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Predicting people's presence in buildings: An empirically based model performance analysis

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ABSTRACT

Building performance is influenced by occupants' presence and actions. Knowledge of occupants' future presence and behaviour in buildings is of central importance to the implementation efforts concerning predictive building systems control strategies. Specifically, prediction of occupants' presence in office buildings represents a necessary condition for predicting their interactions with building systems. In the present contribution, we focus on the evaluation of a number of occupancy models to explore the potential of monitored past occupancy data towards predicting future presence of occupants. Towards this end, we obtained long-term high-resolution monitored occupancy data from a number of workplaces (in open, semi-open, and closed office settings) in a university building. Using this data, we trained two existing probabilistic occupancy models and an original non-probabilistic occupancy model to predict the occupancy profiles of the same workplaces on a daily basis. The predictions were evaluated via comparison with monitored daily occupancy profiles. To conduct the model evaluation in a rigorous manner, separate sets of data were used to train and evaluate the models. A set of five specific evaluation statistics was deployed for model comparison. In general, the obtained level of predictive accuracy of all models considered was found to be rather low. However, the proposed non-probabilistic model performed better in view of short-term occupancy predictions. The results thus facilitate a discussion of the potential and limitations of predicting building occupants' future presence patterns based on past monitoring data.

1. Introduction

Occupants influence buildings' energy and indoor environmental performance due to their presence (via releasing sensible and latent heat) and actions (operation of devices such as windows, shades, luminaries, radiators, and fans) [1]. To quantify such influences, both empirical and simulation-aided studies have been deployed. For instance, Azar and Menassa [2] observed that energy models of office buildings' in different climatic zones in USA are highly sensitive to occupancy-related behavioural parameters. More specifically, Yang et al. [3] showed that application of HVAC schedules that use observation-based personalized occupancy profiles in a three-story office building test bed could save up to 9% energy compared to the conventional (default) schedules.

Most commonly, representation of occupancy in building performance simulation relies on libraries of standardized diversity factors and schedules. These diversity profiles, which represent typical presence probability profiles, are derived from long term monitored data in different classes of buildings. In this context, multiple efforts are being undertaken to derive more reliable building occupancy profiles. For example, Davis and Nutter [4] used data from different sources (building security cameras, doorway electronic counting sensors, semester classroom scheduling data, and personal observations) to derive occupancy diversity profiles for six types of university buildings. Another study [5] used data obtained from 629 occupancy sensors mounted in an 11-story commercial office building to detail occupancy diversity factors for private offices, open offices, hallways, conference rooms, break rooms, and restrooms. The authors point out that the resulting diversity profiles differ as much as 46% from those published in ASHRAE 90.1 2004 [6], which is referenced by many energy modellers regarding occupancy diversity factors for simulations.

Notably, there have also been a number of efforts in the pertinent scientific and professional communities to develop probabilistic models of occupants' presence in buildings. As one of the first attempts, Newsham et al. [7] considered the probabilistic nature of occupancy while developing a stochastic model to predict lighting profiles for a typical office. Their model deployed the

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probability of first arrival and last departure as well as the probability of intermediate departures from and returning back to the workstations. Reinhart [8] further developed this model by using the inverse transform sampling method [9] to generate samples from the distribution functions of arrival and departure times. Moreover, days were divided into three phases (morning, lunch, and afternoon) for which the probabilities of start time and length of breaks were computed. The statistical properties of occupancy in single person offices were further examined by Wang et al. [10]. They proposed a probabilistic model to predict and simulate occupancy in single-occupancy offices. In another effort, Page et al. [11] proposed a generalized stochastic model for the occupancy simulation using the presence probability over a typical week and a parameter of mobility (defined as the ratio of state change probability to state persistence probability). They also included long absence periods (corresponding to business trips, leaves due to sickness, holidays, etc.) as another random component in their model. Richardson et al. [12] presented a similar method for generating stochastic weekday and weekend occupancy time-series data with the aid of a matrix of transition probabilities derived from a 10-min resolution monitoring occupancy data for UK households.

Note that in these studies monitored data has been used to derive a probabilistic model that generates random non-repeating daily profiles of occupancy for a long-term (e.g., annual) building performance simulation. Hence, models are suggested to perform well, if the entire set of generated random realizations of the daily occupancy profiles agrees in tendency with the monitored data over the whole simulation period. However, the agreement of the generated profiles with the monitored data (one-to-one correspondence between generated and monitored daily profiles) is not taken into consideration. Even while modelling long absences [11], the unoccupied days are scattered randomly across the year and do not necessarily match the dates of absences in the measured data. Hence, the models' performance cannot be said to have been documented (let alone validated), if the actual day-to-day prediction of occupancy and control action probabilities is relevant. Such a short-term predictive function is not a theoretical construct. Rather, it represents an essential scenario in the increasing run-time use of simulation models in the building operation phase, as practiced, for example, in model-predictive and simulation-based predictive building systems control approaches [13–15]. In these scenarios, short-term predictions of occupancy and weather are incorporated in the simulation model to predict the near-future performance of the building towards optimizing its operational regime. Thus, the level of achievable agreement between the predicted and real short-term (e.g., daily) occupancy profiles is of utmost importance.

A further issue regarding the existing probabilistic occupancy models pertains to the provided associated "validation" information. With few exceptions (see for example [16]), most of the work on evaluating the probabilistic occupancy models has focused on comparing the model outputs with the very set of data, which has been used to derive the model. In our view, a scientifically sound model evaluation approach must clearly separate the data segments used for model development and model assessment. This is especially important while evaluating the predictive potential of an occupancy model, which is intended to be used for operational purposes (i.e., predictive control) in buildings.

Given this background, we pursue in the present study a systematic empirically based assessment of two previously developed probabilistic occupancy models with regard to their short-term predictive performance. To put the predictive performance of these models in context, we compare it with the performance of a simple original non-probabilistic model that also relies on past observation-based aggregated occupancy data to generate daily Boolean patterns of people's presence in buildings. The latter model was developed within the context of two ongoing EU projects [17,18] to be deployed in run-time simulations incorporated in the control logic of existing buildings.

To assess predictive potential of the two probabilistic models and the non-probabilistic one, we used data from a university campus office area, which is equipped with a monitoring infrastructure and includes a number of open and closed offices. Thereby, long-term high-resolution monitored occupancy data from eight workspaces were obtained. To train and evaluate the models, separate sets of monitored data were used. The comparative assessment of the models' predictive performance was accomplished with the aid of a number of pertinent statistics. Thus, the results of the study facilitate a fact-based discussion of the potential and limitations of models for the prediction of people's presence in buildings. Specifically, the results provide a proper basis towards assessing the fitness of probabilistic occupancy models in view of their incorporation potential in the building operation phase (i.e., predictive building systems control).

2. Approach

2.1. Overview

In the present paper, we evaluate the predictive potential of two existing probabilistic occupancy models. Moreover, we compare their performance with a simple original non-probabilistic model of occupants' presence, which was developed to be deployed in simulation-powered predictive building systems control [15]. These models were used to generate predictions of daily occupancy profiles using the past monitoring occupancy data obtained from eight (individually monitored) workplaces in an office area in a building of the Vienna University of Technology. One workplace is within a closed single-occupancy office, two are within semi-closed individual offices, and the rest are within an open-plan office area.

The main objective was to discern how well the models performed towards predicting daily occupancy profiles for the aforementioned eight workplaces. Model training and model evaluation were based on two separate data sets. Once trained, the models were used to predict the daily occupancy profiles of the eight workplaces for 90 working days. To evaluate the two probabilistic methods, multiple predictions were generated via a 100-run Monte Carlo execution. Model comparison was conducted using a set of five statistics and their distribution.

2.2. Data collection

To obtain occupancy data, wireless ceiling-mounted sensors (motion detectors) were used. The internal microprocessors of the sensors are activated within a time interval of 1.6 min to detect movements. The resulting data log entails a sequence of time-stamped occupied to vacant (values of 0) or vacant to occupied (values of 1) events.

To facilitate data analysis, the event-based data streams were processed to generate 15-min interval data, using stored procedures of the MySQL database [19]. This procedure derives the duration of occupancy states (occupied/vacant) from the stored events and returns the dominant occupancy state of each interval. Occupancy periods before 8:00 and after 19:45 were not included in the study to exclude, amongst other things, the presence of janitorial staff at the offices. Occupancy data for a nine-month period (10th of November 2011 to 25th of July 2012) was used to train and compare the occupancy models.

2.3. First probabilistic occupancy model

The occupancy model developed by Reinhart [8] has been primarily used in Lightswitch-2002 model [20] for the purpose of predicting lighting energy performance of manually and automatically controlled electric lighting and blind systems. The model uses the following probability distributions as input to capture the random nature of occupants' presence:

(1) The cumulative distribution function of first arrival times (CDF_a);
(2) The cumulative distribution function of last departure times (CDF_d);
(3) The probability distribution function of intermediate departure times (PDF_{id});
(4) The probability distribution of length of intermediate absences for morning, lunch, and afternoon periods.

A daily occupancy profile is then generated by identifying the first arrival time, last departure time, intermediate departure times, and the associated length of intermediate absences as follows:

- Using a random number between 0 and 1 (u_1), drawn from the standard uniform distribution, the first arrival time (t_a) is derived from CDF_a such that $CDF_a(t_a) = u_1$.
- Using a random number between 0 and 1 (u_2), drawn from the standard uniform distribution, the last departure time (t_d) is derived from CDF_d such that $CDF_d(t_d) = u_2$.
- To decide if an intermediate departure event occurs at a certain time (t_m), a random number between 0 and 1 (u_m) is compared with the probability of intermediate departure at that time. Once an intermediate departure is identified ($PDF_{id}(t_m) \geq u_m$), the length of the absence is obtained randomly from the corresponding probability function of the length of intermediate absences (morning, lunch time, or afternoon).

2.4. Second probabilistic occupancy model

The stochastic occupancy model developed by Page et al. [11] generates random non-repeating daily occupancy profiles using the profile of presence probability and the parameter of mobility. The model has been formulated based on the hypothesis that the value of occupancy at the next time step depends on the current occupancy state and the probability of transition from this state to either the same state or its opposite state. This is reflected in Eq. (1):

$$P(t+1) = P(t)T_{11}(t) + (1 - P(t))T_{01}(t) \tag{1}$$

Here, $P(t+1)$ and $P(t)$ are the probabilities of presence at the time steps $t+1$ and t, $T_{11}(t)$ is the transition probability from presence state to the same state at the time step t, and $T_{01}(t)$ is the transition probability from absence to the presence state at the time step t. In order to derive the transition probabilities based on the presence probabilities, Page et al. defined the parameter of mobility (to be provided as an input), as the ratio between the probabilities of change of the state of presence over that of no change:

$$\mu(t) = \frac{T_{01}(t) + T_{10}(t)}{T_{00}(t) + T_{11}(t)} \tag{2}$$

Here, $T_{10}(t)$ is the transition probability from presence to the absence state at the time step t, and $T_{00}(t)$ is the transition probability from absence state to the same state at the time step t. From Eqs. (1) and (2), and assuming the parameter of mobility as a constant, the profiles of transition probabilities can be obtained as follows:

$$T_{01}(t) = \frac{\mu - 1}{\mu - 1}P(t) + P(t+1) \tag{3}$$

$$T_{11}(t) = \frac{P(t) - 1}{P(t)}\left[\frac{\mu - 1}{\mu - 1}P(t) + P(t+1)\right] + \frac{P(t+1)}{P(t)} \tag{4}$$

Clearly, the other possible transition probabilities can be calculated via the following equations:

$$T_{00}(t) = 1 - T_{01}(t) \tag{5}$$

$$T_{10}(t) = 1 - T_{11}(t) \tag{6}$$

To generate a daily occupancy profile, the procedure starts from the first time step of the day with a vacant state for commercial buildings. Subsequently, for each time step, a random number between 0 and 1 is generated and compared with the transition probabilities to see if a change of occupancy state occurs. This is a simple case of using the inverse transform sampling method, as the cumulative distribution function of transition probabilities is a histogram of two bins. For example, if the current time step has a vacant state and the generated random number is smaller than T_{01} at that time step, the next time step is assumed to be occupied.

2.5. A non-probabilistic occupancy model

To support the realization of simulation-assisted building systems control approaches, we developed a simple non-probabilistic model (referred to here as the MT model) that generates daily binary occupancy profiles based on aggregated past presence data. The MT model works based on a simple procedure. The statistically aggregated daily probability profile of past presence data represents the starting point. For each time interval of the daily profile to be generated, the interval is assumed to be occupied if the associated presence probability of the aggregated past profile is higher than or equal to a specific threshold probability. Otherwise, the time interval of the daily profile is predicted to be vacant. The threshold probability is simply identified by iteratively comparing the area under the resulting predicted binary occupancy profile with the respective area under the aggregated past probability profile used for model training. Practically speaking, the best-fitting probability threshold is identified such that the area under the resulting binary occupancy profile is as close as possible to the area under the aggregated profile of probability of past presence. Fig. 1 illustrates a sample aggregated profile of past presence probability, the best-fitting threshold, and the resulting Boolean occupancy profile generated by the MT model.

As the MT model does not include a stochastic term, it returns the same daily occupancy profile for any given aggregate profile

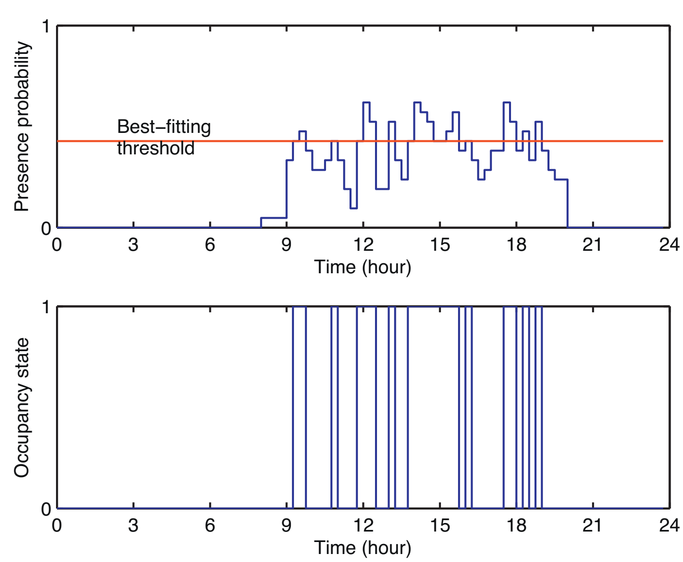

Fig. 1. A sample profile of aggregated presence probability (based on past observations), the best-fitting probability threshold (top), and the resulting binary occupancy profile generated by the MT model (bottom).

of presence probability used for model training. However, if the training profile is changed (for instance, in case of training scenarios with moving temporal horizons), the generated daily profiles is updated accordingly.

2.6. Model training

Implementation of occupancy models in a continuous running mode in building control system raises a number of questions with regard to occupancy data utilization: What length of past occupancy information shall be considered for model development? Would it be advantageous to differently treat days of the week? Shall the model training occur in static or shifting intervals? In previous publications [21,22], we examined the impact of different model training scenarios on the predictive potential of stochastic occupancy models. Concerning the number of days of monitored occupancy data as input to the model, we examined alternatives from 5 to 20 days. Days of the week were treated similarly in “All week’s working days” mode and separately in “Specific week days” mode. Besides, fixed and moving training intervals were considered. In the fixed interval mode, the model was fed once with past data from a specific period and it predicted occupancy for future days. However, in the moving mode, the training interval advanced as the model predicted the occupancy day by day. Amongst other things, the results of this study suggested that the training mode with shifting horizon offers slightly better predictions.

For the purpose of the present study, we applied thus a single moving training scheme as follows. To generate a predicted occupancy profile for each working day, the occupancy models are fed with the monitoring occupancy data obtained from the previous 28 days. This 4-week data set is used to derive the required inputs for the aforementioned occupancy models. These are the probabilities of arrival time, departure time, intermediate departure times, and length of the intermediate absences for the Reinhart model, the presence probability profile and parameter of mobility for the Page model, and the presence probability profile for the proposed non-probabilistic model.

2.7. Model evaluation

To evaluate the predictive potential of the models, we compared predicted and monitored occupancy profiles of 90 working days between the 1st of April and the 25th of July 2012. As for each run the models are fed with the occupancy data from the prior four weeks, separate sets of data are used for training and evaluating the models. To compare the performance of the models, we used five statistics:

(1) First Arrival time (FA) error [h]: The predicted minus the monitored first arrival time.
(2) Last Departure time (LD) error [h]: The predicted minus the monitored last departure time.
(3) Occupancy Duration (OD) error [h]: This metric represents the difference between the predicted and monitored daily presence duration. We calculated the presence duration by counting the number of occupied intervals.
(4) Occupancy State Matching (SM) error [–]: This novel indicator represents the fraction of intervals involving false state predictions and therefore captures the mismatch between the predicted and monitored occupancy states on a daily basis (consisting, in this case, of forty eight 15-min intervals between 8:00 and 19:45). For instance, if the predicted states match the monitored ones for all the 48 intervals, the value of occupancy state monitoring error would be zero. If, however, predictions would be correct for none of the intervals, the error value would be one. Another words, a value of 1 for this indicator suggests zero temporal overlap between predicted and actual occupancy states within a day. A value of zero would suggest full overlap between predicted and actual occupancy states.
(5) Number of Transitions (NT) error [–]: The predicted number of daily occupied-to-vacant transitions minus the monitored number of daily occupied-to-vacant transitions.

For all models, the aforementioned statistics are calculated for each individual day during the evaluation period. However, as it would be inappropriate in case of probabilistic occupancy models to evaluate the accuracy of the predictions by comparing the results of a single run with the measurements, we conducted a 100-run Monte Carlo simulation in order to analyze the distribution of prediction errors. Given the length of validation period (90 working days) and the number of Monte Carlo runs, we obtained 9000 values for each statistic at each space for the probabilistic models, whereas in case of the non-probabilistic model, 90 values were obtained.

Note that we did not intend to predict periods of long absences due to business trips, sickness, holidays, etc. in the present study. In the context of implementations pertaining to predictive building systems control, such whole-day absence instances can be presumably communicated to the building management system and reflected in the operation process. Therefore, in this contribution, only actual working days were included in the evaluation process.

3. Results

Figs. 2–6 illustrate the cumulative distribution of the obtained values of the aforementioned statistics for the eight workplaces, namely prediction errors for AT, DT, and OD (absolute values in hours), SM, and NT (absolute values). A numeric summary of the results is provided in Tables 1 and 2 to provide a general overview

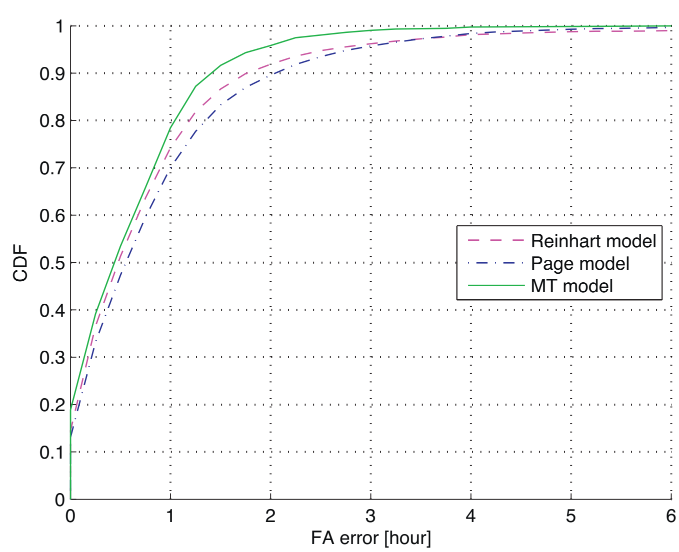

Fig. 2. Cumulative distribution of first arrival time errors.

Table 1
The 80th percentile of the errors for the three models.

Evaluation statistics			Models		
Abb.	Definition	Unit	Reinhart	Page	MT
FA	First Arrival time error	[h]	1.2	1.4	1.0
LD	Last Departure time error	[h]	2.4	2.4	2.4
OD	Occupancy Duration error	[h]	2.3	2.2	1.6
SM	Occupancy State Matching error	[–]	0.48	0.48	0.45
NT	Number of Transitions error	[–]	3.3	3.6	2.9

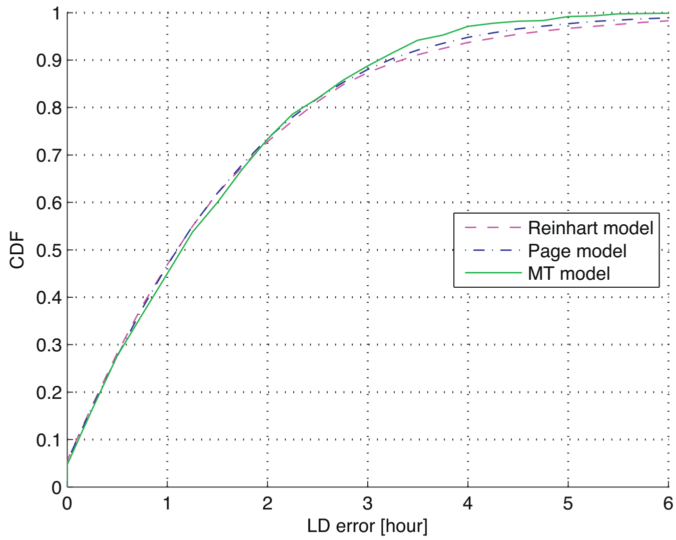

Fig. 3. Cumulative distribution of last departure time errors.

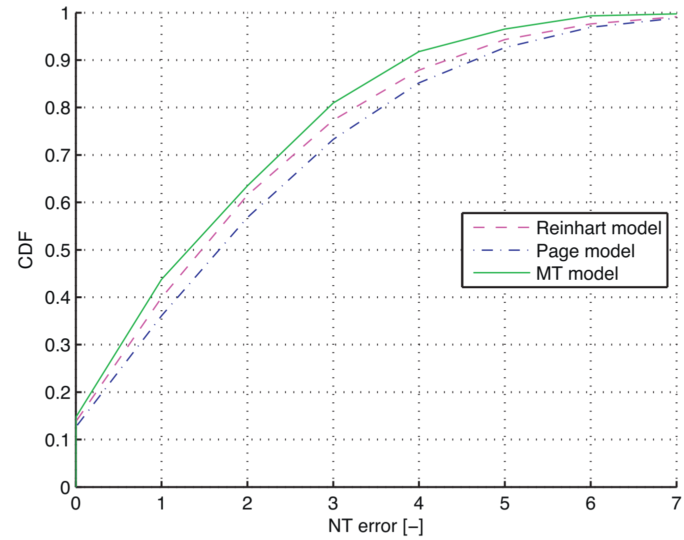

Fig. 6. Cumulative distribution of number of transitions errors.

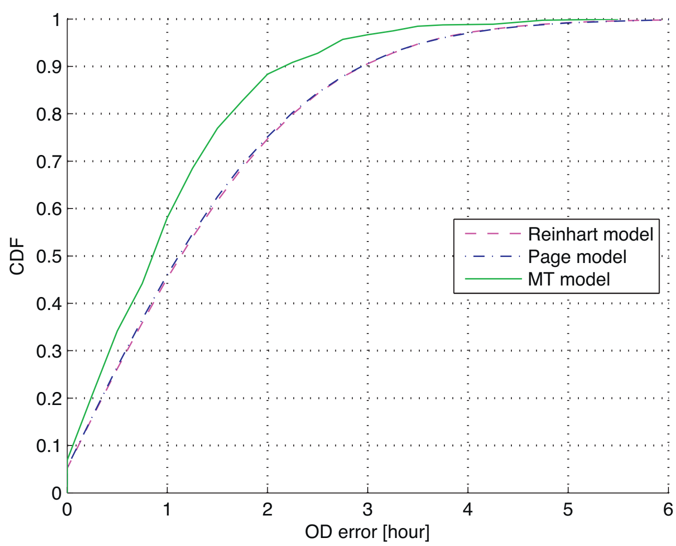

Fig. 4. Cumulative distribution of occupancy duration errors.

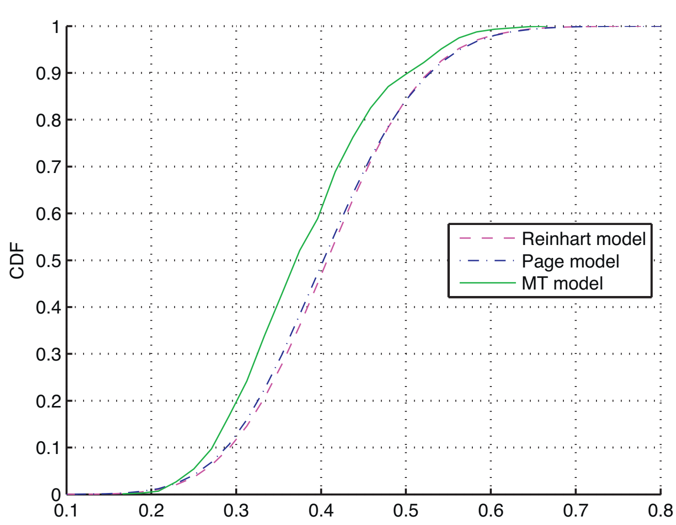

Fig. 5. Cumulative distribution of occupancy state matching errors.

of occupancy prediction errors. Table 1 presents the 80th percentile of the errors. Table 2 shows the percentage of errors (expressed in terms of the five statistics) below five corresponding specific threshold values. These threshold values emerged from discussions within the aforementioned EU projects [17,18] pertaining to the implementation of predictive building systems control strategy and are intended to represent practically relevant minimum performance requirements that occupancy models (intended for deployment in the context of predictive building systems control) would need to meet. More specifically, eighty percent of predictions made by the models would be expected to lay below these threshold error values.

Note that these figures and tables entail the comparison of monitored and predicted values for all eight workplaces. We performed the comparisons also for each of these workplaces individually. However, the corresponding results closely agree in tendency with the combined results of all workplaces. Specifically, the relative performance of the three occupancy models studied did not display any noteworthy dependency on the type of the eight monitored workplaces (closed, semi-closed, open-plan). Hence, the results for individual workplaces are not included here.

4. Discussion

The results shown in Figs. 2–6 and Tables 1 and 2 facilitate a number of observations:

- With the exception of Last Departure errors, where all three models practically display the same performance, the simple non-probabilistic MT model performs best.
- The two probabilistic models generally display a comparable level of performance, even though Reinhart's model could be argued

Table 2
Percentage of predictions with errors below specific thresholds for the five statistics.

Evaluation statistics	Error threshold	Reinhart	Page	MT
FA	1.0 [h]	74.2	70.0	78.5
LD	1.0 [h]	46.9	46.7	46.0
OD	1.0 [h]	45.3	46.1	58.1
SM	0.4 [–]	46.8	48.9	61.0
NT	2.0 [–]	61.5	56.8	63.5

to perform slightly better with regard to the two indicators First Arrival time error (FA) and Number of Transitions error (NT).
- The expectation that at least eighty percent of model predictions would display errors below the aforementioned threshold error values is fulfilled by none of the models. The best performing non-probabilistic MT model comes close to meeting this requirement but only for one statistics (FA).

We suggest that the presented results might have implications beyond the performance comparison of the three models considered:

- Firstly, it must be maintained that the obtained level of predictive accuracy was found to be rather low in general. Given the high quality and resolution of observational data used for model training in the present highly controlled study, the more practical field applications of occupancy prediction models could be arguably expected to perform even poorer. It is important to emphasize that in the present study empirical data for each workplace (occupied by the same individual) was used to train the model for predicting the occupancy pattern at the very same workplace occupied by the very same individual. This circumstance could be reasonably argued to represent an ideal training scenario for occupancy models.
- Secondly, the study's results suggest that the models, which incorporate stochastic elements, do not necessarily display a superior predictive performance. Specifically, the two probabilistic models we examined were outperformed in terms of their predictive potential by the proposed non-probabilistic model. The probabilistic models aim to reflect the random diversity in the occupancy patterns. This could be important in applications (such as the design and sizing of building systems) where the consideration of diversity is critical. However, in the case at hand (short-term occupancy prediction based on historical data), the non-probabilistic model remains close to the overall tendency of the past occupancy patterns, yielding thus a better predictive performance.

These remarks are not meant to suggest that the above-mentioned issues represent conclusive evidence for generally existing limits to the predictive potential of occupancy models. For instance, it may be argued that the observed rather large model errors apply only to the present specific case study, which is limited, amongst other things, in terms of building type (office building) and number of workplaces (only eight). Likewise, the implemented probabilistic models are not necessarily representative of all that is currently available or could be developed in the future. Nonetheless, the obtained results do highlight the necessity for reflection on the achievable levels of accuracy in predicting future occupancy in buildings based on past data. The results of the present case study neither assert the full fidelity of occupancy models in predictive building systems control, nor do they confirm the contended effective pre-eminence of probabilistic occupancy modelling methods. Specifically, for applications involving building systems control, a probabilistic approach to represent the occupants' presence was not shown to enhance the accuracy of the integrated simulation models.

5. Conclusion

As noted at the outset of the paper, deployment of occupancy models in the context of building systems control requires a rigorous standard concerning the evaluation of the models' predictive performance. One cannot simply claim that an occupancy model has a good predictive performance, if it can generate sets of occupancy profiles that "resemble" long term real observations. We need highly transparent research designs and clearly defined statistics to evaluate the predictive performance of an occupancy model. In this paper, we compared two probabilistic and one non-probabilistic occupancy presence models in view of their predictive performance. The models were trained with carefully monitored and processed past data of eight workplaces in an office buildings. The outcome revealed modest levels of predictive performance by all models, especially the probabilistic ones. In this context, we suggest that an evaluative approach similar to the one we suggested and applied in this paper – albeit on a larger scale – would be critical for future studies that intend to evaluate and improve the predictive potential of occupancy models.

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