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On the evaluation of occupancy models at various spatial scales

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Abstract: *Occupancy data is an essential input in occupant studies to predict occupants-building interactions and to automate building controls. Therefore, it is important to find an occupancy modelling approach that can better predict occupancy. While previous research evaluated the performance of occupancy models for individual offices, such evaluation at varying zone sizes is required as well. This research investigates the deviations between measured and predicted occupancy data at various spatial resolutions. Occupancy data were collected in 24 offices in an academic building in Ottawa, Canada. Measured data were compared with predicted data which were estimated by three occupancy models, including an existing occupancy model, a custom schedule-based model, and a classification decision tree-based model. At different spatial scales, using random sampling from the individual monitored offices for the considered number of zones, the deviations between measured and predicted results were calculated. This analysis indicated that the performance of the considered occupancy models varied from one occupancy-related measure to another at different spatial scales. However, the errors of the predicted measures approached consistent values at a given number of offices. For this case study, the existing occupancy model and custom schedule-based model showed better performance compared to the classification decision tree-based model.*

Keywords: *Occupants' presence; Occupancy modelling approach; Spatial resolutions; Measurement and prediction; Evaluation.*

INTRODUCTION

Occupants alter energy performance of built environments in two ways: (1) passively by producing heat loads, and (2) actively by using buildings' elements and control systems (Delzendeh et al., 2017). Therefore, accurately predicting occupants' presence plays a prominent role in the design and operation phases of buildings.

For instance, if occupied periods are estimated accurately, annual energy use of buildings and seasonal impacts of occupants' presence on energy use of buildings can be evaluated with high confidence. Energy-efficient adjustment of HVAC terminal units, such as temperature setback scheduling, and lighting and plug-in appliances control schedules in open-plan offices (Delgoshaei et al., 2017), depends on when occupants arrive and leave their offices. Occupants interact with buildings' systems and components more frequently upon their arrival and leaving their offices than during intermediate periods as well (Page et al., 2008). By knowing number of transitions between presence and absence states, buildings' systems, such as lighting controls, demand-driven control strategy for HVAC systems (Labeodan et al., 2015; Peng et al., 2017), and air quality (Attia et al., 2011), are controlled more efficiently. Accurate estimation of number of occupants in shared/open-plan offices helps improve offices' indoor air quality through accurate calculation of the required ventilation rates and carbon dioxide produced by occupants. Moreover, thermal loads corresponding to occupants, either actively (e.g. occupants' use of plug-in appliances) or passively (e.g. heat gains from occupants), is predicted more accurately for controlling HVAC terminal units, such as variable-air volume (VAV) boxes (Peng et al., 2017).

A summary list of the application of different occupancy-related variables in the prediction of energy performance of buildings is presented in Table 1.

Table 1: A summary application list of different occupancy-related variables in buildings' design and operation

Variable	**Application**
Occupied periods	• Estimating annual energy use of buildings • Evaluating seasonal impacts on energy use of buildings
First arrival and last departure	• Adjusting HVAC terminal units and lighting and plug-in appliances control schedules • Tracking higher rates of occupants' interactions with buildings' systems/components at arrival and departure

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Number of transitions between presence and absence	• Controlling buildings' systems/components • Tracking occupants' interactions with buildings' systems/components
Intermediate presence/absence periods	
Number of occupied private offices if they are all controlled together	• Air quality (i.e. humidity and CO_2) and ventilations rates calculations • Occupant-related thermal loads calculations for controlling HVAC terminal units
Number of occupants in open-plan offices if one single control system is used for the whole open-plan office space	

In recognition of the important impact of occupancy on the energy use of buildings, occupants' presence has been represented in building performance simulations through different methods. One of the common methods is hourly standard schedules, such as for occupancy as suggested by ANSI/ASHRAE/USGBC/IES Standard 189.1 (2014), National Energy Code of Canada for Buildings (NECB) (National Research Council Canada, 2011), and DOE reference office model (Deru et al., 2011).

In an effort to address the variations in occupancy patterns with respect to the hourly schedules suggested by building standards, Duarte et al. (2013) extracted the diversity factors from standard-based schedules through long-term data collection in 629 rooms (including but not limited to private and open-plan offices) in an office building. Duarte et al.'s (2013) study showed a deviation of 46% in daily profile peaks from ASHRAE 90.1-2004 for private offices and a deviation of 12% for open-plan offices.

Standard schedules emulate the fraction of occupants who are present simultaneously at the building scale. While such occupancy standard schedules aim to provide a prediction of a standardized buildings' energy performance and operations at the building scale, they do not represent how often each individual occupant is present or absent at the room level. Furthermore, since current schedules in building codes and standards are steady-periodic, new generations of building technologies (e.g. demand-control ventilation and automated lighting controls) whose great potential for energy savings is highly affected by adapting to fluctuating occupants' presence in buildings, fail to encourage building engineers to use such technologies at the design phase of future buildings. Accordingly, to address the deficiencies in the standard schedules in studying individual occupants' presence and behaviour, several data-driven probabilistic occupancy models have been developed since 1990s. Newsham et al.'s (1995) occupancy model is based on the stochastic nature of occupants' presence at their offices. Their model predicts whether an occupant arrives or leaves for intermediate breaks or for the rest of the day using the probability profiles of first arrivals, last departures, and intermediate vacancies driven from a case study.

To modify Newsham et al.'s (1995) probabilistic occupancy model, Reinhart's (2001) model uses a cumulative distribution function for the prediction of arrival and departure times for the three segments of the day he defined for each work day (i.e. morning, lunch, and afternoon). In a later attempt, Reinhart (2004) developed an occupancy model where the arrival, departure, and three breaks (including lunch at noon and two breaks, one before and one after lunch breaks) are chosen randomly from a normal distribution with the mean times and standard deviations defined for each of the events to represent randomness in occupants' presence. While Reinhart's (2004) model uses a normal distribution to determine the duration for intermediate vacancies, Wang et al.'s (2005) probabilistic occupancy model generates random periods for the intermediate vacancies based on the survival analysis using an exponential distribution.

To consider the stochastic timing of occupants' arrivals, departures, and intermediate vacancies, Page et al. (2008) developed a Markov chain occupancy model based on the weekly occupancy profile, probabilities of transitions, and considering long absences. Similarly, Andersen et al. (2014) developed a Markov chain occupancy model based on the probabilities of transitions, however they developed separate models for high and low occupancy rates by dividing the data. Likewise, Luo et al.'s (2017) occupancy model is a Markov chain based on the past distribution of the first arrivals and last departures times and random transitions between present and absent states.

To simplify modelling occupants' presence, Mahdavi and Tahmasebi (2015) developed a non-probabilistic model in which future occupancy is predicted based on the past recorded data. The other modelling approach that has emerged in the past decade to predict occupancy is to use machine learning methods. For instance, D'Oca et al. (2015) implemented data mining to extract occupancy patterns from a dataset of 16 offices.

A number of the aforementioned studies evaluated the performance of the occupancy models. For instance, Mahdavi and Tahmasebi (2015) calculated the deviations of the predicted occupancy-related variables (such as first

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arrival and last departure times, daily occupied periods, occupancy states, and number of transitions) from the measurement on eight monitored offices. Similarly, Luo et al.'s (2017) calculated the errors of the predicted first arrival and last departure times and the intermediate presence and absence periods. D'Oca et al. (2015) evaluated the models by calculating the true positive and true negative predictions for the occupancy states of 16 monitored offices.

While previous research on modelling occupants' presence evaluated the accuracy of models mostly in individual private offices, there is still the question of whether the predictive power of the models is affected by a building zone size. The main objective of this paper is to assess the impact of occupancy models on the accuracy of the prediction of occupants' presence at different spatial scales. The main questions of this paper are:

- Does the accuracy of the predicted occupancy-related factors vary at different spatial resolutions?
- To answer the above question, does the occupancy modelling type affect the accuracy of the occupancy models?
- Among the occupancy-related variables studied in the current paper (i.e. daily occupied period, earliest first arrival and latest last departure times, and number of simultaneous occupied offices), is the accuracy of a specific variable affected more considerably with the size of a building zone?

The case study where the occupancy data were collected is briefly explained in the next section, followed by a description of the occupancy modelling types implemented in this paper to predict occupancy. Afterwards, the results of the comparison between the predicted and measured occupancy at different spatial scales are presented and discussed. Finally, the findings obtained in this paper are outlined.

DESCRIPTION OF CASE STUDY

Seventeen months' worth of data was collected in 24 private offices. The 24 monitored offices are located in an academic building in Ottawa, Canada. The monitored offices were occupied by faculty members or administrators. All the offices were private offices, except for one which was shared by two people.

Event-based data of occupants' presence in each of the monitored offices were recorded with passive infrared (PIR) motion sensors. The PIR sensors had the distance range of 5 m and the horizontal and coverage angles of 100º and 80º, respectively. All the PIR sensors were integrated with the building automation system (BAS). The BAS recorded occupants' presence and absence at the time of the occurrence of the events, rather than at a specific frequency. The event-based occupancy data were converted to time series of occupancy at five-minute timestep. A five-minute timestep was assumed occupied if a positive event (i.e. presence) occurred at least once within that timestep.

OCCUPANCY MODELLING

The three occupancy models of the current paper are: (1) a model adopted from the literature, (2) a custom schedule-based model, and (3) a classification decision tree-based model. These models are hereafter called Model 1, 2, and 3, respectively. Each model is elaborated in this section.

The accuracy of the predicted occupancy-related factors was evaluated at different spatial scales. Since this paper sought to investigate whether the accuracy of the predicted factors is affected by occupancy models, two models (i.e. Models 2 and 3) were developed in the current research, while an existing occupancy model was incorporated as well.

Note that the aim of this paper was to compare the performance of the occupancy models across varying zone sizes, rather than validation of the models for each individual office. This approach incorporates diversity in occupancy, however it does not generalize results. The models were developed based on the whole dataset, rather than dividing the dataset into a training and test subsets. The limitation of this approach is that it may not predict occupancy accurately for operating buildings (e.g. predictive controls). But this approach is suitable for estimating energy use of buildings at the design phase.

Different occupancy-related variables were used to assess the errors of the predicted occupancy across different spatial scales. These measures consist of: (1) daily occupied period, (2) earliest first arrival time, (3) latest last departure time, and (4) number of simultaneous occupied offices. It is essential for building engineers to have a good estimation of daily occupied periods and number of occupants to predict energy, comfort, and air quality performance of buildings accurately as well as to optimize HVAC systems in the design phase of new constructions. Moreover, HVAC and lighting systems can be controlled more efficiently when they are adjusted to occupancy patterns based on the arrival and departure times of occupants in multi-person offices (see Table 1).

Model 1

To model occupancy based on an existing occupancy model, Page et al.'s (2008) probabilistic occupancy algorithm was implemented. Using Page et al.'s (2008)

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model, the time series of occupants' presence in each of the individual monitored offices was predicted as a discrete-time Markov chain model. To this end, the probability of changes from an occupancy state at each five-minute timestep of a day (i.e. 288 timesteps) to the same state (i.e. T_{00} or T_{11}) or the opposite state (i.e. T_{01} or T_{10}) at the next timestep was calculated. For the calculation of transition probabilities, long absences lasting more than one day were excluded from the occupancy data, except when they corresponded to weekends.

By computing the likelihood of changes in occupancy states, occupants' presence on weekdays, excluding long absences (more than one day), in each of the monitored offices were predicted using the Monte Carlo simulation technique (Gilks et al., 1996). Note that in the current paper, instead of using the typical daily profiles of occupants' presence and the mobility parameter in each monitored office, the probability of transitions, which was calculated for each office, was used to predict the occupancy of that office after removing all of the absence periods longer than one day but not the weekends.

Model 2

In the current study, a model was developed based on the custom schedules for each monitored office to predict occupants' presence on weekdays based on the measured data. To this end, the hourly occupied period and ratio for each weekday of each month were computed for each monitored office using the measured data. Likewise, the median of daily occupied periods was calculated for each weekday of each month. Figure 1 presents an example of the hourly occupied ratio on the day of Tuesday of February and the daily occupied periods for each weekday of February in one of the monitored offices.

For each of the monitored offices, by knowing the total occupied periods and the daily occupied periods for each weekday of each month, the number of occupied days was estimated. At each timestep, number of occupied timesteps was estimated based on the hourly occupied ratio for each weekday of each month.

To mimic occupants' habit for intermediate arrival and departure, the frequencies of changing occupancy states from occupied to unoccupied and vice versa were calculated for each monitored office. The maximum frequency of 80th percentile of the frequency of all the recorded changing occupancy states from the 24 monitored offices was calculated to be 20 minutes. In other words, if an occupant was present (or absent) in an office at a specific five-minute timestep, s/he was present (or absent) for the next 15 minutes.

Based on the calculated frequency of changing occupancy states, occupancy states were changed every 20 minutes. To this end, the occupied timesteps within the same weekday and month were chosen randomly based on the calculated number of occupied days and timesteps. The randomly-chosen timesteps and the subsequent timesteps (based on the calculated frequency of changing occupancy states) were set as occupied. The process of Model 2 is presented in Figure 2.

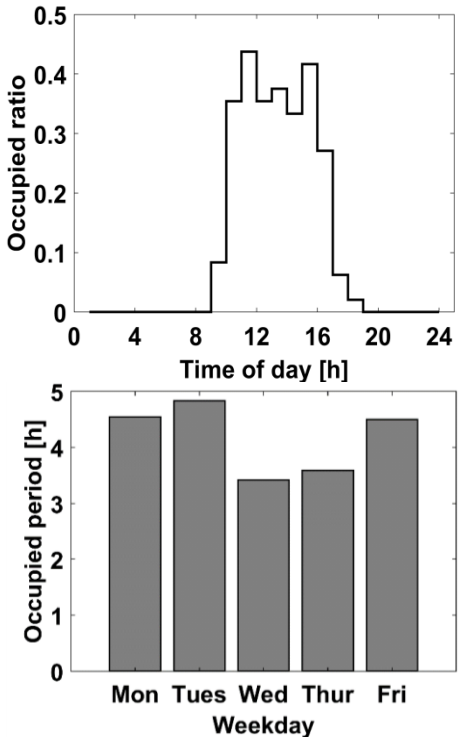

Figure 1: An example of occupancy data extracted from measurements in one of the monitored offices: (top) hourly occupied ratio on Tuesdays of February, and (bottom) daily occupied period for each weekday of February.

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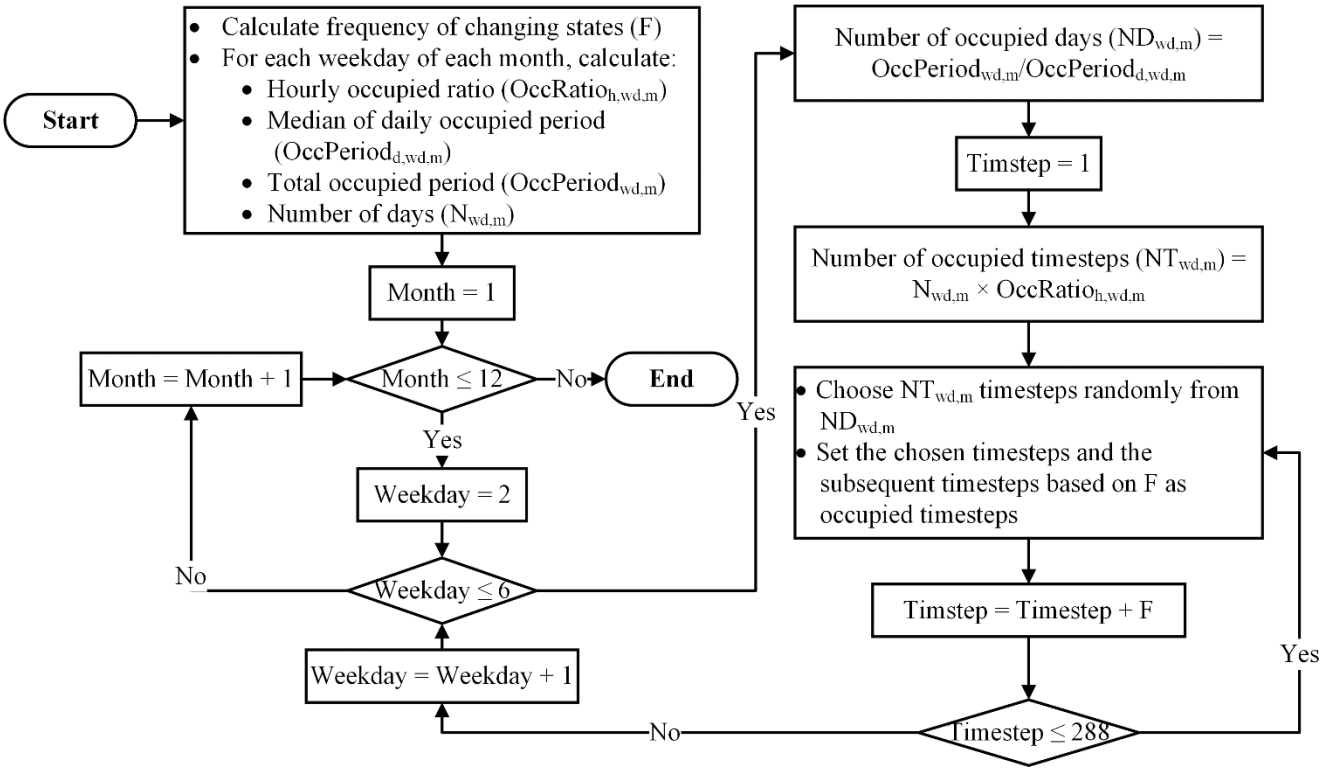

Figure 2: Flowchart of Model 2 for predicting occupancy on weekdays.

Model 3

To transform measured data to an occupancy model for each of the 24 monitored offices, machine learning was the other technique which was applied in the current study. For the prediction of the nominal responses (i.e. 1 as presence and 0 as absence), the classification decision tree algorithm was employed in MATLAB. This machine learning technique has been considered as a widely used technique while it has shown a powerful technique in classifying various types of data using recursive partitioning a dataset (Lantz, 2015). Furthermore, it facilitates extracting rule-based models and custom schedules in future work.

The predictors which were set for the decision tree learning algorithm in the current paper were: (1) month of the year, (2) day of the week, and (3) time of day. Using the Classification And Regression Trees algorithm (known as *CART*) (Breiman et al., 1984), the dataset is split into binary partitions until each partition contains the highest possible single class based a measure called *information gain* (Lantz, 2015).

After generating the occupancy model using the classification decision tree leaning algorithm based on the occupancy data of each monitored office, the occupancy of that office was predicted using the developed model for that office in MATLAB.

SIMULATION

Using the occupancy models (as explained in the previous section), occupancy states at the recorded timesteps of the 24 monitored offices were simulated in MATLAB. Figure 3 presents an example of the measured and predicted occupancy states using the three occupancy models explained in the previous section. Figure 3 shows that Model 3 generally did not provide a good prediction at the timestep scale for this monitored office. However, as mentioned in the previous section, the aim of this paper was not to validate the developed models for each individual office, rather to evaluate the predictive power of the models for a group of offices at different spatial resolutions. Moreover, note that the monitored offices were occupied by faculty members or administrators. For example, a faculty member was the occupant of the office for which occupancy data is presented in Figure 3. In such cases that occupants had more flexible occupancy schedules, Model 3 did not predict occupancy accurately, which resulted in higher deviation from measured data with respect to the considered occupancy-related factors (as presented in the next section).

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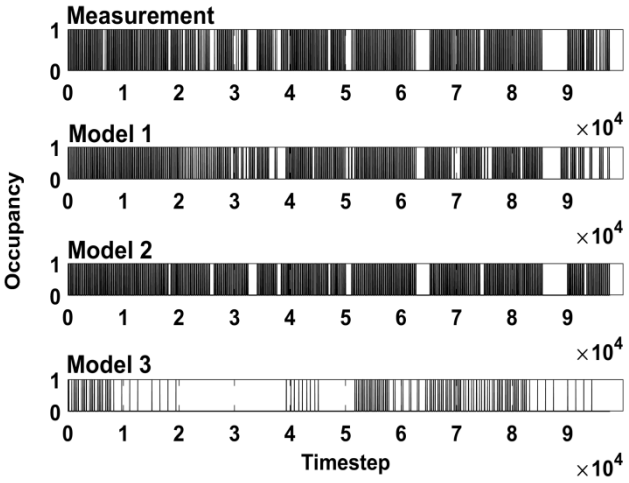

Figure 3. An example of the occupancy states measured and predicted using Models 1, 2 and 3 for one of the monitored offices.

To keep the same time period for all the monitored offices, the common first day and last day of data collection among all the monitored offices were found. In total, 339 days, excluding weekends, were common among the 24 monitored offices.

For the evaluation of the performance of the occupancy models, 100 samples were chosen randomly with replacement from the 24 monitored offices at different spatial scales (i.e. 1 to 100 offices). Each of the randomly-chosen samples had a size identical to the considered zone size. The errors of the predicted occupancy-related variables for all the monitored weekdays or timesteps (whichever applicable with respect to the relevant occupancy-related measure) were computed for the group of the randomly-chosen offices. Then, the 80th percentile of the errors, similarly to (Mahdavi and Tahmasebi, 2015), was calculated. Afterwards, the average and standard deviation of the 80th percentile of the errors across the 100 samples were calculated for each of the considered zone sizes.

Figure 4 shows an example of the measured and simulated daily occupied periods, which was predicted using Model 2, for the first 120 monitored weekdays for one of the 100 samples, which were comprised of 10 offices. This figure presents the average measured and predicted daily occupied periods across the 10 randomly-chosen offices. The absolute errors of the average predicted daily occupied periods for the first 120 monitored weekdays are shown in this figure as well. For each of the 100 samples, the absolute errors of the average predicted daily occupied periods were calculated for the 339 monitored weekdays. The errors of different fractions of weekdays of the sample of 10 offices (i.e. Figure 4) are presented in Figure 5 with a thick line. The errors of the other 99 samples are also populated in Figure 5. The average of the 80th percentiles of the errors across the 100 samples for this zone size (i.e. 10 offices) was obtained 1.1 hours using Model 2 (as shown in Figure 6).

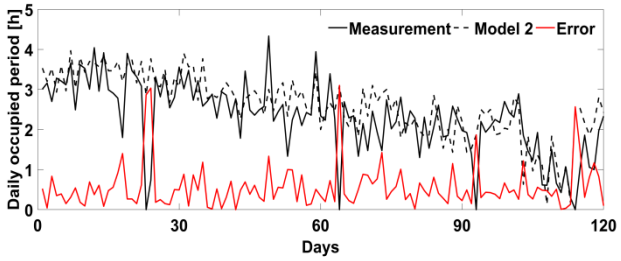

Figure 4. An example of the measured and predicted daily occupied periods and the corresponding absolute errors for the first 120 monitored weekdays for one of the samples with a size of 10 offices.

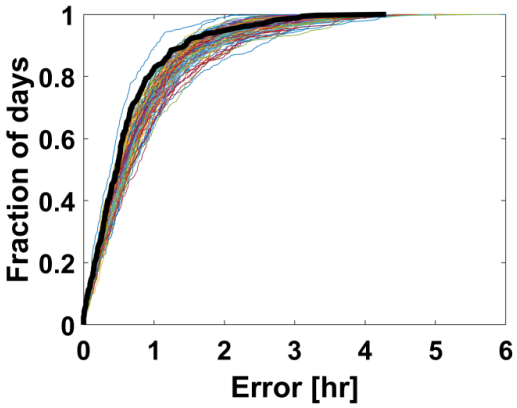

Figure 5. An example of the errors of different fractions of days for 100 samples. The errors for the sample shown in Figure 4 are presented by a thick black line.

The same procedure was implemented for the other considered occupancy-related measures to find the average and standard deviation of the errors of occupancy predictions across different zone sizes. Next section presents and discusses the study results.

RESULTS AND DISCUSSION

This section presents and discusses the results of the predicted occupancy-related variables (i.e. daily occupied periods, earliest first arrival and latest last departure times, and number of simultaneous occupied offices) compared to the corresponding measured values.

As per the procedure explained in the previous section, the mean and standard deviation of the 80th percentile of the

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errors for the 339 monitored weekdays were calculated for daily occupied periods at different zone sizes (Figure 6). Figure 6 shows that the mean errors of the predicted daily occupied periods in random sampling of different numbers of offices are almost consistent after a given number of offices. The standard deviation of the errors becomes smaller after a given number of offices. This observation follows the *Central Limit Theorem*. Based on this theorem, the distribution of random samples with different sizes (n) from a population with a variance of σ^2 tends to be a normal distribution one with a mean equal to the mean of the population and a standard deviation of $\sigma/\sqrt{n}$. The ratio of the standard deviation to the mean errors (i.e. coefficient of variation (*CV*)) fell below 10% with the zone sizes of larger than 25 and 26 offices with the mean errors of about one hour using Models 1 and 2, while the *CV* fell below 10% for the zone sizes of larger than 14 offices with the mean error of about two hours using Model 3. These errors are in line with the 1.6-hour error of Mahdavi and Tahmasebi's (2015) occupancy model in predicting the daily occupied periods.

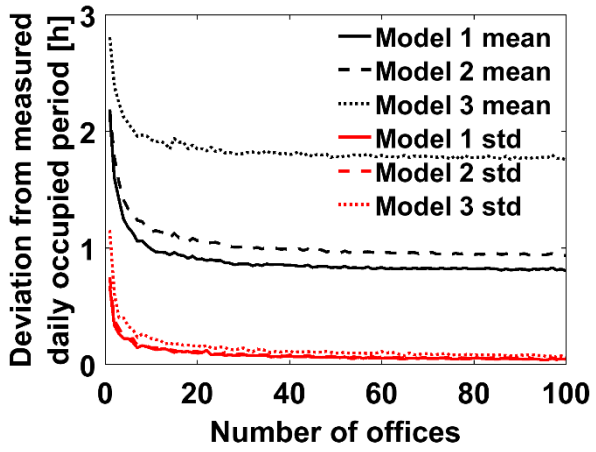

Figure 6. Mean and standard deviation of discrepancy between the measured and predicted average daily occupied periods at different spatial scales using Models 1, 2, and 3.

Figure 7 shows the mean and standard deviation of the errors on the predicted earliest first arrival and latest last departure times between 7 AM and 10 PM among the considered numbers of offices. Similar to daily occupied periods, the mean and standard deviation of the 80th percentile of the errors for the 339 monitored weekdays were calculated at different zone sizes. Compared to the daily occupied periods, the *CV* of the earliest first arrival and latest last departure times fell below 10% at larger zone sizes. This observation is especially the case for the earliest first arrival time among the group of offices. For example, the average errors in the predicted earliest first arrival time fell below about an hour for zone sizes of larger than 49 offices and the latest last departure time fell below about two hours for zone sizes of larger than 46 offices using Model 2. Similarly, Mahdavi and Tahmasebi's (2015) occupancy model predicted first arrival and last departure times with an error of one hour and 2.4 hours, respectively. Note that if none of the randomly-chosen offices were predicted occupied on all the 339 monitored weekdays, the earliest first arrival and latest last departure times were assumed to be zero. Consequently, at the smaller zone sizes, the errors of the predicted earliest first arrival and latest last departure times are higher than the larger zone sizes, which is especially the case for the simulated arrival and departure times predicted using Model 3.

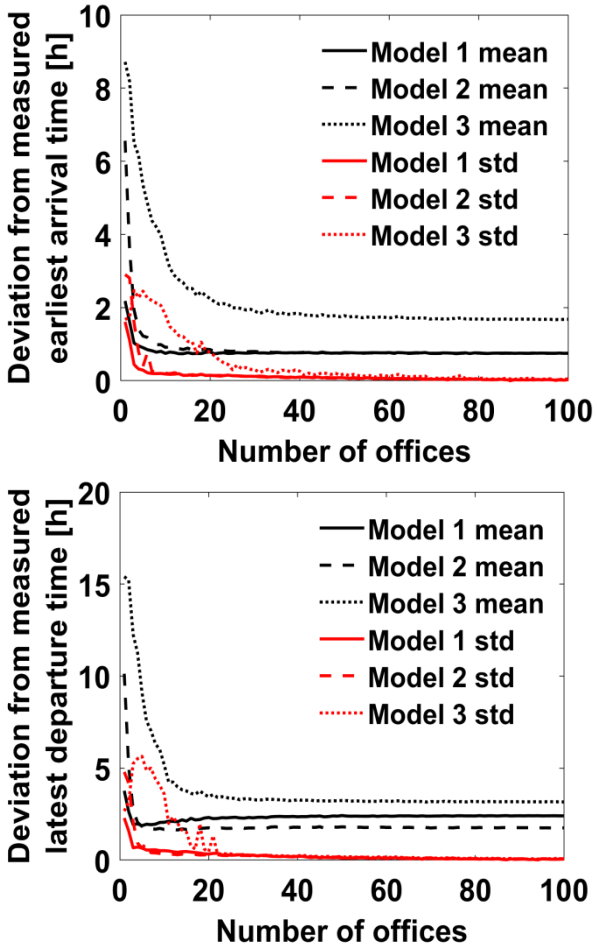

Figure 7. Mean and standard deviation of discrepancy between the measured and predicted earliest first arrival (top) and latest last departure times (bottom) between 7 AM and 10 PM at different spatial scales using Models 1, 2, and 3.

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Using the procedure explained in the previous section, the average and standard deviation of the errors of the predicted number of the offices which were occupied simultaneously at different spatial scales (i.e. 1 to 100 offices) at each timestep of the 339 weekdays were calculated (Figure 8). The results indicate that the deviation between the predicted and measured number of occupied offices accumulates as the zone size increases. While Model 1 in the current study showed a good performance on the prediction of the daily occupied period at various spatial scales (see Figure 6), Models 2 and 3 outperform Model 1 in predicting the number of simultaneous occupied offices. The errors of the predicted number of occupied offices decreased by about half using Models 2 and 3 compared to Model 1. The standard deviation to the average errors of the predicted number of occupied offices in Figure 8 indicates that the extent of the uncertainty in the errors reduces as the building zone size increases. For instance, the standard deviation decreased to 10% of the average errors for a zone size of larger than 47 offices using Models 1 and 3.

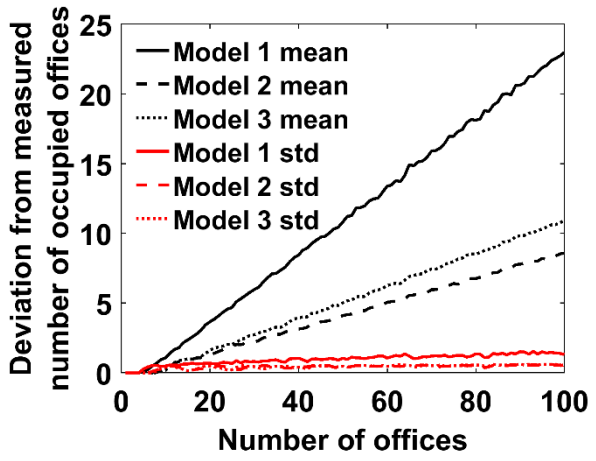

Figure 8. Mean and standard deviation of discrepancy between the measured and predicted number of occupied offices at different spatial scales using Models 1, 2, and 3.

The results presented in this section indicate that the accuracy of the predicted occupancy-related factors varies at different spatial scales. When the zone size increases, the uncertainty corresponding to occupancy-related factors decreases as the errors approached a consistent value. This principle is useful for the reliable prediction of the energy performance of a larger group of offices than each individual office. Note that this fact should not be interpreted that it is more energy-efficient to control larger zones together.

Furthermore, using the consistent error as a multiplier, the energy-related predictions corresponding to each occupancy-related factor can be modified.

Among the variables which were considered in the current study to evaluate the performance of the considered occupancy models, the mean value of the daily occupied periods converged at smaller zone sizes than the other variables.

With respect to the three occupancy models in the current study, Page et al.'s (2008) probabilistic occupancy algorithm and the custom schedule-based model outperformed the classification decision tree-based model. Since the monitored offices were mostly occupied by faculty members who had more flexible schedules, classifying occupancy data using the time-based predictors did not perform well in predicting occupancy.

CONCLUSION AND FUTURE WORK

This paper evaluated the performance of different occupancy modelling types at different spatial scales. The impact of the occupancy models on the accuracy of the predicted occupancy was assessed by comparing the prediction with measurement.

The results showed that the performance of the occupancy models in the prediction of the occupancy-related variables is not the same at larger zone sizes as that at smaller zone sizes. The occupancy modelling type is an important factor in addition to the spatial scales.

At a given number of offices, the coefficient of variation of the occupancy-related variables which were considered in the current paper (i.e. earliest first arrival and latest last departure times and daily occupied periods) approached zero at larger zone sizes. This observation indicates that when the occupancy data of a given number of offices are predicted, a building designer/operator can predict and adjust occupancy-based energy demands of a building zone more reliably. Among the occupancy-related variables considered in the current paper, daily occupied periods showed a lower sensitivity to the zone size.

The findings of this paper indicated the potential of typical detailed rule-based models and custom schedules to reduce the error of the predicted occupancy in a simulation-based analysis. Such rule-based models and custom schedules can be generated using machine learning methods and average-value models. This research developed occupancy models for each monitored office. The performance of the models was evaluated for the group of offices at different spatial scales. While this approach incorporated diversity in occupancy, it did not provide generalizable results that can be applied to other

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cases. Research on extracting generalizable rule-based models and custom schedules which are derived from large datasets in various building archetypes is necessary future work. Moreover, data collection on a variety of occupancy patterns in buildings is required to facilitate the extrapolation of the models.

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