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# Modeling occupancy distribution in large building spaces for HVAC energy efficiency

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**Abstract**

In large spaces, co-operative HVAC terminals are usually installed to provide services for different virtual thermal zones. The lack of high-resolution occupancy distribution in large spaces is often perceived as one of the main causes of underperformed HAVC systems. Current studies usually considered occupancy information of the whole space or room, such as occupancy count level, other than the zone-level occupancy distribution. Although the count of total occupants in space might stay constant, the actual occupancy distribution might be different, which will bring with different operations for each HVAC terminal. Therefore, to find out one high-resolution occupancy level, this research proposed the idea of integrating k-Means clustering and k Nearest Neighbors (kNN) classification algorithm to detect the occupancy distribution via the dual Bluetooth Low Energy (BLE) and Wi-Fi signal technology networks. One experiment place was conducted in one indoor area of the typical office room at the City University of Hong Kong for measuring the signal distribution of BLE and Wi-Fi. In this study, the occupancy preference cluster could be mapped into the indoor thermal zones and three case studies are chosen for validation of occupant number confirmation in each thermal zone. Finally, zone occupancy based energy performance analysis was presented with the assistance of wireless sensors nodes to compare energy saving potential under actual occupancy distribution and detected occupancy distribution and the importance of zone occupancy information for the demand-driven control mechanism is stressed.



*Keywords:* cluster-classification algorithm, occupancy distribution, HVAC energy efficiency

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## 1. Introduction

Building energy management in HVAC systems is crucial in the examination of how building energy conservation can be potentially achieved. Close upon ameliorative control modes in HVAC system according to the term "demand driven operation" [1,2], occupancy information, defined as the number and time-based schedule of occupants in buildings, plays an important role in normally determining building heating and cooling load [2–4]. Demand-driven operation mainly refers to the actual requirement of building appliance and thermal comfort, in consequence, that building energy would be wasted once supplies are more than demands. To achieve an acceptable thermal comfort level and energy efficiency, some researchers proposed the idea of temperature sensors based control modes for adjusting operation of air-conditions and those control modes could achieve certain energy saving in such room without zone divisions. For example, Lin and Claridge proposed a temperature-based Days Exceeding Threshold-Toa (DET-Toa) method to detect persisting small increase or decrease to assess the cooling or heating demand in a given period [5]. Zeng et al. developed a data-driven predictive model to balance the temperature and air static pressure setting point with the actual demand to optimize HVAC operation [6]. Zhou et al. proposed a demand-based temperature control model with breathing level temperature sensors to eliminate data bias due to temperature vertical distribution [7]. Also in Zhou's work, it could achieve at least a 20% to 30% reduction in supply airflow when zone is fully- or half-occupied. It was obvious to find out that they are limited in the large-scale rooms where need to consider the occupancy information. Large-scale rooms are profiled by high capacity and large areas to serve relatively more users and consumed more energy. However, it would be commonly found that load distribution in such areas could be uneven since the occupancy preference would be randomly and occupants in those areas might sit or walk in a relatively ambulatory pattern. Although in the same room, some zones may be occupied by a large number of users while other zones may only serve few users or even none. In such type of building areas, once without considering occupied information of individual zones, some zones may be over over-cooled and others may be sub-cooled, which cause mismatching between demand and supply [7]. The worst case is that facilities is still working in unoccupied zones as if unoccupied. Therefore, the deficiency of occupancy distribution could totally give a discount of performance of temperature-based control methods.

In some occupancy-based zone-climate control studies, it has concluded that a significant amount of energy can be achieved without sacrificing thermal comfort and indoor air quality by using occupancy measurement methods [8,9]. However, detailed occupancy profiles in building room level are straightforwardly determined, but how those people are occupied in zone level is not clear when in search of energy conservation and thermal comfort at the zone level. Therefore, this study proposed one cluster-classification algorithm to detect occupancy distribution information. One on-site experiment was conducted to validate the proposed algorithm. Finally, simulation was applied to evaluate the energy saving potentials of using occupancy distribution information.

## 2. Methodology

After collection of BLE and Wi-Fi signal fingerprinting point s, it could format each point as one unique signal vector. Supposed that there are *R* thermal zones, *N* total signal sources (Wi-Fi and BLE). It's supposed there are *M* knew signal fingerprinting points and zone objective function *f(x)*, then signal vector for one feature point *x* can be defined as follow:

$$\{x = < S_1(x), S_2(x), \ldots, S_v(x), \ldots S_N(x) >, f(x) = r\} \quad (1)$$

While $S_v(x)$ denotes the signal strength of point *x* received from signal source $v$ $1 \leq v \leq N$, $x \to M$, $r \to R$.

In the k-Means cluster algorithm, the Euclidean distance between two signal vectors could be denoted as following:

$$d^2(x_1, x_2) = \sum_{v=1}^{N}(s_v(x_1) - s_v(x_2))^2 \quad (2)$$

In order to find out the thermal zone clusters, it could follow the pseudocode 1 of k-Means cluster algorithm. At first, it would initialize k cluster centroids (c1, c2 … ck) randomly and assign the points into the initial centroids of clusters by the measure of distance. And then for each point $x_i$ in one cluster $c_j$ , it needs to find out the closest centroids of clusters by:

$$argmin\|x_i - c_j\|^2 = argmin \sum_{v=1}^{N}(s_v(x_i) - s_v(c_j))^2 \quad (3)$$

Also for each cluster center $j$, it should satisfy:

$$argmin\ SSE = \sum_{x=1}^{M}\sum_{j=1}^{k} d^2(x_i, c_j) \quad (4)$$

In k-Means cluster algorithm, it could be iterated by the sequential process of "calculate centroids-reassign centroids-recalculate" until the centroids of each cluster would not change finally. After this algorithm process, every fingerprinting point would be assigned into corresponding clusters, that's, in this case, the geometrical location of fingerprinting would be assigned into corresponding zones. For each signal vector, it would be reassigned as

$$\{x = < S_1(x), S_2(x), \ldots, S_v(x), \ldots S_N(x) >, f'(x) = c_j\} \quad (5)$$

Based on the feature of received signal strength of fingerprinting point in the accessible indoor areas, the k-Means cluster algorithm could divide the indoor area into serval zones. In order to refine the occupancy distribution information in each thermal zone, k-NN algorithm is adopted to estimate the most possible zone that the occupant belongs to. In the previous results of cluster algorithm, we could add all fingerprinting points into training samples M and each sample would be formatted as the vector of equation 19. Suppose there are $U$ unknown-location users, and then for one RSS of the unknown-location user $(u)$ in one room, it could determine the distance between it and each training sample by equation 16.

$$< (x_1, f'(x_1)), (x_2, f'(x_2)), \ldots, (x_k, f'(x_k)) > \quad (6)$$

In the above vector, the $(x_k, f'(x_k)$ represents the kth point belong to the thermal zone cluster $f'(x_k)$. So, it could be presented as following:

$$< (x_1, c), (x_2, f'(x_2)), \ldots, (x_k, f'(x_k)) > \quad (7)$$

Then define weight factor:

$$w_i = 1/d^2(u, x_i) \quad (8)$$

Also define auxiliary function: $\delta(x, y)$ While $\delta(x, y) = 1$ if x=y, or $\delta(x, y) = 0$,

$$c_u \leftarrow \widehat{f}'(u) = \operatorname*{arg\,max}_{c \in c_k} \sum_{i=1}^{k} w_i \delta(c, f'(x_i)) \quad (9)$$

Where the $\widehat{f'}(u)$ and $c_u$ present the estimated thermal zone cluster of the user u.

## 3. Experiment validation

Aiming at testing the methodology using the cluster-classification algorithm with the BLE signal network, we chose one experiment area in one general office room in an institutional building, showed in Fig. 3 and the area contains office desks, computers, and partitions and so on. From network setting in Fig. 3, six iBeacons were installed in the known locations in the open area. Since signal fingerprinting method has been applied in some works by mapping the received signal strength (RSS) into the geometrical location in that area [10–13], after ascertaining signal sources, signal fingerprinting methods would be implemented in the experiment area for office room and it was sequenced by setting 180 fingerprinting points in Zone 1-4, and 90 fingerprinting points in Zone 5-6, respectively, showed in Fig. 3. It has been tested that all the signal sources could be received and all the signal references could be reached in this room. To eliminate the influence caused by fluctuation of the signal, RSS of all points in the experiment would be recorded and averaged by three times. Fig. 4 shows the received signal strength (RSS) distribution for BLE sources and the values for signal strength are kept absolute for brevity.

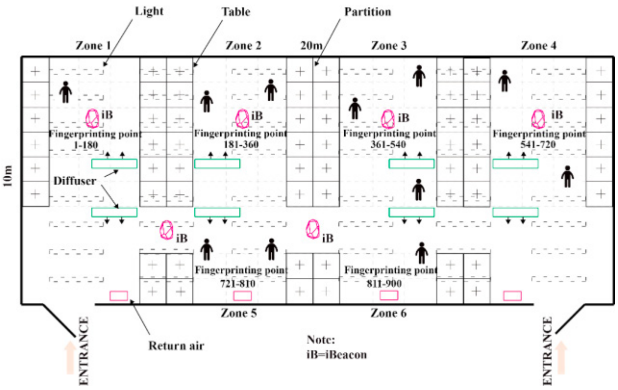


Fig. 1. The schematic view of an office room area in this experiment.

## 4. Results

### 4.1. Occupancy distribution

Three typical cases of office occupancy distribution were picked up at 10:00am, 13:00 pm and 16:00 pm. In the selected cases, there are totally 19 occupants in this office. In section 2.2, it introduced the sequential algorithm and how to find out the maximum probability area of the occupant using the k-NN algorithm. However, the received signal strength of devices would fluctuate in a small range but since the movement of occupants is continuous, the location is an occupant is based on his/her the last location, for example, one occupant currently staying at the Zone 1, he/she couldn't be located in the Zone 3 or 4. Therefore, in order to find maximum expectation of occupied area, we record received signal strengths of continuous steps for one occupant and embed a probability of occupants' location as following:

$$f_{-EM}(p) = max(p1, p2, p3, p4, p5, p6) \tag{10}$$

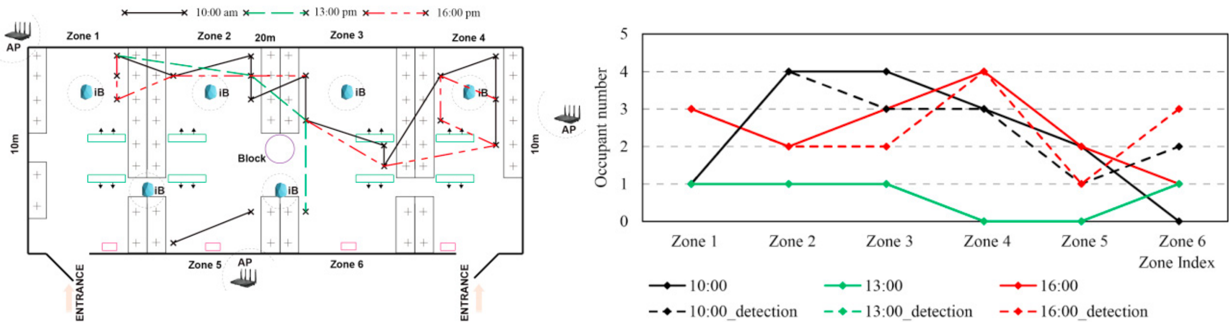


Fig. 2. The occupancy distribution cases of three-time spots in the office (left) and actual and detected occupants' number at each case (right).

It could be found that the occupants in the Zone 3 and 5 might be in Zone 6 and in the physical zone locations, Zone 3 and 5 are both the adjacent zone of Zone 6. For occupant 8 and 16 are located in Zone 6 with maximum-expectation probability and however, occupant 18 has a probability of being located in Zone 3, but still being in Zone 6 with maximum-expectation. In the result of Figure 10, the occupant number could be detected in each thermal zone and it reveals that some zones would be unoccupied at selected cases and compared with actual occupancy information, the mismatch between actual and detected occupancy results probably was in the Zone 3, 5 and 6.

*4.2 Energy performance*

This study simulated thermal load during different months using typical Hong Kong weather data and compared the performance of different occupancy information in reducing energy cost. Table 3 shows the total thermal load estimation and savings in four months for the three cases. The simulation was conducted in one-hour time step. We simulated three scenarios for comparison: thermal load under Actual Occupancy with Standard Temperature (25℃) and Relative Humidity (50%) (AO-S-T/RH), thermal load under Actual Occupancy with Actual Temperature and Relative Humidity (AO-A-T/RH), and thermal load under Detected Occupancy with Standard Temperature and Relative Humidity (DO-S-T/RH). Fig. 12 shows the thermal load simulation in four months and each zone under three scenarios. Table 3 shows how it would save energy when temperature control takes into consideration uneven occupancy distribution and avoid unoccupied zones. Compared with actual operation in AO-A-T/RH, energy costs to remove thermal load in AO-S-T/RH could save 13.81%, 14.16%, 11.69%, and 13.21%, respectively in January, April, July, and October, and total savings can reach 13.12%. On the other hand, DO-S-T/RH could save 12.04%, 12.3%, 10.11%, and 11.53% compared with energy cost in AO-A-T/RH, respectively in January, April, July, and October. The total thermal load reduction is 11.4%. From the table, thermal load based on detected occupancy under recommended environmental variables settings is lower than it under actual operation while closer to performance of actual occupancy. It would save more energy when unoccupied zones could be defined and occupancy distribution-driven HVAC control could be applied.

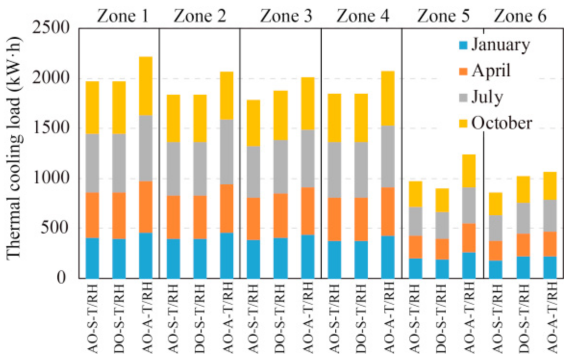


Fig. 3. Thermal load simulation in four months and each zone under three scenarios

Table 3 Average thermal load estimation (kW · h) in one hour under three scenarios.

| | AO-S-T/RH | DO-S-T/RH | AO-A-T/RH | Saving 1 | Saving 2 |
|---|---|---|---|---|---|
| January | 1950.48 | 1990.48 | 2263.0 | 13.81% | 12.04% |
| April | 2153.25 | 2199.83 | 2508.52 | 14.16% | 12.3% |
| July | 2744.32 | 2793.34 | 3107.57 | 11.69% | 10.11% |
| October | 2428.67 | 2476.7 | 2798.41 | 13.21% | 11.53% |
| Total | 9276.73 | 9460.35 | 10677.5 | 13.12% | 11.4% |

Note: Saving 1 and Saving 2 mean thermal load savings of AO-S-T/RH and DO-S-T/RH, respectively compared to AO-A-T/RH

## 5. Discussion and conclusion

In this study, Wi-Fi and BLE technologies are chosen in the occupancy distribution detection works and in this research occupancy distribution acquired by two dual networks are generated as a demand-driven signal. In the algorithm process, cluster-classification sequence is utilized with the idea that the detection system initially defines room occupancy distribution clusters based on the signal distribution clusters of occupancy activities and then intensively study the occupancy distribution classification. Based on such information, we can get the detected occupancy distribution from three cases and utilize the results in the assessment of energy performance under the comparisons of actual occupancy information and actual operation with the assistance of wireless sensors node. Although the core of this research is focused on determining occupancy distribution and then controlling air supply modes in VAV systems, such demand-driven control systems also can be extended to other building service systems and enable more sophisticated control design and the potential applications are far more extensive.

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