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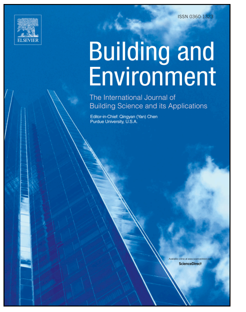

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Occupancy prediction model for open-plan offices using real-time location system and inhomogeneous Markov chain

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Abstract

Implementing intelligent control strategies of building systems can significantly improve building energy performance and maintain or increase occupants' comfort level. However, these control strategies are dependent on the occupancy models. A good occupancy prediction model requires enough input data pertinent to the occupants' space utilization patterns. However, most of the occupancy detection systems cannot provide this detailed information. As a result, most of the research works that considered shared multi-occupied offices did not distinguish between different individuals. Therefore, their practicality is reduced when they are used for open-plan offices. In this study, the occupancy modeling (i.e., occupants' profiles) has been further enhanced using inhomogeneous Markov chain prediction model based on real occupancy data collected by a Real Time Locating System (RTLS). After extracting the detailed occupancy information with varying time-steps from the collected RTLS occupancy data, an adaptive probabilistic occupancy prediction model is developed. The comparison between the occupancy profiles resulting from the prediction model and the actual profiles showed that the prediction model was able to capture the actual behavior of occupants at occupant and zone levels with high accuracy. The proposed model distinguishes the temporal behavior of different occupants within an open-plan office and can be used for various levels of resolution required for the application

of intelligent, occupancy-centered local control strategies of different building systems. This would eventually lead to a more robust control of building systems as well as more satisfied occupants.

1. Introduction

It is estimated that the world energy consumption will increase by 56% from 2010 through 2040 [1]. The fact that buildings contribute a large portion of the global energy consumption indicates a need for detailed investigation towards more effective energy performance of buildings. The International Energy Agency (IEA), Energy in the Buildings and Communities Program (EBC), Annex 53 recognized the following parameters as the most influential for energy consumption in buildings: (1) climate, (2) building envelope, (3) building energy and service systems, (4) indoor design criteria, (5) building operation and maintenance, and (6) occupant behavior [2]. Some of these parameters are easy to determine, being related to the physical characteristics of the building (e.g., building size, orientation, construction materials, Heating, Ventilation, and Air Conditioning (HVAC) system size and type, etc.). On the other hand, some parameters that vary with time are difficult to predict, such as occupancy input. Thus, providing a comprehensive and reliable occupancy model is still under development.

Occupancy models, which are derived based on space utilization patterns and occupant behavior, are key factors to accurately estimate the energy consumption of buildings. According to [4, 5], there are different resolution levels for occupancy models, which are highly context dependent. These levels should be determined according to the required granularity of occupancy models used for different purposes. For instance, a finer level of granularity is needed to apply lighting control strategies. Given that HVAC systems need some time to adjust the indoor temperature to a specified target set-point, less accuracy in occupancy detection may not lead to a significant thermal discomfort [6]. The high-resolution occupancy models provide the following information: (1) the location of occupants, (2) their identities, (3) the number of occupants in each zone of the building, and (4) their activities at each time-step. Having this information helps to determine the occupants' interactions with building systems [7]. This will eventually lead to the application of occupancy-centered local control strategies on the systems. Furthermore, occupancy-related information is useful for different energy management purposes as well as other areas, such as safety, security, and emergency response.

Based on the above discussion, occupancy modeling is a complicated procedure and many occupant behavior analytics (data processing) steps are required to filter the input data and create a reliable occupancy model. Monitoring and data collection are important steps to develop a detailed occupancy model. A good occupancy model requires enough input data pertinent to the occupants' space utilization patterns. This data is gathered for a reasonable period through monitoring techniques, such as different Real Time Locating Systems (RTLSs). However, most of the occupancy detection systems cannot provide the number of occupants and the specific location of each occupant (i.e., the x and y coordinates of the occupant) when they are used for open-plan offices. Most of the research works that consider shared multi-occupied offices did not distinguish between different individuals. Therefore, their practicality is reduced for open-plan offices, which have multiple thermal zones [8]. In addition, they lack detailed investigation of the effect of the individual preferences of occupants sharing the same area on the energy consumption of the building. Therefore, there is a need to use proper sensing and occupancy modeling techniques to distinguish between different occupants in multi-occupied offices and apply their preferences.

This paper aims to develop a new adaptive probabilistic occupancy prediction model for open-plan offices based on occupancy data. In this study, the occupancy modeling (i.e., occupants' profiles) has been further enhanced using inhomogeneous Markov chain prediction model, which distinguishes the temporal behavior of different occupants within an open-plan office based on occupancy space utilization patterns data. To this end, the occupants' detailed data (who, where, when) is collected using a relatively new monitoring technology (i.e., Bluetooth RTLS) that responds to occupancy changes in open-plan office buildings with acceptable accuracy. After developing the personal profile for each occupant with varying time-steps using advanced data analysis, a new adaptive probabilistic occupancy prediction model is developed to be used for occupancy prediction of open-plan offices. The proposed model is verified using a case study. Finally, comparing the building's real occupancy and produced results by the occupancy prediction model provides the validation of the applicability of the proposed model.

The rest of this paper is organized as follows: Section 2 reviews related research studies with a focus on monitoring techniques as well as occupancy models being developed using stochastic methods; Section 3 discusses the proposed research methodology; implementation and case study are explored in Section 4. Finally, the conclusions, limitations of the current research study and future work are discussed in Section 5.

2. Related Research Studies

2.1. Occupancy Monitoring

Occupancy data can be collected using different types of monitoring techniques for a reasonable period. A comprehensive literature review with the focus on different monitoring techniques used to collect occupancy data in office buildings has been conducted by the authors [9]. According to [9], the usage of radio frequency (RF)-based localization technologies, such as Wi-

Fi and Bluetooth, has increased in recent years due to their deployment flexibility, communication range and ability to work without line of sight [10]. Apart from the easy deployment of Wi-Fi system to represent occupancy patterns with reasonable accuracy, there may be connection problems that highly affect the performance of this monitoring technique. Moreover, the battery life of connected devices to Wi-Fi is another major concern when using this kind of monitoring system. Furthermore, the total number of Wi-Fi connections may not be enough for accurate occupancy detection for large-scale buildings and a large number of occupants [11, 12]. On the other hand, the ability to track multiple moving objects in real-time makes Bluetooth Low Energy (BLE) systems optimal RTLSs for different applications, such as building energy efficiency, sport, and healthcare applications, optimizing store layout, security, and emergency situations [13].

Comparing different research works shows that detailed data regarding occupants' location, their number, identities, and activities can be collected using BLE location sensors [9]. Having high-resolution occupancy data will result in distinguishing between different occupants in multi-occupied offices and providing a more reliable and accurate estimation of occupants' space utilization patterns.

2.2. Occupancy Modeling

Considering the effect of space utilization patterns and occupant behavior on the building energy consumption, accurately predicting these parameters leads to saving energy. Besides the importance of having insight regarding occupant behavior, collecting information pertinent to the space utilization patterns, which derived from occupants' presence, is a very crucial aspect to determine. In this context, occupancy information, such as occupants' presence schedule (e.g., occupants' profiles), the locations of occupants, and their number for each space (and each time-step) of a building are the most important parameters to predict.

Occupancy-related parameters are highly dependent on the season, weather, time of the day, and occupants' habits [14]. Therefore, there is an urgent need to consider the probabilistic modeling of occupants' parameters and profiles to reflect these dependencies [3]. Probabilistic occupancy prediction models should be integrated with simulation tools to realistically estimate energy consumption of buildings. In order to find a comprehensive occupancy prediction model, which captures the diverse activities of different occupants within a building, stochastic analysis methods should be leveraged.

Stochastic methods use real data pertinent to the occupants' location, movement, and actions, being collected over a reasonable period, to predict the probability of an event (i.e., occupant being present in a space) or an activity (e.g., window opening behavior) and generate the probabilistic profiles [15, 16]. Monte Carlo methods, Markov Chain, discrete and semi-hidden Markov Chain models, as well as Poisson model are in the category of stochastic methods. Since the occupant's next state is highly dependent on his/her present state, which is the basis of the Markov chain process, modeling occupancy space utilization patterns using Markov chain is one of the most utilized techniques by researchers.

Based on the above discussion, an overview of the comparison between different research works using Markov chain models and the recent study is shown in Figure 1. The comparison is done in terms of the type of Markov chain model, occupancy model level, type of space, and information resolution derived from the occupancy model. Although some similarity can be seen between the reviewed papers and the current paper, none of them developed the occupancy model at all three levels (i.e., individual, zone, and room levels). In addition, all space types (i.e., shared and private) are considered in this study. Moreover, the proposed occupancy model in this study provides high-resolution information regarding variations in occupancy patterns by considering the temporal behavior of occupants through defining the detailed work states, which are explained in detail in Section 3. Last but not least, none of the reviewed papers considered the combination of all these aspects in a real-world scenario.

	Type of Model		Occupancy Model Level			Type of Space		Information Resolution from Occupancy Model						
										Absence				Occupancy Modeling Method
	Homogeneous	Inhomogeneous	Individual	Zone	Room	Shared	Private	First Arrival	Presence	Short Break	Lunch	Long Break/Meetings	Last Departure	
[17]	✓				✓		✓	✓	✓		✓		✓	Markov chain
[18]		✓			✓		✓	✓	✓	✓	✓	✓	✓	Markov chain
[19]		✓			✓	✓		✓	✓				✓	HMM, SVM, and ANN
[20]		✓			✓	✓		✓	✓				✓	HMM, SVM, and ANN
[3]	✓		✓		✓	✓	✓	✓	✓		✓	✓	✓	Markov chain
[21]		✓			✓	✓		✓	✓				✓	GMM-HMM and SMM
[22]		✓			✓	✓		✓	✓				✓	CDMC and BMC
[15]	✓				✓	✓	✓		✓			✓		Markov chain
[23]		✓			✓	✓		✓	✓				✓	HMM and Autoregressive Hidden Markov Model
[24]		✓			✓	✓	✓		✓					Layered Hidden Markov Model
[25, 26]		✓		*✓		**NS	**NS	✓	✓				✓	Markov chain
[27]		✓			✓	✓		✓	✓				✓	Autoregressive Hidden Markov Model
[28]		✓			✓		✓	✓	✓		✓		✓	ARMA, ANN, Markov chain, and Regression model
[29, 30]		✓			✓	✓		✓	✓				✓	Markov chain
[31]		✓			✓		✓	✓	✓		✓		✓	Markov chain
[32]	✓				✓	✓		✓	✓				✓	MCMC and Polynomial Regression (Cubic)
[33]	✓				✓	✓		✓	✓				✓	Markov chain and Affinity propagation
[12]		✓			✓	✓		✓	✓		✓		✓	DMTWI , ARMA, and SVR
Current study		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Markov chain

HMM: Hidden Markov Model
SVM: Support Vector Machine
ANN: Artificial Neural Network
SMM: Hidden Semi Markov Model
CDMC: Closest Distance Markov Chain
BMC: Blended Markov Chain
ARMA: Auto-Regressive Moving Average
GMM-HMM: Gaussian Mixture Model based Hidden Markov Models
MCMC: Markov chain–Monte Carlo
DMTWI: Dynamic Markov Time-Window Inference
*✓: The whole building is assumed as one zone.
**NS: Not specified in paper

Figure 1 Comparison of Recent Literature on Occupancy Modeling

3. Research Methodology

The main goal of this paper is to develop a new adaptive probabilistic occupancy prediction model based on the RTLS data to distinguish between different occupants within an open-plan office. There are many factors determining the accuracy of the occupancy model including the occupants' identities, the duration of the occupants' presence, their locations in different zones of a building, and their preferences. The zoning concept plays an important role in capturing the detailed occupancy information in real open-plan offices and improving the accuracy of the occupancy prediction model. Open-plan offices should be divided into multiple zones to assign different probabilistic occupancy information to each zone. The zoning is applied to consider the effect of (1) different types of activities performed in each zone; (2) different number of the HVAC terminal units or the number of luminaires; (3) different facade orientation for perimeter zones, to name a few. New RTLSs can provide the identity, location, and duration of presence while the preference data can be collected by a survey. The occupancy prediction model is used to determine the occupants-specific probabilistic profiles based on their presence data. The main benefits of this dynamic and probabilistic occupancy prediction model are: (1) Probabilistic feature benefit: unlike models that rely on averaging the various occupants' schedules, the probabilistic occupancy prediction model can capture the diversity of the different occupants' presence patterns using stochastic methods, which is very important factor in open-plan offices; (2) Dynamic update benefit: real-time monitoring and the resulting decision making are the closest way to emulate the real patterns of occupants' presence and their interaction with building systems. The probabilistic occupancy prediction model can distinguish between different occupants' schedules and habits.

To consider the variations in the occupants' profiles due to their temporal behavior, each day is divided into different time slots. There are typical events of importance in office buildings that should be captured while defining these time slots, such as the first arrival to the office. These time slots are determined based on the patterns seen in the collected data as will be explained in Section 4.2. The events of importance indicate the typical patterns of the occupants' activities in open-plan offices. These activities are referred to as work states in this study as shown in Table 1. The duration of each work state is determined using the monitoring data. The first arrival to the office is defined as the first reading of the occupant's presence in the office after his/her long absence during the night. The last departure from the office is determined as the point when there is no recording of the occupants' presence for a duration greater than four hours after that point. Lunch break is defined as a break happening around noon with the duration greater than half an hour. Other breaks during the day with duration shorter than half an hour are considered as short breaks. Meetings, as one example of long breaks, are events that are happening based on a predefined schedule, such as weekly, bi-weekly, etc.

Table 1 Typical Occupancy Work States in Office Buildings

Work State	Description	Label (in Prediction Model)
1	Working in Occupant's Station (Occupant's Zone)	S_{oc}
2	Working in Other Occupants' Station (Other Zones)	S_{ot}
3	Lunch Break (L)	S_{lb}
4	Short Break (SB)	S_{sb}
5	Long Break/Meeting (LB)	S_{lm}

Figure 2 shows the proposed framework towards developing a new adaptive probabilistic occupancy prediction model. This framework comprises three main steps including data collection, data processing, and occupancy prediction model. Data collection is discussed in the following section. During the occupant behavior analytics (data processing), the analysis is required to find important occupancy features, such as the number of present occupants, periods of absence and presence, and other occasional variations in the occupants' profiles. Calculation of the occupancy rate is explained in Section 0 after discussion regarding the data processing phases in Section 3.2. The development procedure of the occupancy prediction model is then explained in Section 3.3.

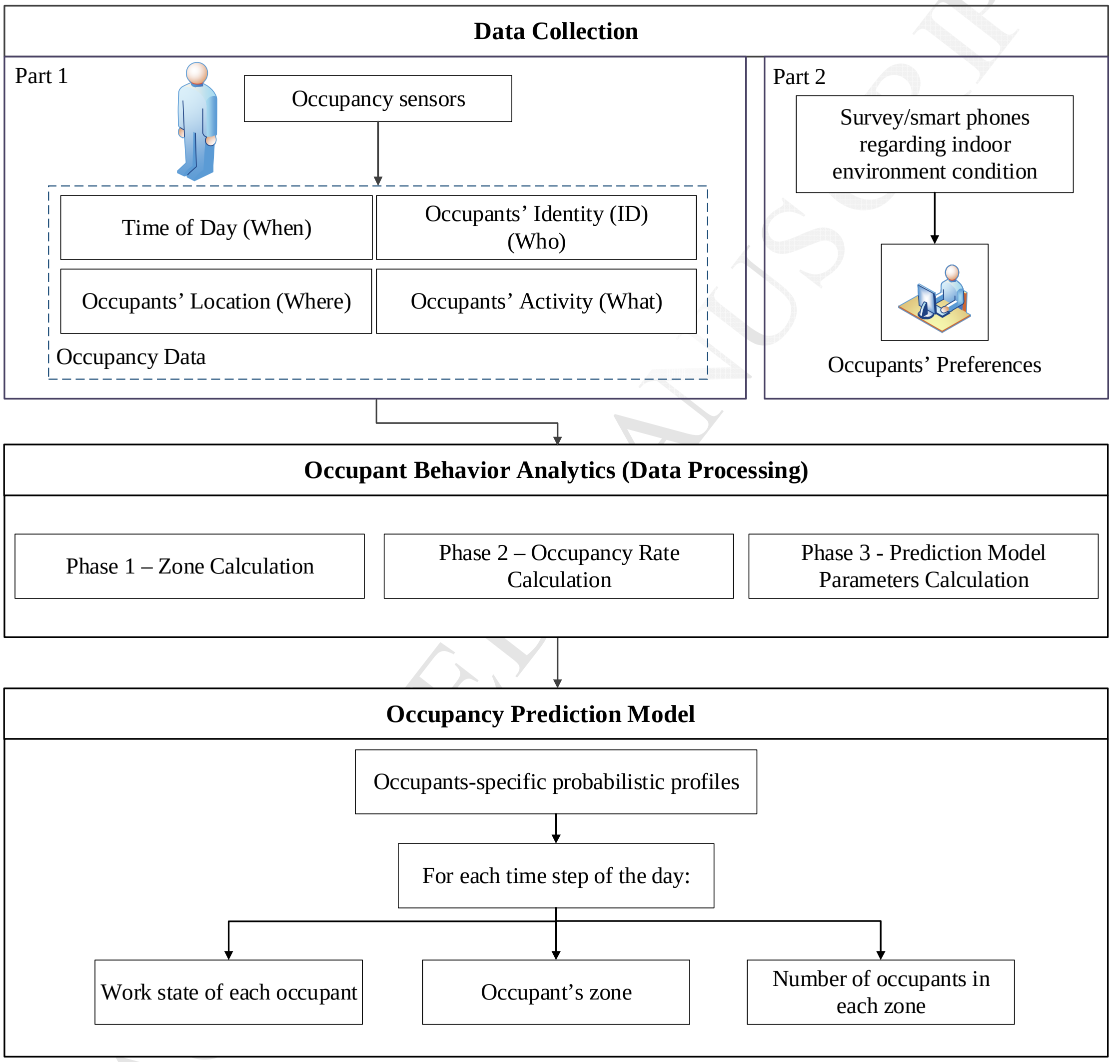


Figure 2 Proposed Framework for Occupancy Prediction

3.1. Data Collection

Considering that the energy performance of an open-plan office is mainly influenced by its occupants, the office occupants' schedules and habits determine the input to the occupancy prediction model. To this end, the office occupants need to be monitored. The data collection step includes two parts to gather all important occupancy data. As mentioned in Section 1, occupants should be monitored over a reasonable period using RTLS to get occupants' location, their identities, presence time, and the type of activities and find the spatiotemporal patterns of the occupant's behavior (part 1). RTLSs are wireless systems that are used to automatically identify and monitor the location of objects or people in a defined space at a point in time that is or is close to, real-time [34]. RTLS comprises of different components: (1) various tags and badges or cell phones to send signals to the sensors (locators); (2) locators for reading tags; (3) platforms (Wi-Fi, Infrared, Ultrasound, Radio Frequency, and others); (4) timing cables or wireless bridges, for the connectivity of sensors with each other and with the host computer; (5) location engine, for calculating tag's position using various techniques; and (6) end-user software application for recording data [35].

To monitor occupants within an open-plan office using Bluetooth technology, either tags or cell phones can be used. These tags will send signals to the RTLS. Each tag has a unique ID number; thus, when a person moves in the area covered by locators, the system detects the unique ID number of the tag and measures the direction of a radio signal transmitted by the tag. Using Angle-of-Arrival (AoA) signal processing method, the incidence angles of the received signals are calculated with respect to the known positions of the locators. Applying a triangulation method, the position of tags can be determined [36]. As illustrated in Figure 3, an accurate 3D position is determined using at least two locators. In practical applications, several locators should be used, depending on the size of the monitored office, to detect the tags providing continuous positioning and substantially improving the accuracy and reliability of the results [37].

The main targets of data collection procedure are the office occupants who are assigned to the office. Thus, visitors, who may enter the office during the day, do not interfere with the data collection procedure and would not affect the accuracy or performance of the proposed model since there is no tag associated with them. The proposed occupancy prediction model is developed based on the office occupants' data and will predict the future occupancy profiles of the office occupants.

In addition, occupants are questioned regarding the settings of the building energy-consuming systems to know their preferences (part 2). It is important to mention that the focus of this paper is on part 1 of the data collection and gathering information regarding the occupants' preferences is out of the scope of this paper.

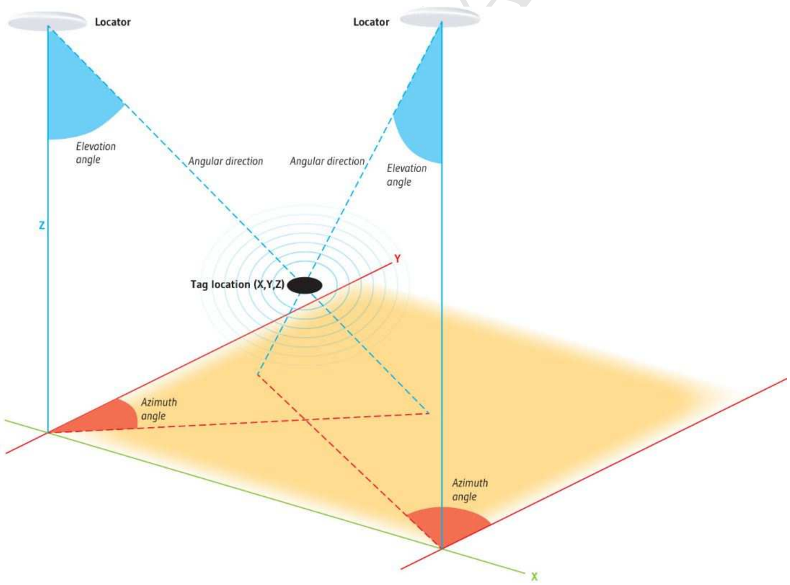


Figure 3 3D Positioning using RTLS **[37]**

3.2. Occupancy Behavior Analytics (Data Processing)

The occupancy behavior analytics (data processing), which is comprised of three phases, is performed to find important occupancy features, such as the number of present occupants, periods of absence and presence, and other occasional variations in the occupants' profiles. Figure 4 depicts the pseudocode showing how the collected data is converted to the occupancy location and presence duration information to calculate the occupancy zone and rate, respectively. All the phases of the data processing procedure are also shown in Figure 5.

Set W = the total number of weeks of the data collection, w = week, D = the total days of a week, d = the day of a week, o = occupant, N_o = the total number of occupants in the office, t^{dr}= detection time resolution, z = occupant zone, n_o = the number of present occupants, occ_r = occupancy rate

For each d in D
  For each w in W
    For each o in N_o
      T^{o}_{start}= the first time that the occupant o is detected in the morning
      T^{o}_{end} = the last time that the occupant o is detected in the evening
      PT^{o} = T^{o}_{end} - T^{o}_{start}
      For t^{dr}_{i} in PT^{o}
        if there are multiple readings for each t^{dr}_{i}:
          calculate the average coordinates of readings with the same t^{dr}_{i}
        if there is a missing data:
          assign the coordinates of t^{dr}_{i-1} to t^{dr}_{i}
        determine z based on the coordinates of o from the tracking system and the office dimensions
      end
    end
  end
  T^{total}_{start}= the earliest arrival time to the office among all occupants
  T^{total}_{end} = the latest departure time from the office among all occupants
  TOD = T^{total}_{end} - T^{total}_{start}
  For t^{dr}_{i}in TOD
    if o is present:
      add 1 to $n_{o}^{t^{dr}_{i},d_i}$
      calculate the occ_r based one $n_{o}^{t^{dr}_{i},d_i}$
    else no change in the number of present occupants
  end
end

Figure 4 Pseudocode for Data Processing Phases: Zone and Occupancy Rate Calculations

The occupant's zones for each time-step of the total daily presence time (*PT*) are determined at the end of Phase 1 according to the *x* and *y* coordinates of his/her tag for each time-step. Using the information from phase one, the number of present occupants, and eventually the occupancy rate of the office, as will be explained in Section 0, are determined at zone and room levels for each time-step of the total occupancy duration (TOD), each day of a week (d), and for the total number of weeks of the data collection (W) during phase 2. Phase 3 of the data processing focuses on the

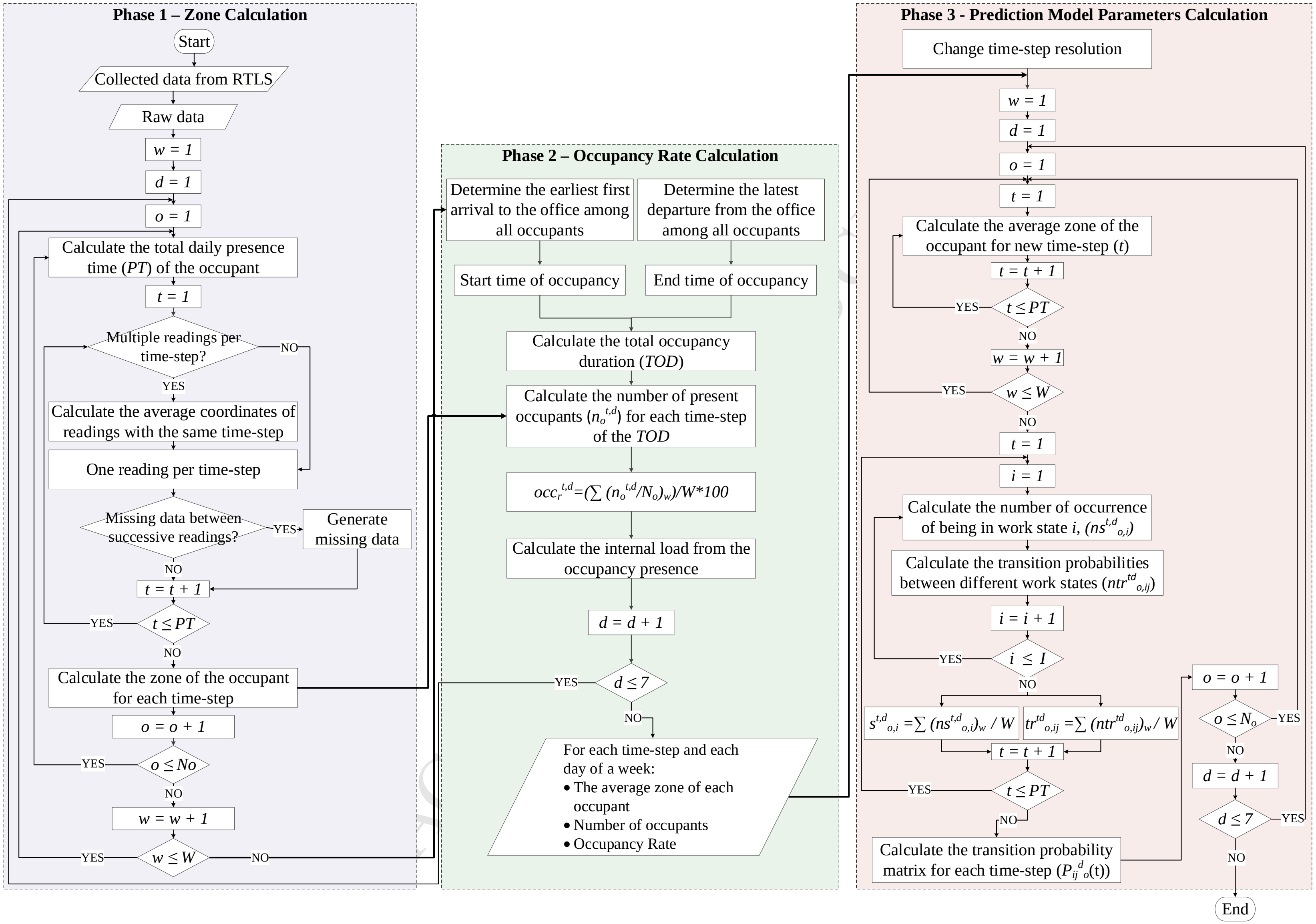


Figure 5 Occupant Behavior Analytics *(*Data Processing) Phases

analysis required to obtain the occupant-specific transition probability matrices, as will be explained in Section 3.3.1, for each time-step of each day of a week. This phase starts with changing the time-step resolution according to the purpose of the occupancy model. For instance, HVAC system local control strategies require longer time-steps knowing that it takes time for the system to adjust the zone temperature.

3.2.1. Occupancy Rate

The occupancy rate for time-step t, ($occ_r^{t,d}$), is the average occupancy rate for each day of a week based on the total number of weeks of the data collection (W). After collecting data for a certain period, the occupancy rate (%) of all zones within an office is calculated for each time-step (e.g., one minute) and for each day of a week (including weekends) according to Equation 1:

$$occ_r^{t,d} = \frac{\sum_{w=1}^{W} (\frac{n_o^{t,d}}{N_o})_w}{W} \times 100\% \tag{1}$$

where $n_o^{t,d}$ is the number of present occupants at time-step t and day d, and N_o is the total number of occupants sharing the same open-plan office during day d.

3.3. Markov Chain Occupancy Prediction Model

In this research, the Markov chain technique is used for the analysis aiming to develop the probabilistic occupancy profiles. Since the occupants' movement among the zones inside and outside open-plan offices creates the occupancy profile, random mobility between different work states is assumed. This assumption allows modeling the transitions among work states as a Markov chain process. Therefore, the next work state of the occupant only depends on his/her present state and some rules about work states.

A Markov chain is a sequence of random variables with the Markovian property presented as [38]:

$$\begin{aligned} P\{X_{t+1} = j | X_t = i, X_{t-1} = i_{t-1}, X_{t-2} = i_{t-2}, \ldots, X_1 = i_1, X_0 = i_0\} \\ = P\{X_{t+1} = j | X_t = i\} = P_{ij}(t+1) \end{aligned} \tag{2}$$

where X_t is a random variable representing different occupants' work states, t is the time-step, and all states $i_0, i_1, \ldots, i_{t-1}, i, j$ are nonnegative integers values $\in I = \{0, 1, 2, \ldots\}$. $P_{ij}(t+1)$ shows the probability of transition from state i to state j at time $t + 1$.

Knowing that the future state of the occupant depends on his/her current state, the transitions of states are defined in Markov matrices. Since the whole day is clustered into different time slots, as mentioned in Section 3, the probability of occurrence of different states varies with the time of the day; and consequently, the transition probability matrices are different for each of these time slots as illustrated in Figure 6. This figure shows the transition probabilities during the lunch break. For instance, if an occupant is going out of the office (at time *t*) for the lunch break at time *t+1*, there is a higher probability to either stay at lunch break or go back to his/her zone at time *t+2* and no probability to go to a short break. This makes the transition probabilities to be time-dependent. This type of Markov chain process is called inhomogeneous Markov chain [39].

In the proposed inhomogeneous Markov chain model for prediction of space occupancy in multi-occupied offices, the states of the Markov chain are occupants' work states as shown in Table 1. This results in having 5×5 transition probability matrices independent of the maximum number of occupants in open-plan offices. Compared to methods that define transition probability matrices based on the number of occupants in a zone, [e.g. 23, 27, 40], or methods that consider some restrictions regarding the movement of occupants between zones to reduce the order of transition matrices [e.g. 29], using the proposed method significantly simplifies the calculation of transition probability matrices. Transition probability matrices are key parameters in Markov chain models and reducing their order has a high impact on the overall complexity of the Markov models, especially for inhomogeneous Markov chain models with a large number of transition matrices.

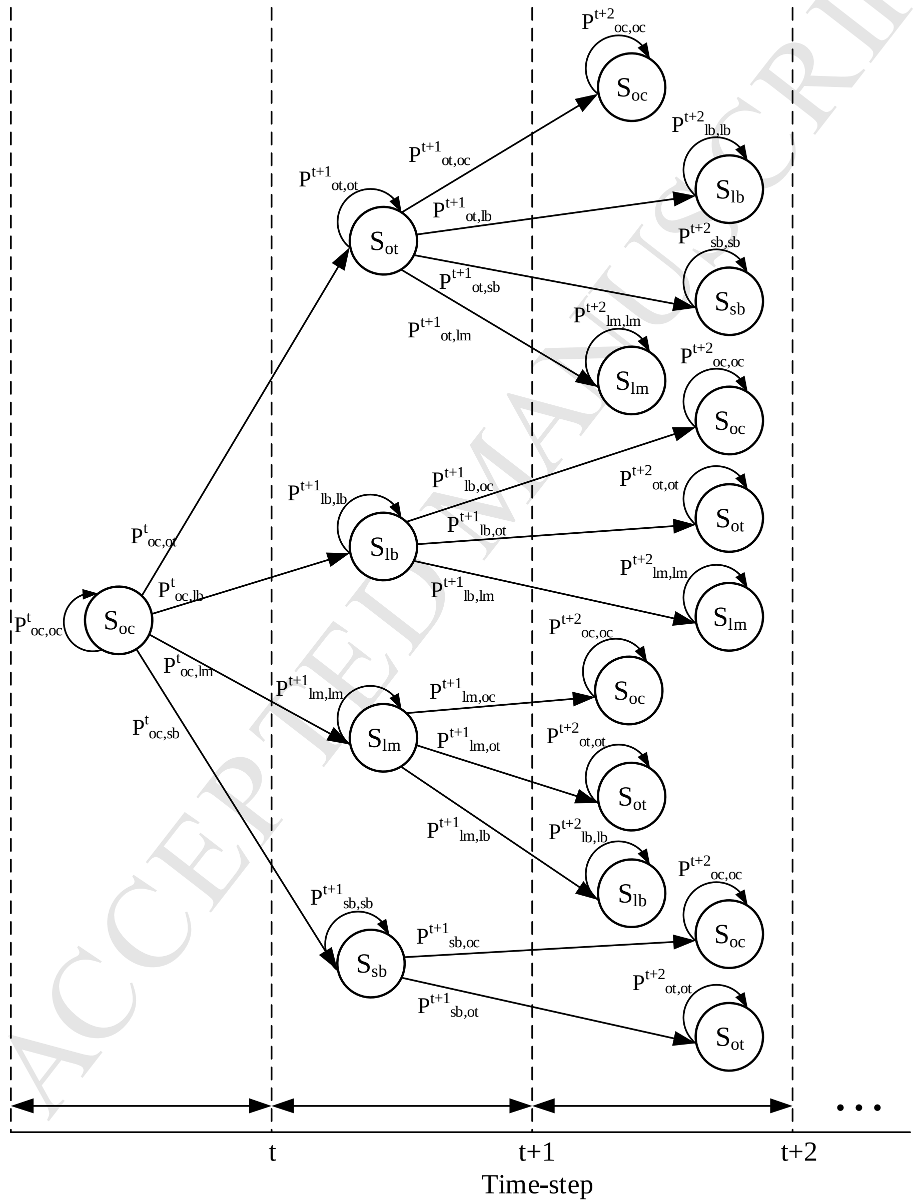


Figure 6 Sample Transition Process from Time *t* to *t+2* during Lunch Break

The output of the proposed inhomogeneous Markov chain model is the probabilistic profiles of each specific occupant. Work state of each occupant, his/her location and the total number of present occupants can be derived from these profiles. Eventually, building energy-consuming systems are adjusted based on this information to reflect the variations in different occupants' daily profiles.

3.3.1. Transition Probability Matrices

In the first step of determining the transition probability matrices, the PT of each occupant for different days of a week along with the distribution of being in different work states during the PT are deduced from the results of the Phases 1 and 2 of the data processing step. Next, the transition probabilities between different work states are calculated. To do so, two parameters are required: (1) the percentage distribution of each work state for each occupant; and (2) the transition occurrences between different work states for each occupant. The transition probability matrix is then calculated using Equations 3 and 4:

$$P_{ij} = 1 - s_i + s_i \times tr_{ij} \qquad (if\ i = j) \tag{3}$$

$$P_{ij} = s_i \times tr_{ij} \qquad (if\ i \neq j) \tag{4}$$

where s_i shows the probability of being in state *i*, which is calculated based on the percentage of occurrence of each work state during the monitoring period. The probability of transition occurrences from state *i* to state *j* is indicated by tr_{ij}. These formulas are inspired by the work of Yamaguchi et al. [17]. However, improvements are applied to their proposed formula. Firstly, the Markov chain is time-independent in their method. Secondly, they assumed constant numbers for the parameters s_i and tr_{ij}. In this study, the Markov chain and the parameters are time-dependent. In addition, the collected data regarding the actual occupancy of the open-plan office are used to define the parameters s_i and tr_{ij} with some enhancement in their calculation method as discussed below:

(1) For each occupant o ($o = 1,2,\dots,N_o$) and each day of a week d ($d = 1,2,\dots,7$), the probability of being at work state i ($i = 1,2,\dots,I$, where I represents the maximum number of work states) at each time-step t, $s_{o,i}^{t,d}$, is obtained by counting the number of times of being in work state i ($ns_{o,i}^{t,d}$) divided by the total number of weeks over the monitoring period as shown below:

$$s_{o,i}^{t,d} = \frac{\sum_{w=1}^{W}(ns_{o,i}^{t,d})_w}{W} \tag{5}$$

This procedure results in personalized probability distribution graphs for each work state at different time-steps over each specific day of a week. The following condition should be considered for each time-step t and each occupant o when calculating the probabilities:

$$\sum_{i=1}^{I} s_{o,i}^{t,d} = 1 \tag{6}$$

(2) For each occupant o, the number of transition occurrences from state i to state j at each time-step t and for each day of a week d, $ntr_{o,ij}^{t,d}$, is obtained from the collected data. Then, the probabilities of transition occurrences are calculated over the monitoring period ($tr_{o,ij}^{t,d}$):

$$tr_{o,i}^{t,d} = \frac{\sum_{w=1}^{W}(ntr_{o,i}^{t,d})_w}{W} \tag{7}$$

In this study, the transition probability matrix for each time-step and for each day of a week is then calculated for each occupant ($P_{ij}{}_{o}^{d}(t)$) using Equations 8 and 9:

$$P_{ij}{}_{o}^{d}(\mathrm{t}) = 1 - s_{o,i}^{t,d} + s_{o,i}^{t,d} \times tr_{o,ij}^{t,d} \qquad (if\ i = j) \tag{8}$$

$$P_{ij}{}_{o}^{d}(\mathrm{t}) = s_{o,i}^{t,d} \times tr_{o,ij}^{t,d} \qquad (if\ i \neq j) \tag{9}$$

Considering five states of the transition probability matrix, this matrix has a dimension of $5 \times 5 \times 288 \times 7$ using 5-minute time-step for one day (i.e., 288) and one matrix for each day of a week (i.e., 7 days). The procedure for finding the transition probability matrix is demonstrated in Figure 7.

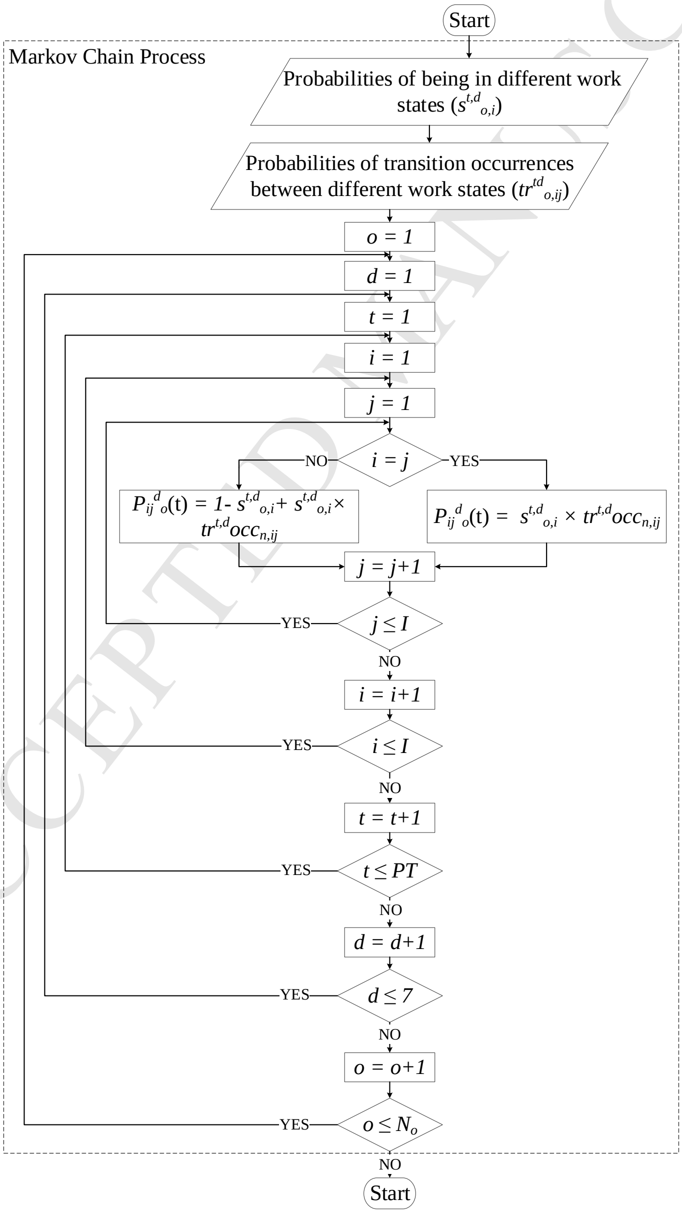
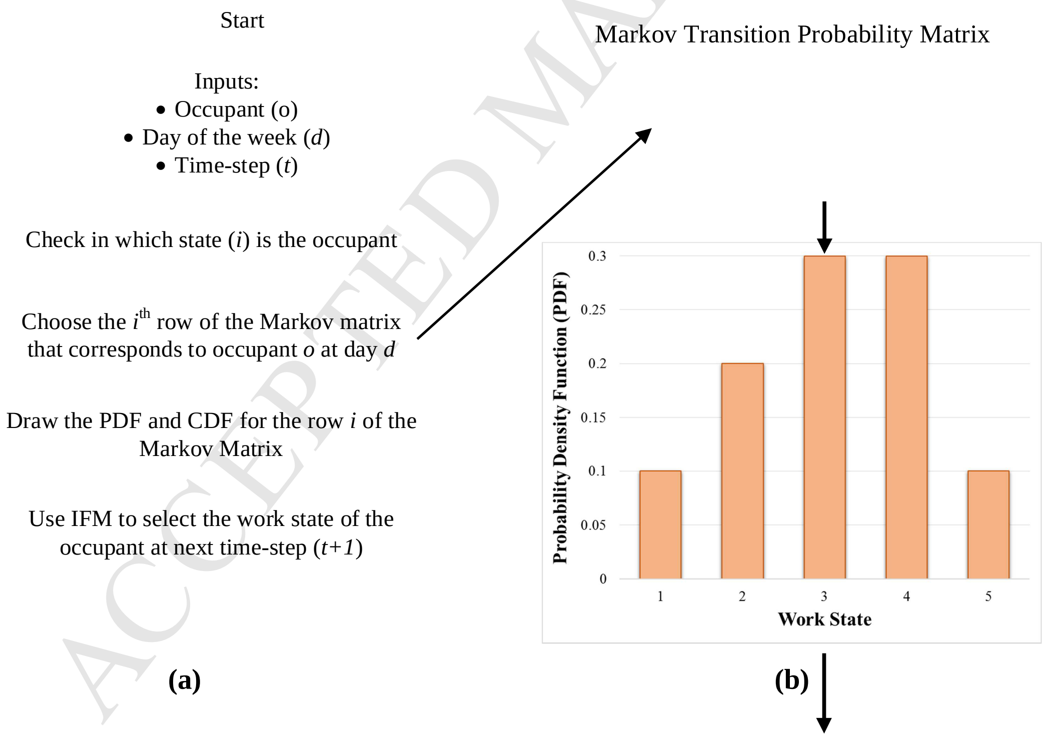
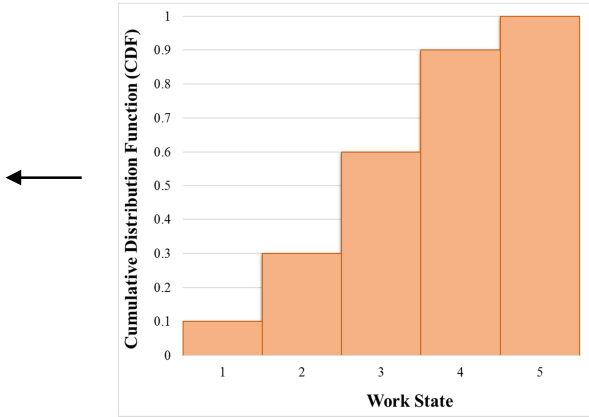


Figure 7 Markov Chain Transition Matrix Flowchart

In the next step, Probability Density Function (PDF) for each time-step t can be deduced from each row of the Markov transition matrix. Further, the Cumulative Distribution Function (CDF) is derived from the PDF for each time-step. The CDF is a histogram of five bins corresponding to the five work states. Each bin shows the probability at which a value of that bin can be randomly selected. Using the Inverse Function Method (IFM) gives the estimation of the work state for the next period $(t + 1)$. The IFM works by inverting the CDF of the parameter of interest. It randomly generates a number between 0 and 1 using a uniform distribution. The random number determines which bin is going to be selected for the parameter of interest using the CDF. Figure 8 illustrates these steps.





(d) **(c)**

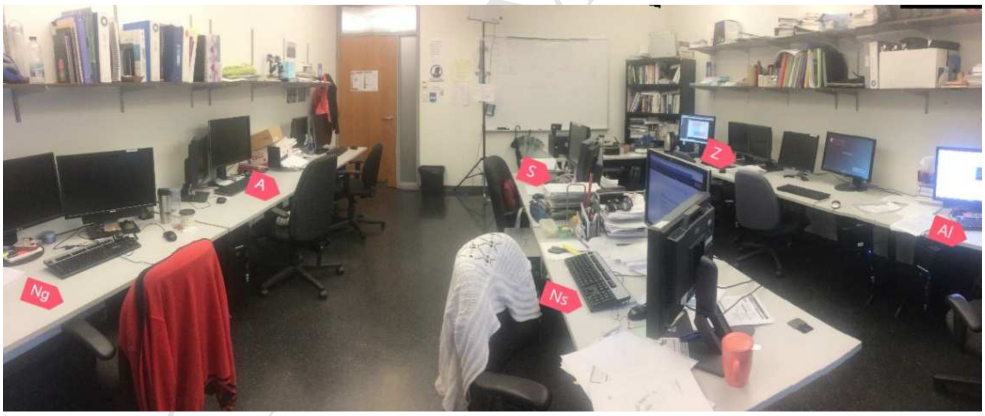
Figure 8 Work State Estimation Flowchart; (b) PDF Generation; (c) CDF Generation; (d) Generation of Series of Work States using IFM

4. Implementation and Case Study

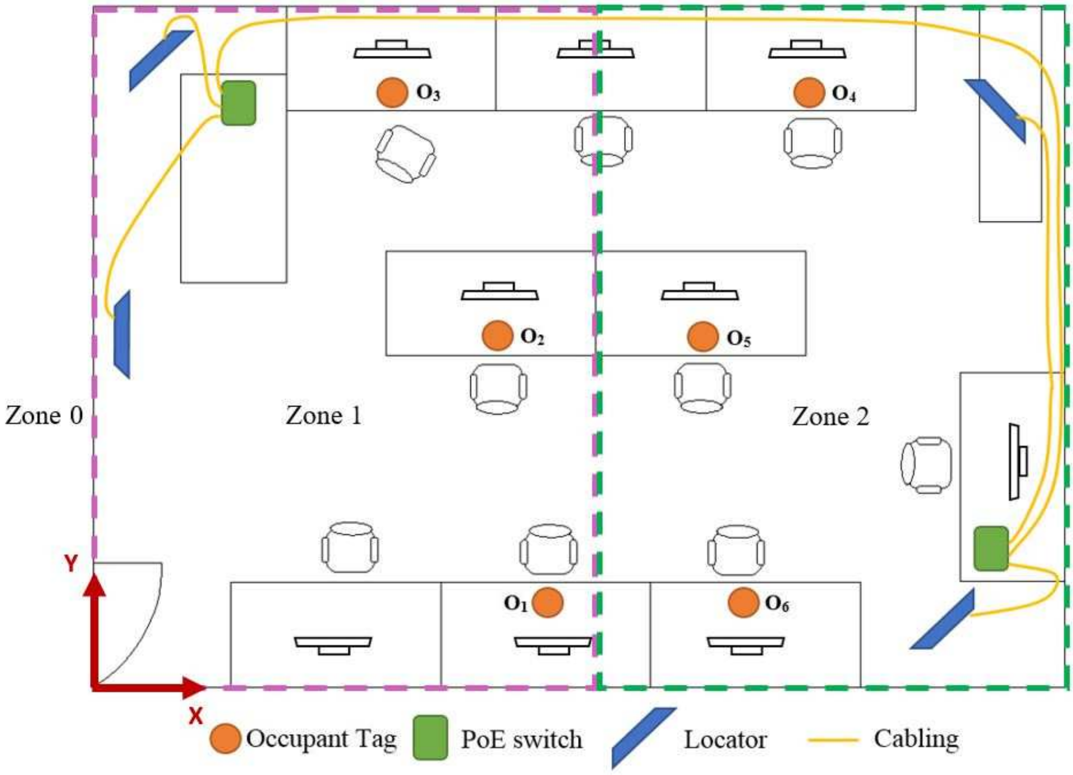
Figures 9 shows the picture of the case study location (a research laboratory) and the monitoring system set up along with the office layout. There are six occupants assigned to the research laboratory. In this case study, the occupancy data were collected every second using Bluetooth Low Energy (BLE) (also known as Bluetooth 4.0 or Bluetooth Smart) for one month. The BLE-based monitoring system used in this research (i.e., Quuppa Intelligent Locating System™) is able to track the latest smartphones and BLE devices with the accuracy of 20-50 *cm* [41, 42]. Based on the measurements made, the size of the monitored office is 5.0 *m*×7.0 *m*×3 *m*. In order to get the required data for the prediction model, it is important to know whether the occupant is at zone 1, 2 or 0 (which is the outside of the office) as shown in Figure 9. According to the dimensions of each zone (i.e., 5.0 *m*×3.5 *m*), the accuracy of 20-50 *cm* is precise enough for the purpose of this study.

Quuppa system uses AoA approach to calculate the position of different objects (e.g., people, equipment, etc.) as discussed in Section 3.1. This system offers many advantages including long tag battery lifetime, compatibility with standard mobile devices, and the ability to carry sensor data alongside the positioning data [43].

As shown in Figure 9-(b), four locators are used in this study to accurately monitor the occupants and their movement. According to [44], distances of 6-10 meters between indoor locators are convenient for a good coverage. In our case, locators are placed with the distances between them less than 7 meters. In addition, the coverage quality estimate is checked and demonstrated in Figure 10. As shown in this figure, the red color represents bad quality and green color represents good quality. Thus, the coverage quality of four locators in the room is good for tracking. In the case of having larger offices, more sensors are required to accurately cover the whole space in order to collect precise occupancy data. Having enough number of locators with distances within the suggested range, the same accuracy of 20-50 cm is achievable.



(a)



(b)

Figure 9 (a) Case Study Location (Graduate Research Lab); (b) Monitoring System Setup and Office Layout

4.1. Occupancy Probabilistic Profiles

The probabilistic profile of each occupant shows the probability of the occupant's presence at the certain time of the day at a specific location. This profile can be used for predicting the status of the occupants and adjusting building operational systems in advance to save energy as well as to satisfy the occupants' indoor environment comfort levels.

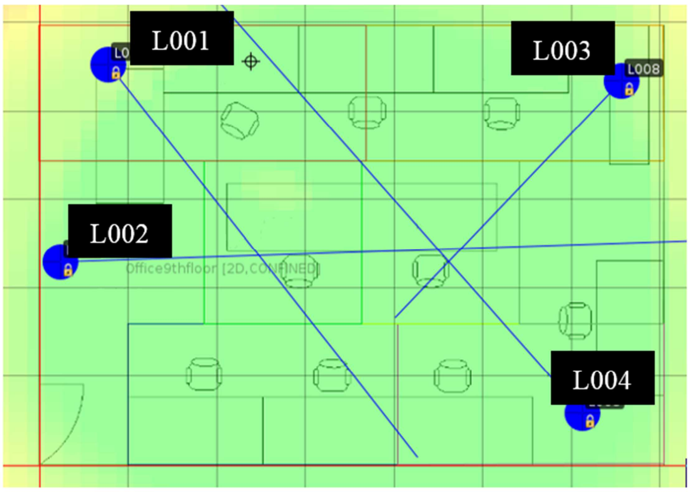


Figure 10 Coverage Quality Estimate of the Locators (L001-L004 are the four locators used in the monitoring process)

In this study, the test was run for one month and since the collected data from the monitoring system could be used for different purposes with different levels of accuracy, the BLE system monitored occupants with high resolution (i.e., each second). Collecting the occupancy data with the high resolution of one second generated about 250 MB of the raw data in total. Figure 11 shows the distribution of the size of collected data over the one-month period of the data collection.

All the data processing phases and the development of the occupancy prediction model are performed on a desktop computer with properties as Intel Xeon CPU X5550 @ 2.67 GHz, 6 GB Random Access Memory (RAM), and running Windows 7 Professional Dell computer. Collecting the occupancy data with the high resolution of one second generated about 250 MB of the raw data in total. It takes some time to polish this raw data, such as producing the missing data or removing duplication in the collected raw data, as explained in Section 3.2.

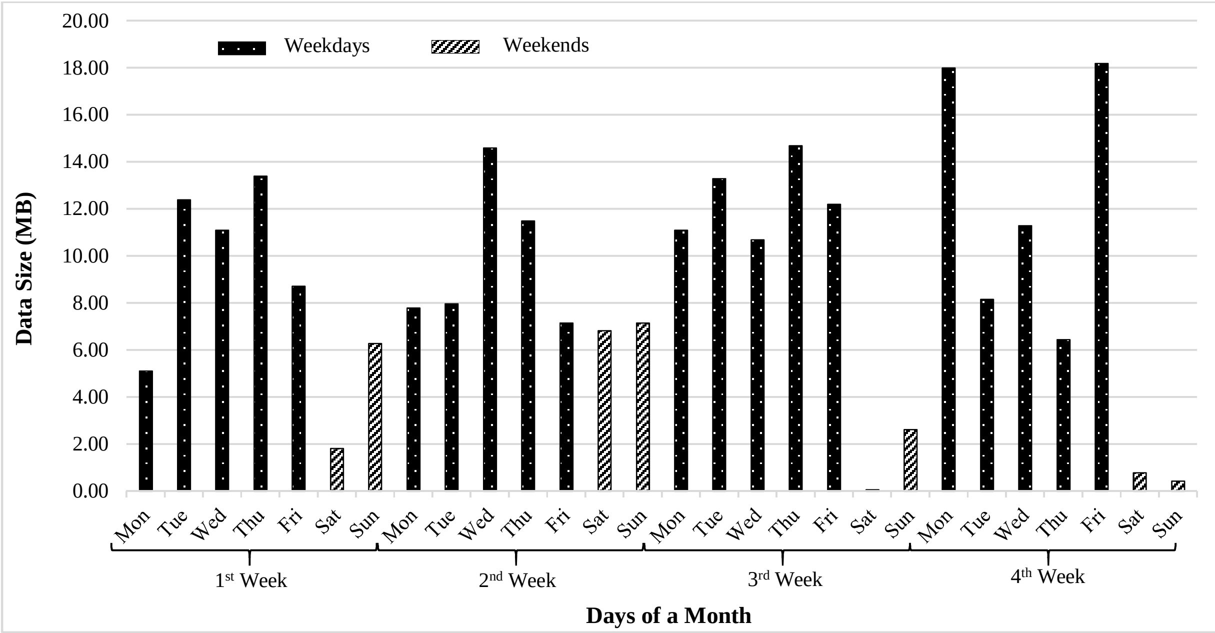


Figure 11 Size of the Collected Data per Day

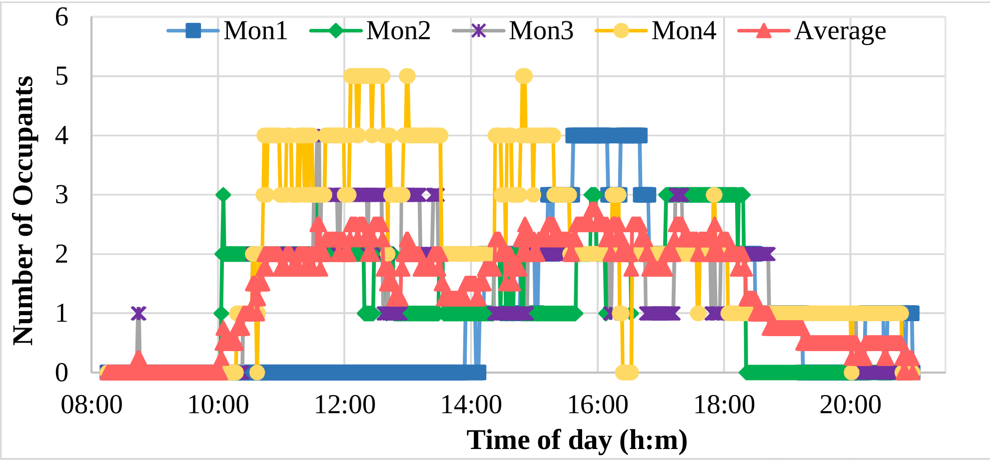
The data processing phases are used to produce the input data to the prediction model with the desired time-step. The required computational time is about four hours for one month of the collected data. However, the high granularity of one second is not required for building energy management. Therefore, the occupants' zones are calculated every five minutes according to Section 3.2. During a five-minute time-step, the final selected zone for that time-step will be the zone in which the occupant spent more minutes. In this study, the number of defined zones is equal $\boldsymbol{M}$ plus one zone for the outside of the office. For instance, three zones are considered for a shared office with zones 1 and 2, being within the office, and one zone for outside of the office (i.e., zone 0).

After determining the occupant's zones for each time-step of *PT*, the average number of occupants present at each zone of the room are calculated for each day of a week for five-minute time-step resolution. The average occupancy rate for each day of a week (average of four series of data) is also calculated using Equation 1. Figure 12 illustrates the results for Mondays. The same results are obtained for other days of the week, which are not included here due to space limitation. This figure shows the number of present occupants at the office level for four Mondays in a month. The average occupancy number of one month is also shown in this figure. Furthermore, the average occupancy numbers for weekdays and weekends are illustrated in Figure 12. As it was expected, the occupancy rate of the office is much lower during weekends. However, it is important to know that the office is always occupied for several hours during the weekends.

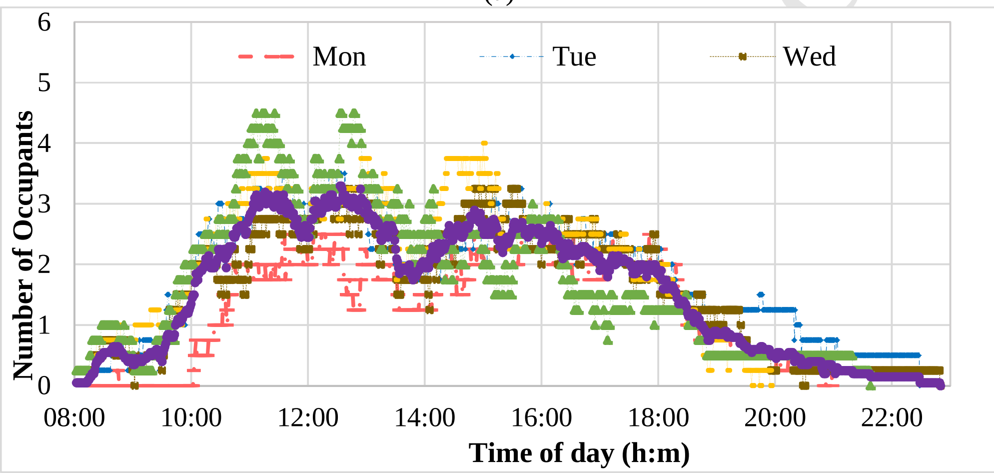
4.2. Validation of the Occupant Behavior Analytics Method

The proposed data processing method is validated by comparing the obtained profiles using the proposed method with those obtained from the ground truth data. A check table is created to collect the ground truth data from April 07 to May 17, 2017, and from May 23 to June 10, 2017. The table includes the time of occupants' first arrival, their lunch break, and the last departure. After logging the information, the PDF of the events of importance, such as the first arrival to the office, is created to determine the actual range of their occurrences (Figure 13). As shown in this figure, the majority of the first arrival event has occurred between 08:15 to 11:30 am. The start and end times of these events based on the ground truth data as well as ranges that are used for data processing at the office level. As discussed in Section 3.1., five typical work states are considered in office buildings (Table 1).

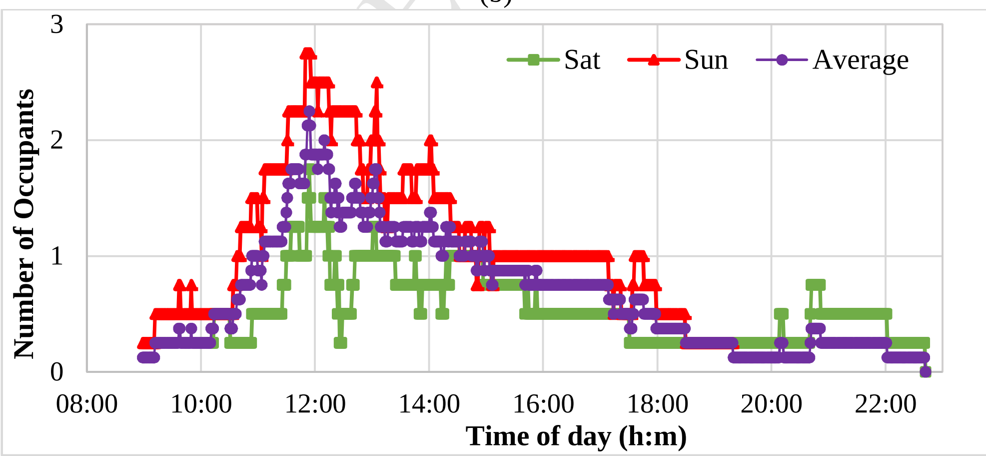
In order to process the raw data to reflect these work states, the ranges derived from ground truth data, as a basis for data processing, are broken down to smaller time slots for each occupant. This helps to have more accurate time slots that are specific to each occupant's pattern of presence for each day of a week. In addition, a window of $\pm$15 minutes is considered at the start and end times of these ranges to give more diversity to these time slots.



(a)



(b)



(c)

434 **Figure 12** Variation in Occupancy Number for (a) Mondays; (b) Weekdays; and (c) Weekends

4.2.1. Comparison with the Ground Truth Data

The comparison between the occupant behavior analytics method and the ground truth data shows that there are some cases that differences are found between the arrival times and the results of the occupant behavior analytics method. The review of the raw data in these cases shows that the occupants arrived and left the room after a short stay (less than five minutes). This results in a delay for the processing methods to capture the first arrival of the occupants. On the other hand, the occupant behavior analytics method could catch the departure times. Hence, it can be concluded that the daily profiles are in accordance with the ground truth data.

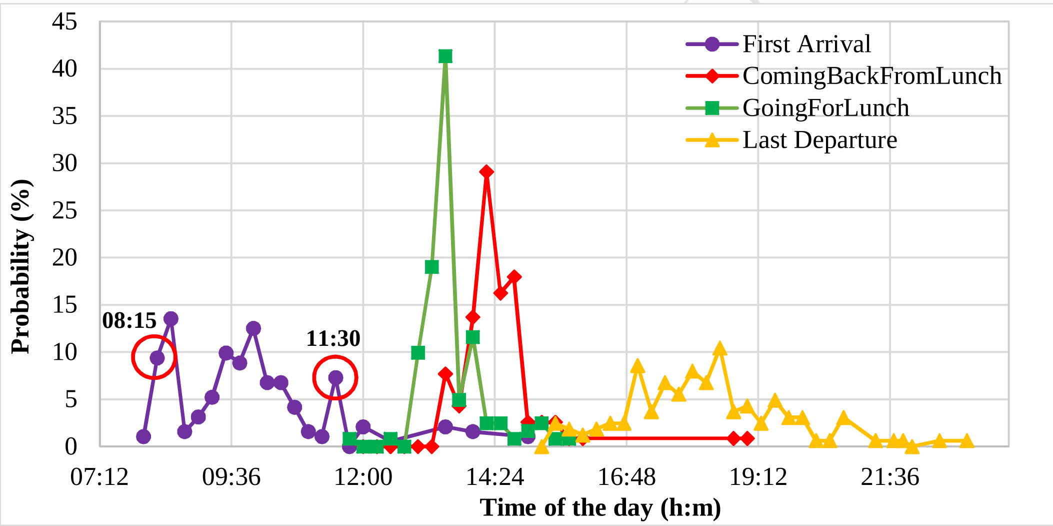


Figure 13 Probability Distributions of Events of Importance during a Day at Office Level

4.2.2. Occupancy Prediction Results using Markov Chain Model

To estimate the occupancy profiles using inhomogeneous Markov chain occupancy prediction model, all states are labeled to show the transition probabilities from one state to another according to Table 1. For example, the transition probability from work state 1 to 3, which is leaving the office (zone 1) for lunch break, is presented by ${P_{oc,lb}}_o^d$(t). The transition probability matrix of ${P_{ij}}_o^d$(t) can be shown as follows:

$$P_{ij}{}_{o}^{d}(\mathrm{t}) = \begin{bmatrix} P_{oc,oc} & P_{oc,ot} & P_{oc,lb} & P_{oc,sb} & P_{oc,lm} \\ P_{ot,oc} & P_{ot,ot} & P_{ot,lb} & P_{ot,sb} & P_{ot,lm} \\ P_{lb,oc} & P_{lb,ot} & P_{lb,lb} & P_{lb,sb} & P_{lb,lm} \\ P_{sb,oc} & P_{sb,ot} & P_{sb,lb} & P_{sb,sb} & P_{sb,lm} \\ P_{lm,oc} & P_{lm,ot} & P_{lm,lb} & P_{lm,sb} & P_{lm,lm} \end{bmatrix} \quad (10)$$

As discussed in Sections 1 and 3.2, different resolution levels are required for controlling different building systems. For instance, a higher level of resolution is needed to apply lighting control strategies, which improve comfort level. However, considering the required lag time for HVAC systems to adjust the indoor temperature to a specified target set-point, lower level of resolution may not lead to a significant thermal discomfort. As a result, two different prediction time-steps are defined to determine occupancy predictions for lighting and HVAC systems control.

Five-minute prediction time-step is considered to predict the office occupancy pattern and accordingly adjust the lighting system. While this time-step changes to 30-minute prediction time-steps to control the HVAC system. Having the occupants' zones for every five-minute time interval, the distribution of the time being spent in the office's zones and outside is determined for each day of a week (i.e., $ns_{o,i}^{t,d}$). After calculating the number of transition occurrences (i.e., $ntr_{o,ij}^{t,d}$), the transition matrices corresponding to each time-step of each day of a week would be calculated using the average values of $tr_{o,ij}^{t,d}$ and $s_{o,i}^{t,d}$ for that specific day of the week throughout the whole month. For instance, the transition matrix of occupant o_5 on Mondays at 02:40 pm is shown below:

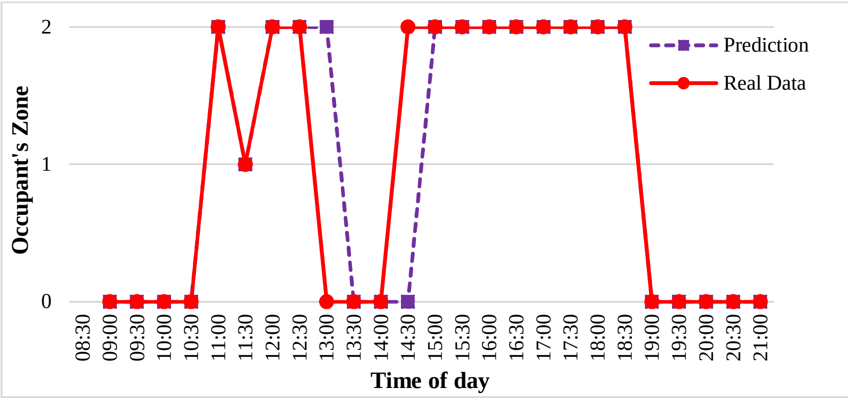
$$P_{ij}{}_{o_5}^{Mon}(02{:}40\ \mathrm{pm}) = \begin{bmatrix} 0.8125 & 0 & 0.0625 & 0 & 0.125 \\ 0 & 0 & 0 & 0 & 0 \\ 0.0625 & 0 & 0.8125 & 0 & 0.125 \\ 0 & 0 & 0 & 0 & 0 \\ 0.125 & 0 & 0.125 & 0 & 0.75 \end{bmatrix} \quad (11)$$

In this matrix, a row of zero probabilities happens when the $s_{o,i}^{t,d}$ is zero. In these cases, since the probability of being in state i is zero at that specific time-step, it is not possible to have probabilities of state transitions.

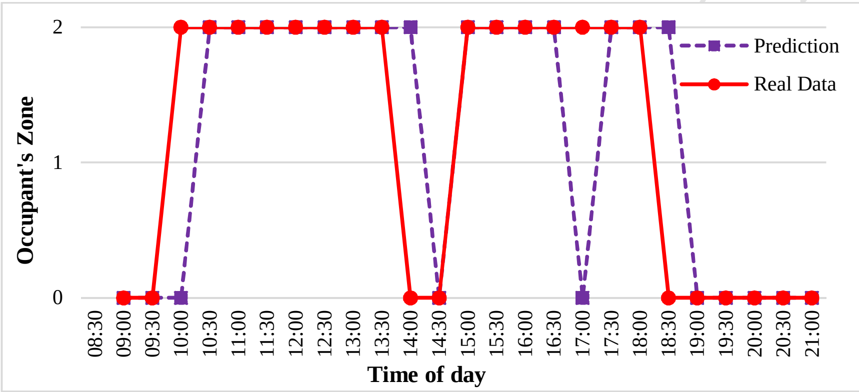
4.2.3. Validation of the Inhomogeneous Markov Chain Occupancy Prediction Model

To validate the performance of the inhomogeneous Markov chain occupancy prediction model, the actual occupancy for different days of a week are compared to those of resulted from the prediction model. The comparison between the occupancy profiles resulting from the prediction model, to be used for the purpose of lighting control (i.e., five-minute time-step prediction), and the real data is illustrated in Figure 14 for occupants o_1 and o_6. This figure shows the zone of each occupant for each five-minute time-step. Comparing the prediction results and the actual occupancy patterns shows the high accuracy of the prediction model (92% and 84% for occupants o_1 and o_6, respectively) in capturing the variations in occupants' zones.

As mentioned in the previous section, two different time-steps are defined to determine occupancy predictions for lighting and HVAC systems' control. In the case of using occupancy prediction to control the HVAC system, the initial state of occupancy is determined using the real-time collected data. Then, the inhomogeneous Markov chain prediction model predicts the occupancy pattern for the next 30 minutes using the transition probability matrices and the IFM method as shown in Figure 8.



(a) Occupant o_1



(b) Occupant o_6

Figure 14 Comparison of Predicted and the Real Occupancy Profiles-Lighting Control Purposes (Mondays)

Since the ${P_{ij}}_{o}^{d}(\mathrm{t})$ matrices are derived based on five-minute time-steps, the prediction model should be run six times to produce the occupancy pattern for the next 30 minutes. Then, the actual occupancy state is read again from the occupancy sensors to restart the prediction procedure. This update improves the accuracy of the prediction model by avoiding accumulation of errors happening at each five-minute time-step. The prediction process is then repeated for the next 30 minutes and this loop is continued till the end time of occupancy *PT*. Figure 15 demonstrates this procedure. The same method is applicable in the case of using occupancy prediction to control the lighting system with the difference of changing the 30-minute to five-minute time-steps. Thus, the prediction model is only run once in this case since the time-step of having the $P_{ij_o}^{d}(t)$ matrices and prediction time-step are identical.

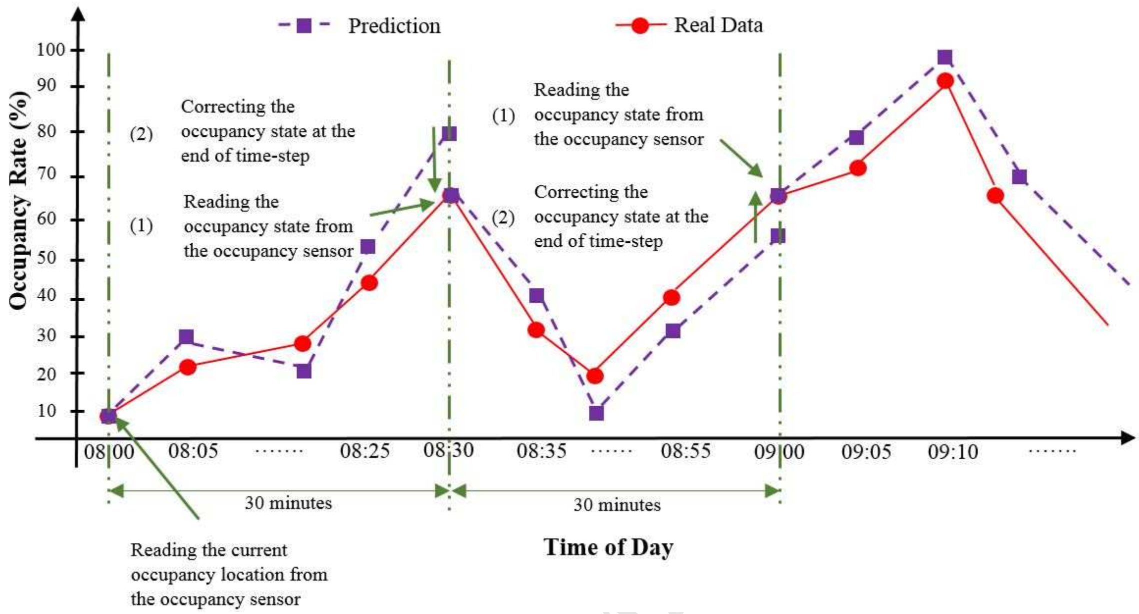
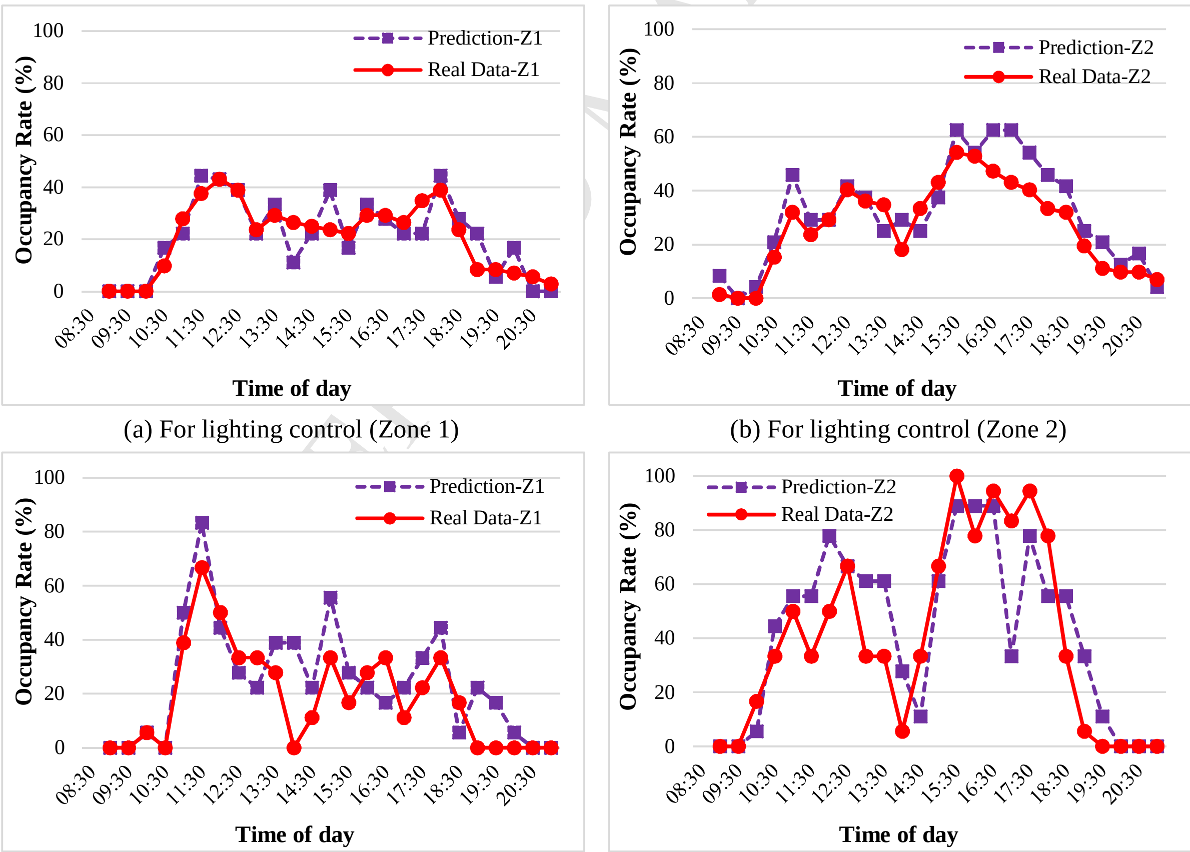


Figure 15 Occupancy Prediction Process and Updates

The proposed prediction model is an adaptive model that evolves and improves itself over time. The adaptive probabilistic occupancy model determines the HVAC and lighting systems' settings at the beginning of each day based on the collected data. In this manner, the HVAC system starts working half an hour before the start time of occupancy to reach to the desired temperature by the time the first occupant arrives at the office. The lighting system will be turned on at the time of arrival of the first occupant. Using the prediction model, the level of occupancy is estimated for the next time-step and the HVAC and lighting systems are accordingly adjusted. This procedure continues for each time-step during the day (as specified for the control purpose) until the estimated end time of occupancy is reached. However, there may be some cases that the real occupancy does not follow the predicted one. This could happen when an unexpected occupancy happens when the prediction model estimates vacancy for space. For instance, one occupant can arrive earlier than the time she/he was expected to start working. In these cases, there would be a switch to real-time operation of building systems where the sensors detect the unexpected occupant and turn on the light automatically. Thus, a real-time occupancy detection and control give an indication of the wrong estimation of occupancy. In such cases, an update is sent to the adaptive prediction model to adjust itself by correcting the current state of occupancy. Using newly collected occupancy data helps the model to capture changes in occupancy space utilization patterns, especially in the case of open-plan offices with varying occupancy (e.g., common labs). In this type of offices, occupancy data should be collected over a shorter period, and more frequent updates are required to reflect changes in occupancy patterns. This would help the model to evolve and become more precise in predicting the office occupancy. Therefore, the idea of frequently updating the occupancy prediction model can improve the reliability of the model for future predictions. However, the data collection period can be longer for offices with fixed occupancy, such as research labs; since there would not be many variations in the space utilization patterns. Using different data collection periods and frequent updates make the proposed prediction model more general for different types of open-plan offices.

Having the occupancy profile prediction for each occupant results in developing the occupancy rate prediction for each zone. After calculating the ${P_{ij}}_o^d$(t) matrices, the number of present occupants in each zone can be predicted. Using Equation 1, the occupancy rate at the zone level is calculated and the results are used to control the lighting system. Since the prediction model demonstrated the same performance for different days of a week, Figure 16 shows the occupancy rates only for Mondays.

The same comparison was made between the occupancy rates resulted from the prediction model to be used for the purpose of HVAC system control (i.e., 30-minute time-step prediction), and the real data as also illustrated in Figure 16. As shown in this figure, the prediction model captures the real behavior of occupants at occupant and zone levels. The prediction model is able to accurately estimate the location of occupants at most periods of data collection during the day, which shows that the overall performance of the prediction model is satisfactory. Table 2 shows the performance measurement of the prediction model using the coefficient of determination (known as R^2) for different cases. The values of R^2 when using the proposed prediction model for the lighting control are 0.8 and 0.92 for zones 1 and 2, respectively. This would result in having 0.86 on average for this parameter (86%) for the application of lighting system control. The same method is used to calculate the average value of R^2 when using the proposed prediction model for the control of the HVAC system (68%). These values indicate the high accuracy of the prediction model in imitating the real occupancy patterns of the open-plan office.



(a) For lighting control (Zone 1) (b) For lighting control (Zone 2)

(c) For HVAC control (Zone 1) (d) For HVAC control (Zone 2)

Figure 16 Comparison of Predicted and the Actual Occupancy Rates (Mondays)

Table 2 Performance Measurement of the Prediction Model

Purpose of use of occupancy prediction	**Level of prediction**	R^2
Lighting control	Zone 1	0.8
	Zone 2	0.92
HVAC Control	Zone 1	0.65
	Zone 2	0.7

5. Conclusions and Future Work

In this study, the occupancy modeling (i.e., occupants' profiles) has been further enhanced using inhomogeneous Markov chain prediction model based on real occupancy patterns data. The main contributions of this research are: (1) developing a method for extracting detailed occupancy information with varying time-steps from collected RTLS occupancy data. This method can capture different resolution levels required for the application of intelligent, occupancy-centered local control strategies of different building systems; (2) developing a new adaptive probabilistic occupancy prediction model based on the extracted occupancy information; and (3) developing time-dependent inhomogeneous Markov chain occupancy model, which distinguishes the temporal behavior of different occupants within an open-plan office.

The proposed prediction model is an adaptive model that evolves and improves itself over time. By frequently updating the occupancy prediction model whenever an unexpected occupancy happens, the model captures changes in occupancy space utilization patterns and becomes more precise in predicting the office occupancy.

Having the occupancy profile prediction for each occupant results in developing the occupancy rate prediction at the zone level. The comparison between the occupancy profiles resulting from the prediction model and the actual profiles showed that the prediction model was able to capture the actual behavior of occupants at occupant and zone levels. The prediction model can accurately estimate the location of occupants at most periods of data collection during the day. High accuracy (86% and 68% on average for the purpose of the lighting and HVAC systems control, respectively) of occupancy patterns prediction also indicates the acceptable performance of the prediction model in capturing the temporal behavior of different occupants working in the same open-plan office.

Although the overall performance of the prediction model was satisfactory, it may not capture variations in occupancy patterns that may happen after the data collection period, especially in the case of open-plan offices with varying occupancy. This limitation could be solved by collecting occupancy data for a longer period of time and frequently updating the prediction model whenever a real-time occupancy detection and control happened to consider changes in the space utilization patterns.

There is a privacy issue when the occupants' identities are used to have detailed occupancy patterns. However, this issue can be resolved by anonymizing the occupants' data through defining occupancy profiles per zone. In addition, having this type of data could be vital for other purposes, such as emergency and safety. Informing the monitored occupants about all the benefits coming from using the real-time monitoring system for a reasonable period could also be helpful to solve this issue.

As future work, the performance of the proposed prediction model should be evaluated using occupancy data collected over a longer period. In addition, the effect of having more data on the overall performance of the proposed model should be investigated using different data collection periods (e.g. using smaller periods to control the lighting system). Future work will also consider applying sensitivity analysis and finding the optimal data collection period to balance between accuracy and computation time.

The main output of this research is an occupancy prediction model that produces the office occupants' profiles. Future work will also use these profiles as inputs to the energy simulation tools. Simulation models are then used to assess different occupancy-centered local control strategies considering occupants' preferences related to building systems (e.g., HVAC and lighting systems). In addition, the proposed occupancy prediction and the energy simulation models will be encapsulated within an optimization algorithm to select the optimal settings for the building systems. The ultimate goal of applying the local controls is achieving two objectives of minimizing the office energy consumption, and at the same time minimizing the office occupants' discomfort. Therefore, the main focus of the research is on the office occupants who are assigned to that office. Running the simulation-based optimization model in near real-time provides more reliable occupancy responsive local control strategies to optimize building energy consumption.

Acknowledgment

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References

[1] SUSRIS, "International Energy Outlook 2013," 25 July 2013. [Online]. Available: http://susris.com/2013/07/25/international-energy-outlook-2013/.

[2] Annex 53, "Total Energy Use in Buildings: Analysis and Evaluation Methods," AECOM Ltd, United Kingdom, 2016.

[3] C. Wang, D. Yan and Y. Jiang, "A novel approach for building occupancy simulation," *Building Simulation,* vol. 4, no. 2, pp. 149-167, 2011.

[4] X. Feng, D. Yan and T. Hong, "Simulation of occupancy in buildings," *Energy and Buildings,* vol. 87, pp. 348-359, 2015.

[5] D. Yan, W. O'Brien, T. Hong, X. Feng, H. B. Gunay, F. Tahmasebi and A. Mahdavi, "Occupant behavior modeling for building performance simulation: Current state and future challenges," *Energy and Buildings,* vol. 107, pp. 264-278, 2015.

[6] W. Shen, G. Newsham and B. Gunay, "Leveraging existing occupancy-related data for optimal control of commercial office buildings: A review," *Advanced Engineering Informatics,* vol. 33, pp. 230-242, 2017.

[7] T. Hong, S. D'Oca, W. J. Turner and S. C. Taylor-Lange, "An ontology to represent energy-related occupant behavior in buildings. Part I: Introduction to the DNAs framework," *Building and Environment,* vol. 92, pp. 764-777, 2015.

[8] N. Li, G. Calis and B. Becerik-Gerber, "Measuring and monitoring occupancy with an RFID based system for demand-driven HVAC operations," *Automation in construction,* vol. 24, pp. 89-99, 2012.

[9] S. Salimi and A. Hammad, "Critical Review and Research Roadmap of Office Building Energy Management Based on Occupancy Monitoring," *Energy and Buildings,* 2018.

[10] M. M. Soltani, A. Motamedi and A. Hammad, "Enhancing Cluster-based RFID Tag Localization using artificial neural networks and virtual reference tags," *Automation in Construction,* vol. 54, pp. 93-105, 2015.

[11] J. Yang, M. Santamouris and S. E. Lee, "Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings," *Energy and Buildings,* vol. 121, pp. 344-349, 2016.

[12] W. Wang, J. Chen and X. Song, "Modeling and predicting occupancy profile in office space with a Wi-Fi probe-based Dynamic Markov Time-Window Inference approach," *Building and Environment,* vol. 124, pp. 130-142, 2017.

[13] Quuppa, "One for all," 2017. [Online]. Available: http://quuppa.com/applications/.

[14] W. K. Chang and T. Hong, "Statistical analysis and modeling of occupancy patterns in open-plan offices using measured lighting-switch data," *In Building Simulation,* vol. 6, no. 1, pp. 23-32, 2013.

[15] J. Virote and R. Neves-Silva, "Stochastic models for building energy prediction based on occupant behavior assessment," *Energy and Buildings,* vol. 53, pp. 183-193, 2012.

[16] S. Wei, J. Yong, B. Ng, J. Tindall, Q. Lu and H. Du, "Occupant Adaptive Behaviour: an Effective Method towards Energy Efficient Buildings," in *CIBSE Technical Symposium*, London, UK, 2018.

[17] Y. Yamaguchi, Y. Shimoda and M. Mizuno, "Development of district energy system simulation model based on detailed energy demand model," in *In Proceeding of Eighth International IBPSA Conference*, Eindhoven, Netherlands, 2003.

[18] J. Page, D. Robinson, N. Morel and J. L. Scartezzini, "A generalised stochastic model for the simulation of occupant presence," *Energy and buildings,* vol. 40, no. 2, pp. 83-98, 2008.

[19] K. P. Lam, M. Höynck, B. Dong, B. Andrews, Y. S. Chiou, R. Zhang, D. Benitez and J. Choi, " Occupancy detection through an extensive environmental sensor network in an open-plan office building. , 145," in *IBPSA Building Simulation*, Glasgow, Scotland, 2009.

[20] B. Dong, B. Andrews, K. P. Lam, M. Höynck, R. Zhang, Y. S. Chiou and D. Benitez, "An

information technology enabled sustainability test-bed (ITEST) for occupancy detection through an environmental sensing network," *Energy and Buildings, 42(7),* vol. 42, no. 7, pp. 1038-1046, 2010.

[21] B. Dong and K. P. Lam, "Building energy and comfort management through occupant behaviour pattern detection based on a large-scale environmental sensor network," *Journal of Building Performance Simulation,* vol. 4, no. 4, pp. 359-369, 2011.

[22] V. L. Erickson, M. Á. Carreira-Perpiñán and A. E. Cerpa, "OBSERVE: Occupancy-based system for efficient reduction of HVAC energy," in *Information Processing in Sensor Networks (IPSN), 10th International Conference,* Chicago, Illinois, 2011.

[23] Z. Han, R. X. Gao and Z. Fan, "Occupancy and indoor environment quality sensing for smart buildings," in *In Instrumentation and Measurement Technology Conference (I2MTC), 2012 IEEE International,* 2012.

[24] M. Milenkovic and O. Amft, "Recognizing energy-related activities using sensors commonly installed in office buildings," *Procedia Computer Science,* vol. 19, pp. 669-677, 2013.

[25] J. R. Dobbs and B. M. Hencey, "Predictive HVAC control using a Markov occupancy model," in *American Control Conference (ACC),* Portland, Oregon, USA, 2014.

[26] J. R. Dobbs and B. M. Hencey, "Model predictive HVAC control with online occupancy model," *Energy and Buildings,* vol. 82, pp. 675-684, 2014.

[27] B. Ai, Z. Fan and R. X. Gao, "Occupancy estimation for smart buildings by an auto-regressive hidden Markov model," in *American Control Conference (ACC),* Portland, Oregon, USA, 2014.

[28] Z. Yang and B. Becerik-Gerber, "Modeling personalized occupancy profiles for representing long term patterns by using ambient context," *Building and Environment,* vol. 78, pp. 23-35, 2014.

[29] Z. Chen, J. Xu and Y. C. Soh, "Modeling regular occupancy in commercial buildings using stochastic models.," *Energy and Buildings,* vol. 103, pp. 216-223, 2015.

[30] Z. Chen and Y. C. Soh, "Modeling building occupancy using a novel inhomogeneous Markov chain approach," in *Automation Science and Engineering (CASE), 2014 IEEE International Conference,* 2014.

[31] C. Sandels, J. Widén and L. Nordström, "Simulating occupancy in office buildings with non-homogeneous Markov chains for demand response analysis," in *Power & Energy Society General Meeting,* 2015.

[32] Z. Wang and Y. Ding, "An occupant-based energy consumption prediction model for office equipment," *Energy and Buildings,* vol. 109, pp. 12-22, 2015.

[33] S. Jain and N. Madamopoulos, "Ahorrar: Indoor Occupancy Counting to Enable Smart Energy Efficient Office Buildings," in *Big Data and Cloud Computing (BDCloud), Social Computing and Networking (SocialCom), Sustainable Computing and Communications (SustainCom)(BDCloud-SocialCom-SustainCom),* 2016.

[34] K. Curran, E. Furey, T. Lunney, J. Santos, D. Woods and A. McCaughey, "An evaluation of indoor location determination technologies," *Journal of Location Based Services,* vol. 5, no. 2, pp. 61-78, 2011.

[35] A. Akanmu, S. H. Rasheed and I. A. Qader, "Spatial mapping approach to component tracking using RTLS system," in *Architectural Engineering Conference 2013*, 2013.

[36] S. Azzouzi, M. Cremer, U. Dettmar, T. Knie and R. Kronberger, "Improved AoA based localization of UHF RFID tags using spatial diversity," in *RFID-Technologies and Applications (RFID-TA)*, 2011.

[37] Quuppa, "Unique technology," 01 12 2017. [Online]. Available: http://quuppa.com/technology/.

[38] R. Serfozo, Basics of Applied Stochastic Processes, Probability and its Applications, Verlag Berlin Heidelberg: Springer, 2009.

[39] R. Douc, E. Moulines and J. S. Rosenthal, "Quantitative bounds on convergence of time-inhomogeneous Markov chains," *Annals of Applied Probability,* vol. 14, no. 4, pp. 1643-1665, 2004.

[40] I. Richardson, M. Thomson and D. Infield, "A high-resolution domestic building occupancy model for energy demand simulations," *Energy and buildings,* vol. 40, no. 8, pp. 1560-1566, 2008.

[41] Z. Liu, "Simulation of Local Climate Control in Shared Offices Based on Occupants Locations and Preferences," A thesis in the Department of Building, Civil, and Environmental Engineering, Concordia University, Montreal, Canada, 2017.

[42] Grizzly Analytics, "Seeing Quuppa's indoor location technology at MWC 2015," 2015. [Online]. Available: http://grizzlyanalytics.blogspot.ca/2015/03/seeing-quuppas-indoor-location.html. [Accessed 15 4 2017].

[43] Quuppa Intelligent Locating System™, "Unique Technology," 2016. [Online]. Available: http://quuppa.com/technology/.

[44] Q. I. L. System™, "LD-7L Long Range HAIP Locator," 23 September 2014. [Online]. Available: http://quuppa.com/ld-7l-long-range-haip-locator/.

Highlights:

- Propose an adaptive probabilistic occupancy prediction model
- Monitor and extract occupancy patterns by a RTLS in an open-plan office
- Add the temporal behavior of occupants by developing time-dependent occupancy model
- Investigate the application of intelligent and occupancy-centered local control strategies