. The research reported an energy saving of 20%.
- *Increasing the flexibility of control.* While most of the control proposed in the previous research was done at the building or room levels, Lo and Novoselac [20] extended this scope by arguing that it is possible to establish isolated environments in large open spaces via using multiple slot diffusers to provide angled supply jets, and a central return vent to limit the spreading-out air movements. This suggests that occupants can have more control over their environments, and that demand-driven HVAC operations are applicable to a wider variety of environments including large open spaces.

To better illustrate the implementation of the demand-driven HVAC operations based on the above equations and operation strategies, a flow chart is presented in Fig. 1.

3. Occupancy detection systems

Occupancy detection systems can be categorized as individualized and non-individualized, based on whether every individual in the sensing area is detected, tracked and identified or not. Non-individualized occupancy detection is achieved by sensing the aggregate occupancy of each zone without knowing occupants' identities or their exact coordinates. Passive infrared (PIR) sensors are the most widely used technology for non-individualized occupancy detection. Henze et al. [21] proposed a typical PIR based system by establishing redundant sensor networks that comprised of three PIR sensors and one telephone sensor per room. The system detected occupancy 98% of the time in two rooms. However, PIR sensors suffer from two limitations: there is only binary information indicating whether a room is occupied or not, and stationary occupants are often not detected. To overcome these limitations, PIR sensors are often coupled with other sensors. Dong et al. [22] and Lam et al. [23,24] proposed a system that collected data through CO_2, acoustic, and PIR sensors. Three machine-learning techniques were applied to the data analysis. It was concluded that the hidden Markov model performed the best, with an average accuracy of 73% in counting occupants. One limitation was the dependency on CO_2 concentration, which takes time to build up and is a cumulative effect of various factors other than occupancy, such as outdoor air quality, and ventilation rate. In Meyn et al.'s research [25], cameras and CO_2 sensors were used to estimate the number and flow direction of occupants, which were then augmented by PIR sensor data. Coupled with historical data about building utilization, the proposed sensor-utility-network was able to yield an occupancy detection rate of 89%. Hutchins et al. [26] improved the robustness of such multi-sensor occupancy detection network, at the building level, by introducing various probabilistic models, which could recover up to 50% of missing or corrupted data.

In summary, non-individualized occupancy detection systems are usually non-intrusive, scalable, and easy to deploy. However, these systems cannot provide occupants' coordinates information; therefore they are not able to coordinate multiple VAV boxes or diffusers that serve different locations of the same zone. In addition, the non-individualized occupancy detection systems are not adaptable to situations, where monitored zones are virtually instead of physically partitioned.

Individualized occupancy detection is achieved by localizing every individual in the sensing area, and then totaling the number of occupants in each zone. Individualized systems are of significant value to energy management as they can provide occupants' identities, and track occupants' coordinates. Therefore, the occupancy information can be based on zones that are either physically or virtually partitioned. The latter case is especially important for open-plan spaces that consist of multiple thermal zones. Zhen et al. [31] built and tested an RFID based occupancy detection system for lighting control. The system, running on a supporting vector machine aided algorithm that followed a round-robin comparison rule, was able to accurately locate an occupants that wore an RFID tag at the room level 93% of the time. The latency and scalability needed further development, as the authors noted. To build an occupancy detection system, Akhlaghinia et al. [32] used a WSN (wireless sensor network) based system. The algorithm that aimed at multiple-occupant scenarios was a generalization of earlier algorithms designed for single-occupant scenarios [33,34], using a regional clustering technique. It was reported that the WSN system was able to find the room where an occupant was located with 85% accuracy. However, system scalability for heavily occupied spaces remained unclear.

Previous research that focused on indoor localization also has the potential to be used in individualized occupancy detection. Various technologies have been tested in this area, including motion sensors [35,36], ultrasonic sensors [37], UWB (ultra wide band) [38,39], WLAN (wireless local area network) [39,40], RFID [11,41–43], and WSN [44]. Yet, most of these systems did not provide zone level occupancy information, and they were not tested for tracking multiple mobile occupants. Tracking mobile occupants is essential in that the mobile occupants may stay inside a space and therefore constitute part of the occupancy that should be accounted for when adjusting the HVAC operations. Moreover, it is the authors' intention to integrate the occupancy prediction into the occupancy detection in the long run to reduce hardware dependency. To lay the basis for occupancy prediction, it is necessary to first track mobile occupants over a period of time (e.g. a week) and use the collected data to train and calibrate the occupancy prediction model.

Vision-based systems, which rely on camera images and video analysis techniques, can be used for either non-individualized or individualized occupancy detection. The system proposed by Benezeth et al. [27] followed three steps to count occupants in images: change detection, tracking, and recognition. The number of occupants was counted correctly 93% of the time in an office, and 83% of the time in a corridor. Despite the high detection rate, privacy is an issue that prevents wide implementation of vision-based systems. To address this issue, Sarkar et al. [28] used CMOS (complementary metal–oxide–semiconductor) video cameras that didn't have storage capacity or typical camera appearance. However, the system was course-grained and only able to detect whether a room was occupied or not. There are also individualized vision-based systems that can recognize occupants' identities, as demonstrated in [29,30]; however, such systems can raise serious privacy concerns, as occupants may resist the collection and analysis of their images.

In general, fewer individualized occupancy detection systems applicable for demand-driven HVAC operations were proposed than non-individualized systems. However, the individualized systems are of significant value as they can overcome the limitations of non-individualized systems. In particular, they can provide occupants' identities, and track occupants' coordinates. Therefore, the occupancy information can be based on zones that are either physically or virtually partitioned. The latter case is especially important for open-plan spaces that consist of multiple thermal zones. To benefit from these advantages and provide sufficient support for effective demand-driven HVAC operations, an individualized occupancy detection system is proposed in this research.

4. Methodology

The proposed individualized occupancy detection system, built on RFID technology, has the following components: readers, antennae, tracking and reference tags, and a server. Readers receive and process signals from both the server and the tracking and reference tags; tags store data on board and respond to commands from readers; and antennae establish the communication between readers and tags via the radio signals. Reference and tracking tags are physically the same, and emit signals containing information, including IDs, signal strength, and contact time. Tracking tags are attached to occupants to denote occupants' locations, and reference tags are deployed in the environment to provide references for location estimation with their own known locations. The server retrieves data from readers, performs location calculation, and stores and distributes the results. Zones can be assigned according to building space layout, or arbitrarily based on actual needs such as ventilation control. The boundaries of each zone are recorded as an input to the proposed system. A proximity based algorithm built on the K-nearest neighbor (KNN) technique is used, which locates a target from the known locations of the target's k nearest neighboring reference tags, and reports the zone of the target by comparing the estimated location with the boundaries of all zones.

Initially, the Euclidean distance between each tracking tag and reference tag is established, using the RSSI readings reported by readers. Suppose there are n antennae, m tracking tags, and r reference tags. The signal strength vector of tracking tag i is defined as $\vec{S_i} = (S_{i1}, S_{i2}, \ldots S_{in})$,

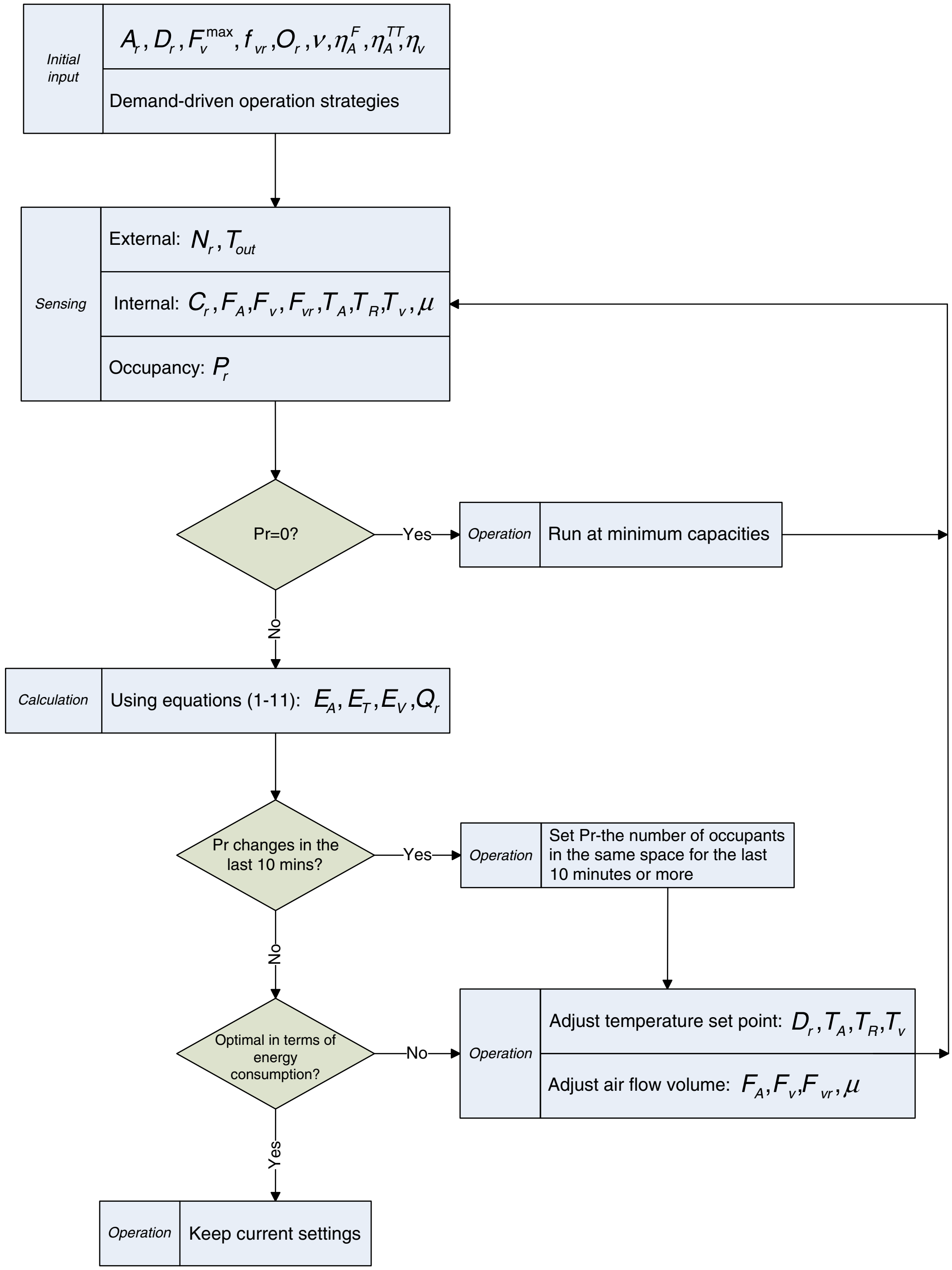

Fig. 1. Proposed integration of the quantification analysis and operation strategies.

where S_{ih} denotes the signal strength of tracking tag i received by antenna h,$i \in (1, m)$, $h \in (1, n)$. Similarly, the signal strength vector of the reference tag j is defined as $\vec{\theta}_j = (\theta_{j1}, \theta_{j2}, \dots \theta_{jn})$, where θ_{jh} denotes the signal strength of the reference point j received by antenna h, $j \in (1, r)$, $h \in (1, n)$. The Euclidean distance between tracking tag i and the reference tag j is then established as in Eq. (12):

$$E_{ij} = \sqrt{\sum_{h=1}^{n} \left(S_{ih} - \theta_{jh}\right)^2} \tag{12}$$

For tracking tag i, vector $\vec{E}_i = (E_{i1}, E_{i2}, \dots E_{ir})$ donates its distance to all reference tags. With this vector, the k nearest neighbors of tracking tag i can be identified.

Lastly, the location of the target is estimated using weighted averages (Eqs. (13) and (14)) of the locations of its k nearest neighbors. $k = 4$ is used in this study to estimate the target's coordinates [45]:

$$(x_i, y_i) = \sum_{j=1}^{k} w_j \left(x_{ij}, y_{ij}\right) \tag{13}$$

$$w_j = \frac{\frac{1}{E_{ij}^2}}{\sum_{j=1}^{k} \frac{1}{E_{ij}^2}} \tag{14}$$

where (x_i, y_i) is the coordinate of the target i,$(x_{ij}, y_{ij})$is the coordinate of the j-th nearest neighbor of tag i, where $j \in (1, k)$, and w_j is the weighing factor.

When the location of tracking tag i is estimated, it is compared with the boundaries of all zones. If the estimated location is within a zone, that zone is then reported. When applied to multiple tracking tags, this process outputs information that enables users to know not only which zone each occupant is located, but also how many occupants are within a specific zone.

5. Data collection

The main objective of the field tests was to identify whether it is technically feasible and reliable to utilize RFID technology and the proposed algorithm to detect and track occupants in thermal zones to reduce HVAC related energy consumption. A thermal zone is an individual indoor space or group of neighboring spaces with similar thermal loads, and that is typically served by a dedicated HVAC subsystem (i.e. VAV boxes). Tests were carried out at a floor of an educational building at the University of Southern California. The test bed building was selected based on its function (i.e. commercial office building type), where there are several shared and individual spaces. The building houses different room types, and has typical obstructions that can be found in office buildings, such as walls and furniture. As the tests focused on detecting and tracking occupants for reducing energy consumption, VAV boxes and thermal zones were specified on the mechanical plans. There is not always a one-to-one relation between a thermal zone and a room. As can be seen from Fig. 2, the conference room (55 m^2) has one thermal zone, where the computer lab (240 m^2) has 6 different thermal zones - each covering 40 m^2 — due to the lab's large area. Thermal zones are not always divided by partitions (e.g., six zones are virtually partitioned in the computer lab). The locations of the reference tags and antennae are also shown in Fig. 2. The locations of the tracking tags are not shown in Fig. 2, as some of the tracking tags kept moving randomly during the tests. During the tests, occupants either walked in and out of the zones or stayed in zones, seated, standing or walking. For each test, the zone each occupant occupied was noted and used as the ground truth.

Tests were conducted using off-the-shelf ultra-high frequency (UHF) active RFID equipment that runs at a frequency of 915 MHz, which provides a read range of up to 100 m according to the manufacturer's specifications. Each reader supported two antennae, which were attached to the reader via data cables. Powered by an AA battery, each tag emitted a non-directional signal every 1.5 s. A C# program was developed and used to communicate with the readers and extract real-time data, including tag IDs, tag model, battery life, RSSI readings, last contact time, and contact count. In order to enable more accurate occupancy detection results, a total of 25 reference tags and 4 readers (each connected to 2 antennae) were placed strategically to cover all 13 thermal zones (Z1-Z13) and also in a way that each tag could be detected by at least two antennae (Fig. 2).

Each occupant wore an active RFID tag throughout the tests. Based on the RSSI readings received from the occupants' tags, locations of the occupants were estimated as described in the methodology section. Next, the thermal zones, in which the occupants were detected, were identified. A total of 5 tests were conducted as listed in Table 2. There were 6 occupants, seated, standing or walking, in tests 1 to 4. A total of 7 data sets were collected for each of the first four tests. Data sets and the sequential estimated locations corresponding to each data set were represented as T_i. In test 5, there were 6 occupants, who walked in and out of thermal zones in certain time intervals. Test 5 included five stages. Test 5 started with 6 occupants (stage 1: T_1 to T_4), then occupants 1 and 3 walked out of the zones towards Z7 (stage 2: T_5 to T_8) followed by occupants 2 and 5 (stage 3: T_9 to T_{12}). Then, occupants 1 and 3 walked back to their previous zones (stage 4: T_{13} to T_{16}) followed by occupants 2 and 5 (stage 5: T_{17} to T_{20}). Occupants 4 and 6 remained seated in their initial zones in all stages. Four data sets were collected for each stage of test 5. Occupants who walked out of the zones preferred standing in Z7 instead of being seated. Three occupant activities (walking, seated, and standing) were evaluated during the tests. As tests 1 to 4 each included 7 data sets and test 5 included 20 data sets, each test lasted at least 15 min. This enabled the identification of the occupants who stayed in a thermal zone for less than 10 min and should be excluded in adjusting the HVAC operations in that zone.

6. Findings

Test results are evaluated to provide occupancy information to proactively adjust HVAC systems, and, thus, establish a framework for demand-driven HVAC operations. In this study, occupancy detection rate does not indicate the rate of accurate sensing of occupant presence (e.g., occupied or unoccupied). Occupancy detection rate refers to the number of occupants detected accurately at the zone level. Occupancy detection rates are provided not only for a single occupant but also for multiple occupants performing multiple activities — walking, seated, and standing. Table 3 shows the occupancy detection rates for tests 1 to 4.

In tests 1 and 2, occupants remained seated in Z12 and Z3 throughout the tests, which simulated an indoor environment similar to a classroom or a conference room. The mean of occupancy detection rates in tests 1 and test 2 were 81% and 95%, respectively. A higher detection rate in test 2 was achieved due to the fact that the thermal zone Z3 (55 m^2) was larger than the thermal zone Z12 (40 m^2) and that more reference tags were deployed in Z3, which increased the detection rate. Hundred percent of the occupants, who were not found in their actual thermal zones, were detected in adjacent thermal zones in test 2. On the other hand, in test 1, only occupant 6 was not detected in his actual thermal zone. In fact, this occupant was detected in Z3 in all data sets, which was not adjacent to the occupant's actual thermal zone, possibly due to systematic malfunction of the attached tracking tag. Fig. 3 illustrates the estimated locations of occupants in tests 1 and 2.

In tests 3 and 4, occupants walked randomly to simulate a dynamic indoor environment similar to a cafeteria. In test 3, occupants walked in thermal zones Z8 to Z13, where in test 4, occupants walked but remained only in Z3. In test 3, the system achieved 100% occupancy detection rate in 4 out of 7 data sets and the mean detection rate of all 7 data sets was 93%. In test 4, the mean detection rate was 31%, which was probably associated with the small size of the zone and that occupants walked close to the boundaries of the zone from time to time. The low detection rate in test 4 could also be associated with the signal interference in that zone as occupants had to walk in a smaller area compared to test 3. Therefore, signal interference in Z3 might have caused occupants to be detected inaccurately. Detailed analysis also demonstrates that 67% and 90% of the occupants, who were detected out of their actual thermal zones, were detected in adjacent thermal zones in tests 3 and 4. Fig. 4 shows the estimated paths of occupants in tests 3 and 4.

In order to assess the impact of occupants' activity on the detection rate accuracy, tests 1 and 2 (occupants that were seated) were compared to tests 3 and 4 (occupants that were walking). The overall mean detection rate was 88% when occupants were seated. On the other hand, the overall mean detection rate decreased to 62% when occupants were walking. The results show the system yielded higher detection rates for stationary occupants than mobile ones. This was due to the fact that the mobile occupants caused a more dynamic environment, and that they walked close to the boundaries of the thermal zones.

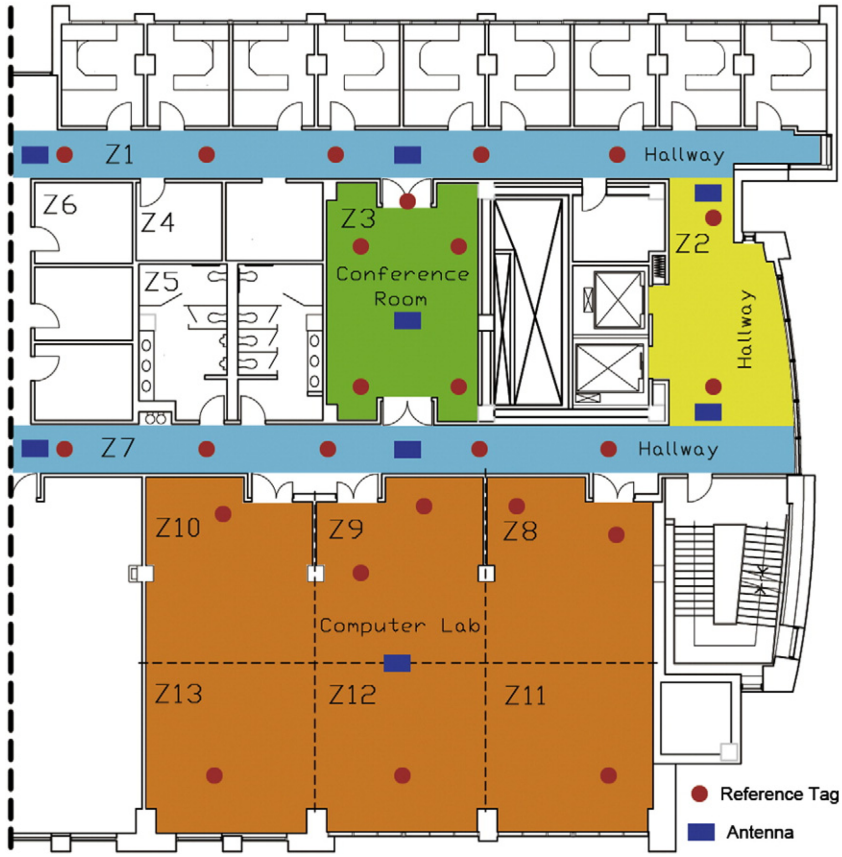

Fig. 2. Test layout with thermal zone divisions.

To assess the consistency of estimated occupancy, scattering in occupant locations was evaluated. Table 4 shows the average distance of each occupant's estimated location from its corresponding centroid in tests 1 to 4. In tests 1 and 2, occupants were seated; therefore, the estimated locations were closer to each other with average distances of 0.99 m and 1.91 m, respectively. The more jitter in test 2 might be associated with the signal interference in Z3, where more reference tags were deployed. The average distances were 3.60 m and 2.88 m in tests 3 and 4, respectively, where occupants were walking. In these tests, one occupant might walk a long distance, while the other occupant walked a smaller distance. Both routes were considered as "walking randomly"; however, they resulted in different jitters. It can be concluded that the values of scattering analyses are highly depended on the routes of occupants and that do not necessarily represent tangible results in dynamic environments (e.g., walking vs. seated). On the other hand, when the mean average distance of tests 1 and 2 (1.45 m) are compared to 3 and 4 (3.24 m), a significant difference is seen between these averages. These results indicate that the activities of the occupants might be estimated via scattering analyses, where more jitter is associated with a more dynamic environment. The estimation of occupants' activities enriches the information that can be used to adjust the HVAC set points accordingly.

Test 5 included five different stages; each representing a different environment and different numbers of occupants that remained in the zones. Table 5 shows the detection rates for test 5. There were 6 occupants seated in Z9, Z11 and Z12 in the first stage (T_1-T_4). The detection rate achieved was 92% on average and the maximum detection rate among all data sets was 100%. Hundred percent of the occupants, who were detected out of their actual thermal zones, were detected in adjacent thermal zones in this stage. In the second stage (T_5–T_8), occupants 1 and 3 walked towards Z7, while the rest of the occupants remained in zones Z9, Z11 and Z12. The average detection rate was 75% in this stage. This result was associated with the latency in the data acquisition process. Because tags emitted signals every 1.5 s and all signals were not received by antennae, the data captured and reported by readers might be time stamped when the occupants were in the middle of the transition of changing their zones, whereas the occupants were already in the new zones. Eighty-three percent of the occupants, who were detected out of their actual thermal zones, were detected in adjacent thermal zones in this stage. In the third stage (T_9-T_{12}), occupants 2 and 5 walked out of their zones towards Z7, where occupants 1 and 3 were standing. In this stage, the average detection rate was 79%, which was slightly higher than the average detection rate of stage 2. This was due to the fact that occupants 1 and 3 were finally detected in the thermal

Table 2
Sequence of tests.

Test #	Actual thermal zone	Activity of occupants	Data sets
1	Z12	Seated	T_1–T_7
2	Z3	Seated	T_1–T_7
3	Z8–Z13	Walking	T_1–T_7
4	Z3	Walking	T_1–T_7
5	Z9, Z11, Z12	Seated	T_1–T_4
	Z9, Z11, Z12, Z7	Seated/Walking	T_5–T_8
	Z9, Z11, Z12, Z7	Seated/Walking/Standing	T_9–T_{12}
	Z9, Z11, Z12, Z7	Seated/Walking	T_{13}–T_{16}
	Z9, Z11, Z12	Seated	T_{16}–T_{20}

Table 3
Occupancy detection rates based on thermal zones for tests 1 to 4.

Test #	Worse (%)	Best (%)	Mean (%)
1	67	83	81
2	83	100	95
3	83	100	93
4	0	83	31

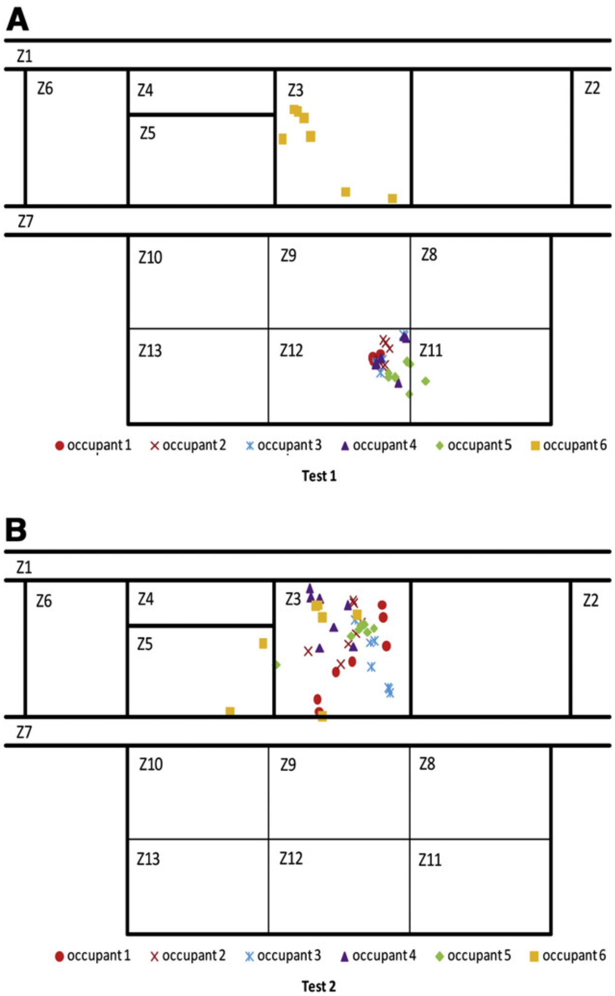

Fig. 3. a and 4b: Estimated locations of occupants in tests 1 and 2.

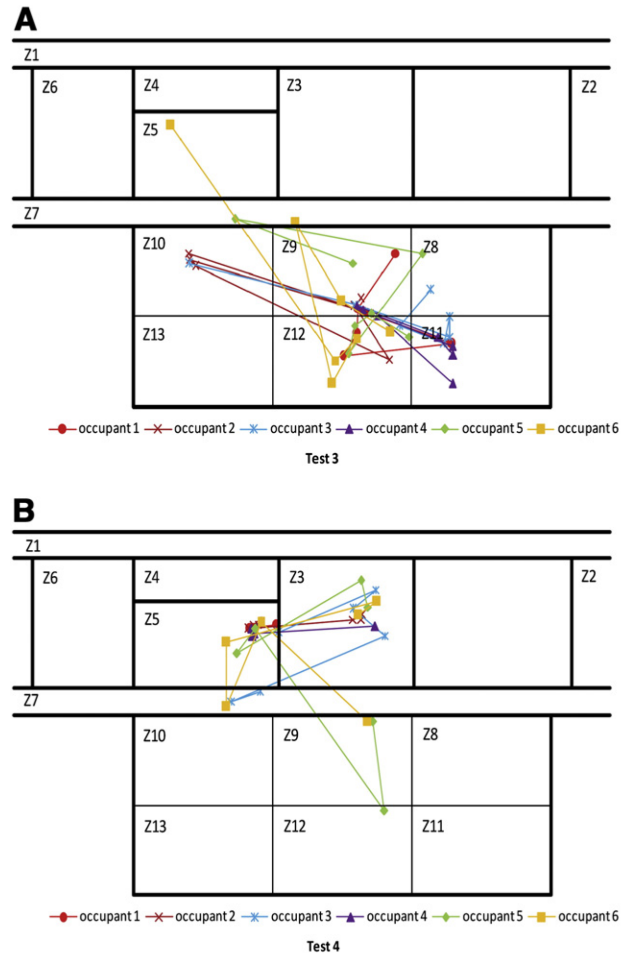

Fig. 4. a and 4b: Estimated paths of occupants in tests 3 and 4.

zone they walked out (Z7), therefore, didn't cause a decline in the detection rate. Sixty percent of the occupants, who were detected out of their actual thermal zones, were detected in adjacent thermal zones in this stage. In the fourth stage (T_{13}–T_{16}), occupants 1 and 3 walked back to their previous zones. Occupants 2 and 5 remained standing in Z7. The mean detection rate in this stage was 71%, which was associated with the latency in the data acquisition process. The data recorded during the transition caused incorrect thermal zone outputs, and, thus, decreased the detection rate. In addition, 100% of the occupants, who were not detected in their actual thermal zones, were detected in adjacent thermal zones. This result also implies that the data was recorded while occupants were still in adjacent thermal zones walking back. In the fifth stage (T_{17}-T_{20}), occupants 2 and 5, who were in Z7, walked back to their previous zones. The mean detection rate was 63%. In this stage, 89% of the occupants, who were detected out of their actual thermal zones, were detected in adjacent thermal zones.

The mean detection rate of all stages in test 5 was 76%. This result was higher than the average mean detection rate of tests 3 and 4 (62%), where occupants walked randomly in the thermal zones. This was due to the fact that some of the occupants were seated or standing in test 5 and had higher detection rates, and, thus, they increased the overall mean detection rate. Tests 1 and 2, where occupants were seated throughout the tests, had an average detection rate of 88%. This result also supports that when the occupants were seated, and, thus, a more stable environment was present, the system yielded higher detection rates. Fig. 5 shows the estimated locations and paths of occupants in test 5. The red lines indicate the time intervals when occupants walked out of or walked back to the room.

Table 4
Average distances from corresponding centroids in tests 1 to 4.

	Test 1 (m)	Test 2 (m)	Test 3 (m)	Test 4 (m)
Occupant 1	0.14	2.41	2.16	0.32
Occupant 2	0.62	1.48	4.51	2.38
Occupant 3	0.91	1.69	3.44	3.57
Occupant 4	1.02	1.56	2.48	1.41
Occupant 5	0.82	1.13	3.59	5.28
Occupant 6	2.41	3.21	5.42	4.33
Average	0.99	1.91	3.60	2.88

Table 6 presents the average distance of each occupant's estimated location from its corresponding centroid in test 5. The lowest average distance (1.62 m) was generated in stage 1, where all occupants were seated, and that represented a more stable environment. The highest average distance (2.55 m) generated was generated in stage 5, after all occupants walked back, and, thus, all occupants were in their initial zones. This result was due to the fact that data associated with T_{17}

Table 5
Thermal zone based occupancy detection rates for test 5.

Test #	Worse (%)	Best (%)	Mean (%)
5	83	100	92
	67	83	75
	50	100	79
	50	83	71
	50	67	63

might represent the transition while occupants were still walking towards their previous thermal zones. Therefore, stage 5 presented a more dynamic environment than stage 1, and, thus, yielded more jitter. The same environment was observed in stages 2 and 3, which also yielded more jitter. The results indicated a similarity in stage 2 and stage 4 in terms of the occupants' activities, where the higher average distances from the corresponding centroids presented a more dynamic environment. The average distance in stage 3 was 1.77 m, which was relatively close to the average distance in stage 1 (1.62 m). This result was probably due to the fact that the occupants, who walked out of their zones, presented a more stable environment while standing in the thermal zone Z7. Overall, the results show that the system can be adopted in real-life problems where the activity of occupants is unpredictable with respect to the time intervals.

7. Discussions

The success of demand-driven HVAC operations relies on the implementation of occupancy based operation strategies. As outlined in Section 2, these strategies include maintaining higher

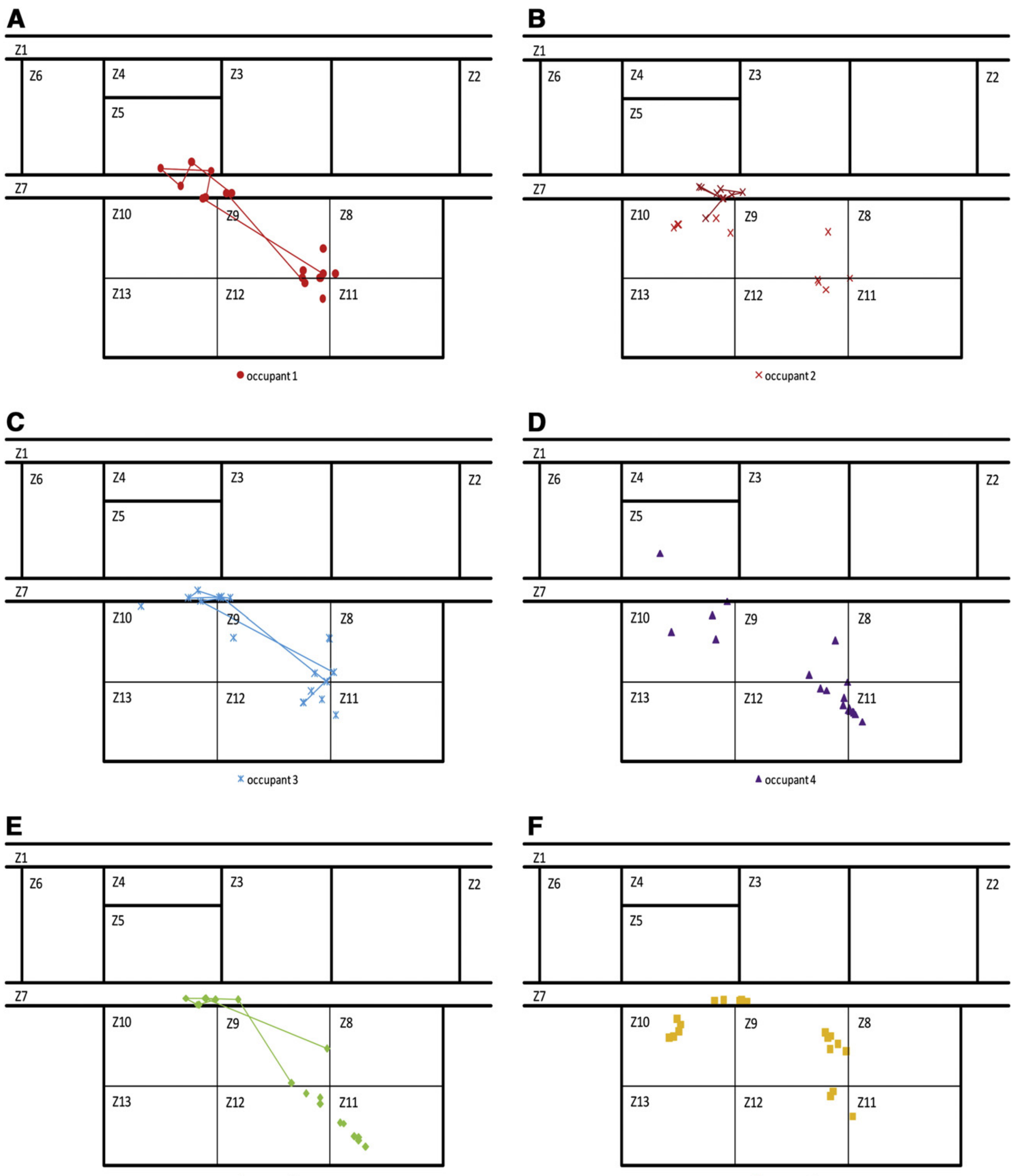

Fig. 5. a–f: Estimated locations and paths of each occupant in test 5.

Table 6
Average distances from corresponding centroids in test 5.

	Stage 1 (T_1–T_4) (m)	Stage 2 (T_5–T_8) (m)	Stage 3 (T_9–T_{12}) (m)	Stage 4 (T_{13}–T_{16}) (m)	Stage 5 (T_{17}–T_{20}) (m)
Occupant 1	2.12	1.58	1.54	0.81	0.87
Occupant 2	4.62	4.39	0.49	0.59	3.19
Occupant 3	0.94	0.73	3.49	4.40	2.33
Occupant 4	0.87	0.38	1.04	4.59	3.91
Occupant 5	0.67	3.11	0.45	1.01	1.20
Occupant 6	0.53	1.75	3.61	0.60	3.81
Average	1.62	1.99	1.77	2.00	2.55

temperatures and lower ventilation rates in unoccupied areas, adjusting conditioned air flows outside air volume based on occupancy, controlling reactively and proactively based on the changes in heat loads, learning and implementing occupant preferences, and increasing control flexibility. When real-time occupancy information is reported by the occupancy detection system, associated variables can be calculated, such as heat loads and minimum ventilation rates, or retrieved from a database, such as preferred temperature set points and patterns of an occupant. The above strategies can then be executed by implementing these variables in the HVAC systems, leading to desired energy savings. It is important to point out that reduction of energy consumption using these strategies, although is the main focus of this research, may lead to compromises of occupant comfort at the same time. Potential downsides include insufficient ventilation [17], high CO2 concentration [18], and limited flow of conditioned air [6]. These downsides need to be taken into consideration when executing the strategies. However, the balance between occupant comfort and energy consumption is more a policy issue than a technical issue, and is beyond the scope of this study.

The success of demand-driven HVAC operations is dependent on the accuracy of the occupancy detection system. Deviations from actual occupancy levels will lead to deviations from actual heat production, and consequently to excessive or insufficient supplies of cooling/heating capacities. In the field tests, the proposed RFID system was able to provide an average zone level detection accuracy of 88% for stationary occupants and 62% for mobile occupants.

Two factors have been noticed to have effects on the occupancy detection rate. The first factor is the density of the reference tags, which is a potential explanation to the low detection rate in test 4. Increasing the tag density increases the risk of radio signal collision, causing the accuracy of location computation to decline [45]. Therefore, a reasonable tag density must be investigated and implemented to ensure a high and stable detection rate. Another factor that affects the occupancy detection rate is the locations of the targets. This factor has caused the lower detection rates for mobile occupants compared to the stationary occupants observed in the tests, as mobile targets were not well covered by reference tags when they moved to the boundaries of the sensing area. One solution is to deploy more reference tags to cover a larger area, so that targets are less likely to be close to the boundaries.

An area that will be explored to further improve the effectiveness of the demand-driven HVAC operations is the detection of occupants' activities, as knowing the activities of occupants is beneficial for determining the heat loads in addition to the number of occupants [46]. Test results show that a simple quantification of occupants' activities can be accessed via scattering analysis, in which higher average distances from corresponding centroids indicate more dynamic environments. This analysis enriches the information usable in adjusting the HVAC set points. However, a closer examination is needed to better reveal occupants' activities, and to more accurately drive the HVAC systems to satisfy changing cooling/heating and ventilation needs. Moreover, the authors have monitored the occupancy flow and occupants' activities over a period of time. This provides the possibility of occupancy prediction, which has the potential to lower the investment on hardware and reduce the intrusion to the infrastructure in the long run.

8. Conclusions

In this study, current HVAC work procedures were analyzed, and two major energy consumers were identified. Then the impact of occupancy information on HVAC energy consumption was examined, based on which a series of eight demand-driven HVAC operation strategies were presented. To support the demand-driven HVAC operations with real-time and accurate occupancy information, an RFID-based occupancy detection system was proposed. The system was tested on a floor of an educational building. The results showed that the proposed system had the ability of detecting and reporting the number of multiple occupants – both stationary and mobile – at the thermal zone level. Occupancy presence detection rate was 100% for both stationary and mobile occupants in all tests. Moreover, in tests 1 to 4, the average zone level detection accuracy was 88% for stationary and 62% for mobile occupants, respectively. In test 5, where a more dynamic environment was simulated, zone level detection rate was 76%. For the scattering analysis, in tests 1 and 2, where occupants were seated, the average distances were 0.99 m and 1.91 m, respectively, while in tests 3 and 4, where occupants were walking randomly, the average distances were 3.60 m and 2.88 m, respectively. More jitter was associated with a more dynamic condition (walking vs. seated), and, thus, the system could provide a simplified activity classification of detected occupants. HVAC energy consumption is expected to be reduced with the integration of the occupancy detection system and the demand-driven HVAC operation strategies. In the future, the authors will examine the sensitivity of the energy savings to the accuracy of occupancy detection, and explore the use of estimating the occupants' activities and predicting the occupancy in supporting demand-driven HVAC operations.

References

[1] DOE, Building energy data book, US Department of Energy, 2011.
[2] I. Shelley, H. Roessner, RFID tagging, http://www.global-id-magazine.com/0904/140904.pdf 2009Last accessed: Dec. 15, 2010.
[3] Y. Tachwali, H. Refai, J.E. Fagan, Minimizing HVAC energy consumption using a wireless sensor network, Proceedings of the33rd Annual Conference of the IEEE Industrial Electronics, IEEE, Piscataway, NJ, USA, 2007, pp. 439–444.
[4] G.R. Newsham, B.J. Birt, Building-level occupancy data to improve ARIMA-based electricity use forecasts, Association for Computing Machinery, Zurich, Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Switzerland, 2010, pp. 13–18.
[5] B.F. Warren, N.C. Harper, Demand controlled ventilation by room CO2 concentration: a comparison of simulated energy savings in an auditorium space, Energy and Buildings 17 (1991) 87–96.
[6] V.L. Erickson, A.E. Cerpa, Occupancy based demand response HVAC control strategy, Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Association for Computing Machinery, Zurich, Switzerland, 2010, pp. 7–12.
[7] V.L. Erickson, Y. Lin, A. Kamthe, R. Brahme, A. Surana, A.E. Cerpa, Energy efficient building environment control strategies using real-time occupancy measurements, Proceedings of the 1st ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Association for Computing Machinery, Berkeley, CA, United states, 2009, pp. 19–24.
[8] Z. Sun, S. Wang, Z. Ma, In-situ implementation and validation of a CO2-based adaptive demand-controlled ventilation strategy in a multi-zone office building, Building and Environment 46 (2011) 124–133.
[9] L.M. Ni, Y. Liu, C.L. Yiu, A.P. Patil, LANDMARC: indoor location sensing using active RFID, Wireless Networks 10 (2004) 701–710.
[10] N. Li, B. Becerik-Gerber, Performance-based evaluation of RFID-based indoor location sensing solutions for the built environment, Advanced Engineering Informatics 25 (2011) 535–546.
[11] A. Pradhan, E. Ergen, B. Akinci, Technological Assessment of Radio Frequency Identification Technology for Indoor Localization, Journal of Computing in Civil Engineering 23 (2009) 230–238.
[12] A. Motamedi, A. Hammad, Lifecycle management of facilities components using radio frequency identification and building information model, *ITcon*, 14, 2009, pp. 238–262.
[13] K. Domdouzis, B. Kumar, C. Anumba, Radio-Frequency Identification (RFID) applications: a brief introduction, Advanced Engineering Informatics 21 (2007) 350–355.

[14] M.J. Brandemuehl, J.E. Braun, Impact of demand-controlled and economizer ventilation strategies on energy use in buildings, ASHRAE, 105 Seattle, WA, USA, 1999 PART 2.

[15] ASHRAEA, SHRAE Handbook: Fundamentals 2009, Atlanta, GA, 2009.

[16] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, T. Weng, Occupancy-driven energy management for smart building automation, Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings, Association for Computing Machinery, Zurich, Switzerland, 2010, pp. 1–6.

[17] V. Pavlovas, Demand controlled ventilation a case study for existing Swedish multifamily buildings, Energy and Buildings 36 (2004) 1029–1034.

[18] X. Yang, X. Jin, Z. Du, B. Fan, X. Chai, Evaluation of four control strategies for building VAV air-conditioning systems, Energy and Buildings 43 (2011) 414–422.

[19] L. Klein, J. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, M. Tambe, Coordinating occupant behavior for building energy and comfort management using multi-agent system, Automation in Construction 22 (2012) 525–536.

[20] L.J. Lo, A. Novoselac, Localized air-conditioning with occupancy control in an open office, Energy and Buildings 42 (2010) 1120–1128.

[21] G.P. Henze, R.H. Dodier, D.K. Tiller, X. Guo, Building occupancy detection through sensor belief networks, Energy and Buildings 38 (2006) 1033–1043.

[22] B. Dong, B. Andrews, K.P. Lam, M. Höynck, R. Zhang, Y. Chiou, et al., An information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network, Energy and Buildings 42 (2010) 1038–1046.

[23] K.P. Lam, M. Höynck, B. Dong, B. Andrews, Y. Chiou, R. Zhang, Occupancy detection through an extensive environmental sensor network in an open-plan office building, Proceedings of the Eleventh International IBPSA Conference, 2009, Glasgow, Scotland.

[24] K.P. Lam, M. Hoynck, R. Zhang, B. Andrews, Y. Chiou, B. Dong, Information-theoretic environmental features selection for occupancy detection in open office, Proceedings of the Eleventh International IBPSA Conference, 2009.

[25] S. Meyn, A. Surana, Y. Lin, S.M. Oggianu, S. Narayanan, T.A. Frewen, A sensor-utility-network method for estimation of occupancy in buildings, Proceedings of 48th IEEE Conference on Decision and Control held jointly with 2009 28th Chinese Control Conference, Institute of Electrical and Electronics Engineers Inc., Shanghai, China, 2009, pp. 1494–1500.

[26] J. Hutchins, A. Ihler, P. Smyth, Modeling count data from multiple sensors: a building occupancy model, Proceedings of 2nd IEEE International Workshop on Computational Advances in Multi-Sensor Adaptive, IEEE, Piscataway, NJ, USA, 2007, pp. 241–244.

[27] Y. Benezeth, H. Laurent, B. Emile, C. Rosenberger, Towards a sensor for detecting human presence and characterizing activity, Energy and Buildings 43 (2011) 305–314.

[28] A. Sarkar, M. Fairchild, C. Salvaggio, Integrated daylight harvesting and occupancy detection using digital imaging, Proceedings of Sensors, Cameras, and Systems for Industrial/Scientific Applications IX, SPIE, San Jose, CA, United states, 2008.

[29] C. Kuo, R. Nevatia, How does person identity recognition help multi-person tracking? Proceedings of 2011 IEEE Conference on Computer Vision and Pattern Recognition, IEEE Computer Society, Colorado Springs, CO, United states, 2011, pp. 1217–1224.

[30] C. Busso, S. Hernanz, C. Chu, S. Kwon, S. Lee, P.G. Georgiou, Smart room: participant and speaker localization and identification, Proceedings of 2005 IEEE Conference on Acoustics, Sppech, and Signal Processing, Institute of Electrical and Electronics Engineers Inc, II Philadelphia, PA, United states, 2005, pp. II1117–II1120.

[31] Z. Zhen, Q. Jia, C. Song, X. Guan, An indoor localization algorithm for lighting control using RFID, Proceedings of 2008 IEEE Energy 2030 Conference, Inst. of Elec. and Elec. Eng. Computer Society, Atlanta, GA, United states, 2008.

[32] M.J. Akhlaghinia, A. Lotfi, C. Langensiepen, Localising agents in multiple-occupant intelligent environments, Proceedings of the 6th IEEE World Congress on Computational Intelligence, IEEE Computer Society, Barcelona, Spain, 2010.

[33] M.J. Akhlaghinia, A. Lotfi, C. Langensiepen, N. Sherkat, Occupant behaviour prediction in ambient intelligence computing environment, Journal of Uncertain Systems 2 (2008) 85–100.

[34] M.J. Akhlaghinia, A. Lotfi, C. Langensiepen, N. Sherkat, Fuzzy predictor model in an inhabited intelligent environment, Proceedings of WCCI 2008, IEEE, 2008, pp. 939–946.

[35] J.D. Jackson, D.W. Callahan, P.F. Wang, A preliminary examination of inertial navigation using accelerometers, WSEAS Transactions on Circuits and Systems 5 (2006) 1789–1794.

[36] A.R. Jimenez, F. Seco, C. Prieto, J. Guevara, A comparison of pedestrian dead-reckoning algorithms using a low-cost MEMS IMU, Proceedings of WISP 2009, IEEE, Piscataway, NJ, USA, 2009, pp. 37–42.

[37] N.B. Priyantha, A. Chakraborty, H. Balakrishnan, The Cricket location-support system, Proceedings of the Sixth Annual International Conference on Mobile Computing and Networking, ACM, New York, NY, USA, 2000, pp. 32–43.

[38] B. Becker, Application range of UWB-technologies, SMART Solutions 2008, 2008 Isernhagen, Germany.

[39] H.M. Khoury, V.R. Kamat, Evaluation of position tracking technologies for user localization in indoor construction environments, Automation in Construction 18 (2009) 444–457.

[40] P. Bahl, V.N. Padmanabhan, RADAR: an in-building RF-based user location and tracking system, Proceedings of the Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies, IEEE, Piscataway, NJ, USA, 2000, pp. 775–784.

[41] J. Zhou, J. Shi, A comprehensive multi-factor analysis on RFID localization capability, Advanced Engineering Informatics 25 (2011) 32–40.

[42] D.G. Torrent, C.H. Caldas, Methodology for automating the identification and localization of construction components on industrial projects, Journal of Computing in Civil Engineering 23 (2009) 3–13.

[43] X. Luo, W.J. O'Brien, C.L. Julien, Comparative evaluation of Received Signal-Strength Index (RSSI) based indoor localization techniques for construction jobsites, Advanced Engineering Informatics 25 (2011) 355–363.

[44] S. Woo, S. Jeong, E. Mok, L. Xia, C. Choi, M. Pyeon, et al., Application of WiFi-based indoor positioning system for labor tracking at construction sites: a case study in Guangzhou MTR, Automation in Construction 20 (2011) 3–13.

[45] N. Li, S. Li, B. Becerik-Gerber, G. Calis, Deployment strategies and performance evaluation of a virtual-tag-enabled indoor location sensing approach, Journal of Computing in Civil Engineering 1 (2011) 111.

[46] B. Dong, B. Andrew, Sensor-based occupancy behavioral pattern recognition for energy and comfort management in intelligent buildings, Proceedings of Building Simulation '2009, an IBPSA Conference, 2009.