INTERNATIONAL BUILDING PERFORMANCE SIMULATION ASSOCIATION ENGLAND

Proceedings of BSO-V 2020
5th Building Simulation and Optimization Virtual Conference
21-22 September 2020
Loughborough, UK

Occupant Behaviour: A Data Driven Modelling Approach for Occupancy Presence in Residential Buildings.

Benjamin Halls, Steven K Firth
Loughborough University, Loughborough, United Kingdom

Abstract

The presence and movement of occupants in a building can have a significant influence on energy demand. This is due to the requirement that occupants need to be present to interact with buildings systems such as lighting, heating, and appliances. Currently, building simulation tools use standard and repeatable occupancy schedules to simulate occupants and predict energy demand. This may not represent the stochastic nature of occupants in a building environment which can contribute to the performance gap. A better understanding of when occupants are present in a building can aid in improving energy demand predictions. This study investigates occupancy presence in domestic buildings with monitored data from 20 houses. The study aims to develop a better understanding of occupancy presence and to develop a stochastic model to integrate into building simulation tools. The results suggest occupancy presence varies noticeably across different homes, time of week, and number of occupants in a household. The average difference between the predicted and observed means is between 14-17.5% for whole house and room level predictions. The stochastic approach can introduce a level of uncertainty into energy demand predictions, showing the variation with occupant behaviour. Further work will investigate the application of occupant behaviour models in building design.

Introduction

The built environment accounts for 40% of total energy demand in the EU (EU, 2015). This suggests there is significant potential to reduce energy demand in the built environment, through improving energy efficiency and in the development of low energy buildings. Energy efficiency measures and building energy policies will be essential in delivering low energy building development. The UK building regulation is to ensure buildings achieve a minimum energy performance. Building simulation tools are used to optimise building design and building operation to improve energy efficiency measures and reduce the energy demand of buildings.

However, it is apparent that actual energy demand can vary significantly from predicted by building simulation tools. Demanuele et al, (2010) identified a 100% difference between measured and predicted energy demand in UK schools. Menezes et al, (2012) suggests differences of up to 250% between measured and actual energy demand in non-domestic buildings. This is known as the performance gap, which describes the inaccuracies between predicted and actual energy demand.

Reasons for the performance gap can range from poorly constructed buildings and lack of workmanship skills to changes in the operation of the building (De Wilde et al, 2014). Energy demand has been observed to vary by 50% between measured and predicted in an office building due to poor estimation of building operation (Korjenic et al, 2012). Incorrect assumptions in building operation fail to represent how occupants will use the building and interact with building systems, which can lead to deviations from the expected energy demand. Occupant behaviour has been suggested to be a major influence of energy demand. Up to 300% differences in energy consumption for identical residential buildings has been observed by Andersen et al, (2009). Eguaras-Martinez et al, (2014) observed a 30% difference in energy demand predictions when using actual occupant behaviour compared to a standard occupancy schedule in a building simulation tool for a commercial building. Improving understanding of occupant behaviour and occupancy presence has been suggested as an important step in improving energy demand predictions (Da Yan et al, 2015).

Occupancy presence describes the presence and movement of occupants in a building, a requirement for interactions with building systems, which use energy. The presence of occupants will affect such actions as lighting, heating, appliance use and contribute to internal gains (Hong et al, 2016). It is therefore important to better understand when occupants are present in a building as this can provide useful information on when energy will be used. However, building simulation tools typically use simplistic and repeatable occupancy schedules in energy demand predictions. The use of simplistic occupancy schedules does not represent the dynamic and variable behaviour of occupants. This can lead to inaccuracies in energy demand predictions (Page et al, 2008). A standard occupancy schedule for commercial buildings typically used in building simulation tools considers occupants as being present between 9am-5pm on weekdays, with lower presence levels at the weekend (Duarte et al, 2013). But Duarte et al, (2013) compares a standard occupancy schedule for commercial buildings with monitored data from an office building and identifies significant differences. The study found a 46% difference in occupancy presence between the monitored and standard occupancy profile. This is due to using repeatable schedules which do not consider any variability by occupant. They also fail to consider the stochastic nature of occupants, with schedules which may vary daily. Using highly detailed occupancy schedules in building simulation tools may improve the energy predictions for a building as this will give a greater understanding of when occupants are present within a building and likely to interact with building systems.

Occupancy Models

To integrate highly detailed occupancy schedules into building simulation tools, stochastic (random behaviour) modelling techniques have been examined. A common modelling technique used in occupancy presence studies is the Markov model. The Markov model is a stochastic (random) model which uses the previous state of occupancy to predict the next state (Da Yan et al, 2015). Occupancy state typically refers to the occupants being present or absent in the building. Page et al, (2008) develops a Markov model to predict occupancy presence in office buildings. The Markov model is shown to produce accurate and representative occupancy schedules. Validation of the Markov model with monitored data shows the models ability to predict factors such as time of arrival and departure and the duration of absence or presence in an office building. Wang et al, (2011) developed a Markov model at an individual occupant level in office buildings. The model was able to consider the number of occupants in an office building and predict factors such as time of arrival and departure. Richardson et al, (2008) applies the Markov model to reproduce occupancy patterns for domestic buildings with time use survey data. The study observed variations in occupancy presence by weekdays and weekend. The Markov model was able to reproduce occupancy schedules which consider weekday and weekend variations and take into consideration the number of occupants in a household. The Markov model is commonly used with two states: absent and present. McKenna et al, (2015) develops a four state Markov model. This expands occupancy presence further to also consider if the occupant is active or inactive. This can be useful information as an inactive occupant (e.g. sleeping) will not make any interactions with building systems. The ability to differentiate between active and inactive occupancy provides further detail into the modelling of occupants.

Data in occupancy presence is limited and this is a challenge in the field of occupant behaviour. Many studies use time use survey data which can obtain a large sample (Yilmaz et al, 2017. Andersen et al, 2009. Richardson et al, 2008). However, time use survey data is self-reported and participants may misrepresent when reporting (Lutzenhiser, 1993). Monitored data may show true occupant behaviour as there is no interaction with the occupant (Balvedi et al, 2018). However, monitored data is limited and it has been suggested that no large database exists for monitored occupancy presence in domestic buildings (Flett et al, 2016). This study uses monitored data from 20 English domestic buildings to gain an insight into occupancy presence in domestic buildings. The study also applies the Markov model to determine if this is an appropriate modelling technique to reproduce and predict occupancy patterns in domestic buildings with monitored data.

Method

Data Collection

The study uses the REFIT dataset, a publicly available dataset which includes household data of 20 English homes (Firth et al, 2016). The dataset covers a varied demographic of occupants living in each house. Table 1 shows a summary of the type of building and information on the age of the oldest occupant and number of occupants in each household. A large proportion of the monitored buildings are detached dwellings. Therefore the sample of dwellings is not representative of the UK housing stock (HMG, 2018). The REFIT dataset includes monitored data of various occupant behaviour types such as window opening, lighting, occupancy presence and door opening. The study uses motion data, captured with RWE, passive infrared (PIR) motion sensors placed in various rooms around each house. The RWE motion sensors detects presence when an occupant is active and moving within range of the device. The requirement for occupancy presence to be detected is therefore movement of an occupant. This means that occupancy presence in this study refers to active occupancy presence. However, the motion sensors are not able to detect the number of occupants moving in a space and may detect pets that are present. 73 motion sensors were placed across the 20 houses. Table 1 also shows the location of the RWE motion sensors and the monitoring period for each house. The living room and kitchen were the most common rooms monitored. The monitoring period for motion capture was between six-nine months for each house.

Data Processing

Presence (motion) is logged in the dataset each time motion is detected by a motion sensor. This generates a value in the dataset at each time motion is detected. The dataset is rearranged into 5-minute timesteps for the monitoring period and the motion data is arranged as 0 for absence and 1 for presence. The dataset thus consists of two values (0 or 1) at each 5-minute timestep, showing periods of occupancy presence (1)

Table 1 Summary of REFIT Dataset

Building	Building Type	House Age	No. Occupants	Oldest Occupant Age	Monitored Rooms	Monitoring Period
1	Detached	1975-1980	2	65-74	LR, K, H, C	23/07/2014-28/04/2015
2	Semi-Detached	1919-1944	4	35-44	LR, K, H, L, G	23/07/2014-28/04/2015
3	Detached	1981-1990	2	65-74	LR, K, H, DR	13/08/2014-28/04/2015
4	Detached	1850-1899	2	65-74	LR, K, L, UR	09/09/2014-28/04/2015
5	Mid Terrace	1850-1899	4	45-54	LR, K, DR	29/08/2014-28/04/2015
6	Detached	Post 2002	2	55-64	LR, S, SS	13/06/2014-28/04/2015
7	Detached	1965-1974	4	35-44	LR, K	12/09/2014-06/04/2015
8	Detached	1965-1974	2	75+	K, H, L	27/07/2014-28/04/2015
9	Detached	1919-1944	2	55-64	LR, K, H, DR	23/07/2014-28/04/2015
10	Detached	1919-1945	4	35-44	LR, K, P, G	30/07/2014-22/03/2015
11	Detached	1945-1964	1	65-74	LR, K, DR	30/10/2014-28/04/2015
12	Detached	1991-1995	2	55-64	LR, K, H, DR	24/09/2014-28/04/2015
13	Detached	Post 2002	4	25-34	LR, K, H, P	08/08/2014-28/04/2015
14	Semi-Detached	1965-1974	1	45-54	LR, K, H, DR	22/09/2014-28/04/2015
15	Detached	1981-1990	6	45-54	LR, K, L	29/08/2014-28/04/2015
16	Detached	1965-1974	3	55-64	LR, K, H, DR	11/09/2014-28/04/2015
17	Detached	1965-1975	2	65-74	LR, K, L, DR	23/07/2014-28/04/2015
18	Semi-Detached	1945-1964	4	35-44	LR, K, H, DR	14/10/2014-28/04/2015
19	Detached	1965-1974	3	55-64	LR, K, DR	09/09/2014-28/04/2015
20	Detached	1975-1980	4	35-44	LR, K, L, DR	26/09/2014-28/04/2015

Denotations for the monitored rooms are as follows: LR-Living Room, K-Kitchen, H-Hallway, C-Conservatory, L-Landing, G-Garage, DR-Dining Room, UR-Utility Room, S-Study, SS-Sitting Space, P-Playroom

and absence (0) with time. Occupancy profiles can be generated using this rearranged motion data to investigate how occupancy presence varies with time of day. An occupancy profile is a probability function, showing the average presence rate with time of day. Presence rate refers to the percentage of time an occupant was detected at each time point across the monitoring period. The occupancy profiles are generated for a 24-hour period (time of day) and this is achieved by averaging the values of the motion data (0 or 1) at each 5-minute timestep across the monitoring period. The occupancy profile will show the likelihood an occupant is active and present across the time of day. Occupancy profiles can be used to investigate active occupancy in various rooms around the house. Occupancy profiles were generated at a room level and house level. House level is an aggregate of all monitored rooms in the house.

Inhomogeneous Markov Model

The developed Markov model is based on the approach implemented by Richardson et al, (2008). The Markov model uses the previous state to determine the next state. In this case, the Markov model uses the previous state of occupancy (absent or present) to determine if the occupant will be present at the next state. In total, there are four potential state transitions between the previous state and the next state. The probability of transition from state Si to Sj in the time step from t-1 to t is given by equation 1 (Li et al, 2017)

$$\boldsymbol{P_t^{ij} = p(x_{t+1} = S_j | x_t = S_i)} \tag{1}$$

Where p is the probability of state transition, t is the time step, x is the variables and S is the occupancy states in the Markov chain. As there is more than one state transition, the probabilities for each transition can be calculated with a transition matrix P. This transition matrix is used to calculate the probability of transition from the previous state to the present state, given by a defined transition probability pij. For states Si and Sj where 0 is occupancy absence and 1 is occupancy presence, the transition matrix is defined as:

$$\mathbf{P} = \boldsymbol{p_{ij}} = \begin{pmatrix} \boldsymbol{p_{00}} & \boldsymbol{p_{01}} \\ \boldsymbol{p_{10}} & \boldsymbol{p_{11}} \end{pmatrix} \quad (2)$$

Each row in the transition matrix is defined as a pair of states. The transition probabilities are calculated by dividing the observed frequency of a state transition, n over the total number of transitions in each row. For states Si and Sj, this is defined as:

$$\boldsymbol{p_{ij}} = \frac{\boldsymbol{n_{ij}}}{\sum \boldsymbol{n_{ij}}} \quad (3)$$

For an inhomogeneous Markov model, the transition probabilities are assumed different with time. Therefore a transition matrix is calculated at each timestep. The monitored occupancy data is used as an input to calculate the transition probabilities in the transition matrix.

The Markov model uses the Monte Carlo technique to predict the next state. The Monte Carlo technique uses a random number (between 0 and 1), along with the transition matrix developed as part of the Markov model to predict what the next state of occupancy will be (either 0 or 1). This is repeated for each time step to predict occupancy with time of day. Due to using a random sampling technique, each run of the model will give a different output, a series of 0s and 1s with time of day. By running the model a large amount of times, and averaging the runs, an average presence rate can be determined. This average presence rate will be similar to the occupancy profile of the dataset.

Calibration & Validation

The Markov model was calibrated and validated to ensure the technique is suitable to predict active occupancy in domestic buildings with the use of monitored data. The REFIT dataset is split into two datasets: calibration dataset and validation dataset. The calibration dataset consists of 70% of the REFIT dataset. The validation dataset is the remaining 30% of the REFIT dataset. Calibration of the model was achieved by calculating the transition matrix at each 5-minute timestep for a 24 hour period using the monitored occupancy data as an input. Calibration of the transition matrix uses equation 3 to calculate the transition probabilities at each timestep. The Monte Carlo technique is used alongside the calibrated transition matrices to predict the next state of occupancy. To produce a similar average presence rate as the observed data, the model was run 1000 times and then averaged. The average presence rate with time of day determined through calibration of the model will be compared to the validation dataset. This will give an indication of how well the model is able to predict active occupancy in domestic buildings. The difference between the mean daily presence rate of the predicted and observed will give a good indication of how well the model predicts. The RMSE values will also determine the amount of variation between the predicted and observed. The smaller the RMSE value, the better the prediction. The model was developed in Python programming language and was applied to five scenarios, to consider how well the model will perform at a house level (all monitored rooms) and a room level for each of the 20 buildings. The five scenarios include whole week, weekday and weekend predictions at a house level and living room and kitchen at a room level. In total, 98 models were built across the five scenarios.

Table 2: Summary of occupancy presence by dwelling (Room level)

Average Presence Rate by Dwelling

	Living Room		**Kitchen**		**Hallway**	
Building	**Average (Std Dev)**	**Range**	**Average (Std Dev)**	**Range**	**Average (Std Dev)**	**Range**
1	20% (13%)	0-58%	4% (4%)	0-11%	15% (9%)	0-36%
2	18% (15%)	0-59%	27% (20%)	0-65%	18% (15%)	0-60%
3	9% (8%)	0-24%	22% (17%)	0-52%	18% (14%)	0-50%
4	12% (10%)	0-33%	29% (17%)	0-28%		
5	22% (19%)	0-38%	20% (17%)	0-63%		
6	16% (13%)	0-39%				
7	26% (23%)	0-77%	26% (23%)	0-79%		
8			8% (7%)	0-29%	15% (13%)	0-56%
9	19% (17%)	0-61%	16% (12%)	0-45%	11% (10%)	0-40%
10	22% (17%)	0-68%	21% (17%)	0-56%		
11	13% (8%)	0-33%	16% (10%)	0-37%		
12	19% (14%)	0-55%	16% (13%)	0-45%	19% (15%)	0-57%
13	4% (4%)	0-16%	6% (6%)	0-20%	24% (19%)	0-66%
14	13% (12%)	0-48%	2% (2%)	0-10%	10% (10%)	0-43%
15	39% (21%)	1-77%	35% (19%)	2-75%		
16	28% (21%)	0-70%	9% (8%)	0-34%	26% (21%)	0-67%
17	17% (16%)	0-51%	15% (12%)	0-51%		
18	16% (11%)	0-37%	30% (21%)	0-75%	19% (16%)	0-54%
19	4% (3%)	0-11%	28% (22%)	0-78%		
20	17% (15%)	0-53%	15% (12%)	0-52%		

Results

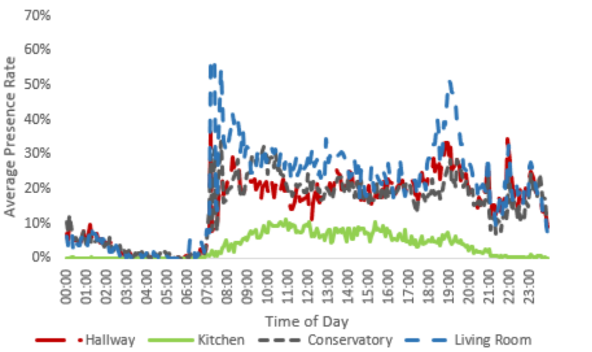

Figure 1: Occupancy Presence by Room (Building 1)

Figure 1 shows the occupancy profile for each monitored room in building 1. The graph shows that active occupancy varies by room. The living room has the highest levels of active occupancy in this building with peaks occurring at around 60%. The kitchen has the lowest levels of occupancy throughout the day, peaking at around 10%. The graph shows a substantial rise in active occupancy occurring at 7am. This could coincide with occupants waking up and moving around the house. Active occupancy peaks at 7:30am, with a further peak at 7pm. For this building, it is shown that active occupancy occurs between 7am – 11pm, with occupants becoming increasingly inactive in all monitored rooms after 11pm. This is likely due to occupants going to bed.

Table 3: Summary of occupancy presence by dwelling

Average Presence Rate by Dwelling				
	Weekday		**Weekend**	
Building	**Average (Std Dev)**	**Range**	**Average (Std Dev)**	**Range**
1	25% (15%)	0-56%	23% (15%)	0-53%
2	38% (28%)	0-84%	33% (22%)	0-70%
3	34% (26%	0-80%	30% (22%)	0-69%
4	35% (22%)	0-75%	34% (21%)	0-74%
5	26% (24%)	0-78%	33% (25%)	0-73%
6	32% (22%)	0-69%	32% (24%)	0-71%
7	28% (25%)	0-83%	38% (25%)	0-83%
8	37% (27%)	0-81%	30% (21%)	0-66%
9	21% (19%)	0-62%	31% (19%)	0-64%
10	27% (23%)	0-84%	28% (20%)	0-74%
11	24% (15%)	0-53%	18% (13%)	0-52%
12	24% (20%)	0-67%	28% (19%)	0-65%
13	27% (24%)	0-79%	36% (27%)	0-78%
14	14% (13%)	0-60%	16% (15%)	0-50%
15	43% (24%)	0-88%	50% (24%)	0-83%
16	38% (29%)	0-91%	44% (31%)	0-92%
17	42% (26%)	1-73%	40% (25%)	0-71%
18	42% (27%)	0-86%	45% (27%)	0-82%
19	40% (29%)	0-88%	38% (29%)	0-92%
20	28% (24%)	0-85%	31% (20%)	0-73%

Table 2 shows a summary for the percentage of occupied hours (average) in the most common monitored rooms in the study (living room, kitchen, and hallway) for each building. Blank rows in the table indicate that room was not monitored in that building. Table 2 summarises the range for average presence rate, average occupied hours, and standard deviation of the occupancy profiles across the monitoring period. The table shows the significant variations in active occupancy by room in each building. Average daily presence rate across all buildings in each of the rooms varies by 4% - 39% in the living room, 2% to 35% in the kitchen and 10% to 24% in the hallway. This shows considerable differences by household suggesting that occupants use these rooms in different ways. The biggest variations are seen in the living room and kitchen. Living rooms are social places, where occupants relax and socialise. Kitchens are primarily for cooking. However, kitchens can also be social places and households may differ how they use these rooms daily. Building 15 is shown to have the most active living room and kitchen with an average daily presence rate of 39% and 35% respectively. Building 13 and building 19 have the lowest levels of active occupancy in the living room with an average daily presence rate of 4%. Building 14 has the lowest levels of occupancy in the kitchen with an average daily presence rate of 2%.

Table 3 shows a summary of occupancy profiles for each building for weekday and weekend patterns. Table shows active occupancy varies substantially by household. The maximum average presence rate varies from 53% to 91% on weekdays and 52% to 92% on weekends. The average daily presence rate also varies by household. Building 15 is shown to have the highest average daily presence rate of 43% on weekdays and 50% on weekends. Building 14 has the lowest average presence rate of 14% on weekdays and 16% on weekends. Standard deviation shows how variable active occupancy is throughout the day. Building 16 has the most variable active occupancy throughout the day with standard deviation 29% on weekdays and 31% on weekends. This highlights the variation of active occupancy in domestic buildings.

Average Occupancy Profile

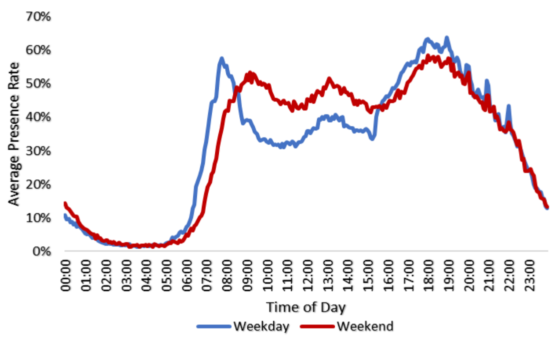

Figure 2: Average Occupancy Profile for all buildings

Figure 2 shows an average occupancy profile for all houses in the dataset. The average occupancy profile is generated by aggregating the monitored rooms of all 20 buildings to produce an overall average. The graph shows noticeable difference in weekday and weekend active occupancy patterns. Weekdays are shown to have more apparent peaks in the early morning between 7:30am – 8:30am and early evening between 6pm – 7pm, with average presence rate peaking at around 60%. Active occupancy between these peaks is substantially lower declining to around 35%. However, weekend occupancy appears more persistent throughout the day. The graph is more plateaued for weekends, suggesting occupants are active in their house throughout the day. On both weekdays and weekends, active occupancy begins to significantly decline from 7pm with occupants being mostly inactive in monitored rooms after midnight.

Markov Model Performance

Figure 3 shows the calibration of the model for building 1 at a house level. Figure 3 shows a comparison between the output of the Markov model and monitored data used in calibration. The graph shows the model is calibrated particularly well with a good agreement between the model output and the monitored data. The graph shows the model can respond to rapid changes in active occupancy, replicating the substantial variations at peak times. Calibration of the model shows that the Markov model works well at replicating the occupancy profiles with monitored data. Model output was compared to data in the validation dataset. Figure 4 shows a comparison between predicted and actual active occupancy for the living room of building 2. The graph shows the model works well at predicting the variability of active occupancy throughout the day. The model can determine the main features such as peak occupancy, minimum occupancy and predict how active occupancy varies with time of day. Active occupancy in the observed data has greater fluctuation than predicted. This could be due to the amount of data available in the validation dataset, with less data resulting in more noise in the results. The model is shown to underpredict at peak occupancy hours, suggesting there are differences in active occupancy between the calibration and validation dataset.

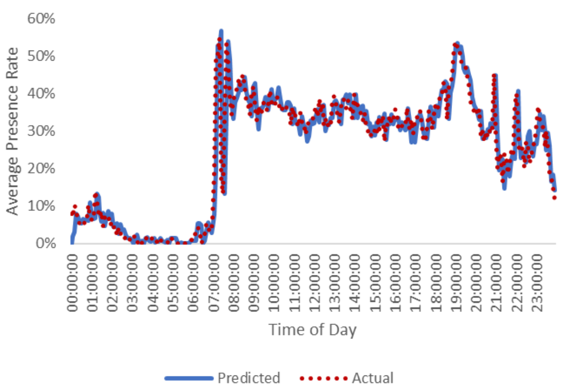

Figure 3: Calibration of the model (building 1)

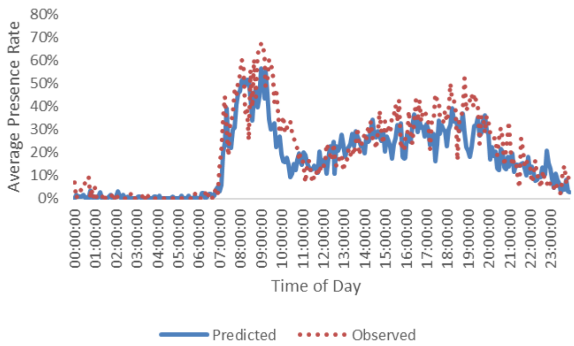

Figure 4: Validation of model for living room (building 2)

Table 4 summarises the RMSE values and the difference between the mean of the predicted and observed, for the predicted model output and the observed data in the validation dataset for each model scenario. Table 4 shows average RMSE normalised value for living room and kitchen predictions is 0.23 and 0.16, respectively. The average difference between predicted and observed means is 17.4% and 17.5%. In some models, the model underpredicts or overpredicts active occupancy. This could be due to occupants using the room differently between the two periods. It could also be caused by long absences from the house which occur in either the calibration or validation dataset. Table 4 shows an overall average difference of 14% and RMSE normalised value of 0.13 for the whole week predictions. Weekday and weekend predictions also perform well at predicting active occupancy. The average difference in mean daily presence rate for weekdays and weekend is 15% and 15.1% respectively with RMSE normalised values of 0.14 and 0.17, respectively. This shows that weekday and weekend predictions are slightly less accurate compared to whole week predictions. This could be due to splitting the dataset, which reduces the amount of data when calibrating the model. Less data may result in more noise in the results.

Table 4: Summary of Model Validation

Model Scenario	% Mean Diff	RMSE	RMSE (Normalised)
All monitored Rooms (All Week)	14.2%	0.09	0.13
All monitored Rooms (Weekday)	15.0%	0.10	0.14
All monitored Rooms (Weekend)	15.1%	0.12	0.17
Living Room	17.4%	0.08	0.23
Kitchen	17.5%	0.07	0.16

Discussion

Active occupancy patterns are shown to be diverse and unique, varying considerably by household. However, trends in occupancy patterns are observed. Table 5 shows that an increase in the number of occupants that live in a household increases the likelihood that at least one occupant is active during the day. Average daily presence rate increases with number of occupants, along with maximum and minimum average presence rate. This is further seen by considering individual houses. Building 15 is shown to have the highest average daily presence rate on weekdays and weekends. This building has six occupants. Building 14 has the lowest level of occupancy, which has one occupant. The results therefore show that number of occupants influence the active occupancy rate in a domestic building.

Table 5: Occupancy presence by No. occupants in dwelling

Average Presence Rate by No. of occupants in each dwelling

No. Occupants	Average (std Dev)	Range
1	18%(11%)	0-43%
2	31%(19%)	0-58%
3	40%(22%)	0-84%
4	32%(27%)	0-72%
6	45%(24%)	0-87%

The average occupancy profile (Figure 2) can be compared to a standard occupancy profile for residential buildings. The standard occupancy profile is derived from EN 16798-1 (Ahmed et al, 2017). Some changes must be made to the standard occupancy profile to consider only active occupancy, making it suitable to compare to the results from this study. It was assumed that between 10pm – 6am, occupants are inactive (Figure 5). The comparison shows considerable differences between the average occupancy rate derived from this study and the standard occupancy profile for domestic buildings. This would suggest that using a standard and repeatable occupancy schedules would not accurately represent occupancy presence in domestic buildings. By comparing the profiles, the standard occupancy schedule may underpredict occupancy presence at certain times of the day such as during the middle of the day where it expects occupants to be largely absent. The standard occupancy schedule is also shown to overpredict occupancy presence such as during peak times in the evening. A comparison shows that active occupancy may be less peaked than what is considered as standard.

Calibration of the model shows the Markov model can reproduce occupancy profiles accurately. The modelling technique works well with monitored data

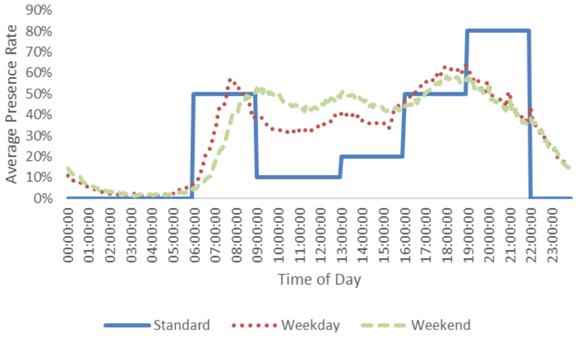

Figure 5: Average occupancy profile vs standard occupancy profile (Ahmed et al, 2017)

at reproducing occupancy patterns at a room level and house level. The model can rapidly respond to the significant changes in average presence rate throughout the day which is required to produce models that are more representative of real-life scenarios. Validation shows the model generally performs well at predicting active occupancy. In some buildings, active occupancy is more variable, and this can be seen in the validation with predicted occupancy varying significantly from observed. Occupants may not have the same schedules or specific routines daily which may be an explanation for the variable performance of the model. Therefore, in cases where occupancy may be more variable, forecasting may be more difficult. Occupants may also have periods of long absence (e.g. holiday). A period of long absence in the dataset will affect the calibration of the model, reducing accuracy in the prediction.

The use of a stochastic modelling approach to generate domestic occupancy profiles has several applications. The model can incorporate diverse and variable occupancy profiles into building simulation tools, providing greater accuracy to predict peak periods within energy demand predictions. This approach can also have useful applications in building stock modelling with the generation of occupancy profiles introducing variable and realistic occupancy patterns for large scale energy demand predictions. Each time the model is run a different result will be produced which can be used produce an energy demand distribution, showing how energy demand may vary across the demographic of occupants. This can give a view of the uncertainty within energy demand predictions.

The study has developed a Markov model to determine how well the modelling technique works with monitored data in domestic buildings. The overall aim to developing an occupancy model is to integrate high detailed occupancy schedules into building simulation tools. This study does not integrate the Markov model into a building simulation tool. Further work will address the practicality and advantages of integrating this modelling technique in simulation tools. This study only develops the Markov model, but further work could look at the development of various modelling techniques, to consider the performance of different approaches with monitored data.

Conclusion

- Occupant behaviour is represented with simple and repeatable occupancy schedules in building simulation tools. This will impact energy demand predictions contributing to the performance gap.
- The study shows that active occupancy varies significantly throughout the day, with periods of high occupancy and inactivity. Peak occupancy hours are observed in many buildings to occur in early morning and early evening with inactivity persisting through the night. Active occupancy is also shown to vary by time of week, and the number of occupants which live in the household.
- The Markov model is shown to perform well at both reproducing occupancy schedules and predicting active occupancy in residential buildings at a room level and a house level, suggesting the model is versatile and can be applied in many situations
- Further work will look at integrating the model into building simulation tools to determine the impact using greater detailed occupancy schedules has on domestic energy demand.

References

Ahmed, K., Akhondzada, A., Kurnitski, J. and Olesen, B. (2017). Occupancy schedules for energy simulation in new prEN16798-1 and ISO/FDIS 17772-1 standards. Sustainable Cities and Society, 35, pp.134-144.

Andersen, R., Toftum, J., Andersen, K. and Olesen, B. (2009). Survey of occupant behaviour and control of indoor environment in Danish dwellings. Energy and Buildings, 41(1), pp.11-16.

Balvedi, B., Ghisi, E. and Lamberts, R. (2018). A review of occupant behaviour in residential buildings. Energy and Buildings, 174, pp.495-505.

de Wilde, P. (2014). The gap between predicted and measured energy performance of buildings: A framework for investigation. Automation in Construction, 41, pp.40-49.

Demanuele, C., Tweddell T., Davies, M. (2010). Bridging the gap between predicted and actual energy performance in schools [online] Available at: http://www.cibsesdg.org/resources/files/e2bfaea.pdf [Accessed 2 Jan. 2019].

Duarte, C., Van Den Wymelenberg, K. and Rieger, C. (2013). Revealing occupancy patterns in an office building through the use of occupancy sensor data. Energy and Buildings, 67, pp.587-595.

Eguaras-Martínez, M., Vidaurre-Arbizu, M. and Martín-Gómez, C. (2014). Simulation and evaluation of Building Information Modeling in a real pilot site. Applied Energy, 114, pp.475-484.

Flett, G. and Kelly, N. (2016). An occupant-differentiated, higher-order Markov Chain method for prediction of domestic occupancy. Energy and Buildings, 125, pp.219-230.

Government, HM. (2018). English Housing Survey [online]. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/774820/2017-18_EHS_Headline_Report.pdf.

Hong, T., Taylor-Lange, S., D'Oca, S., Yan, D. and Corgnati, S. (2016). Advances in research and applications of energy-related occupant behavior in buildings. Energy and Buildings, 116, pp.694-702.

Korjenic, A. and Bednar, T. (2012). Validation and evaluation of total energy use in office buildings: A case study. Automation in Construction, 23, pp.64-70.

Li, Z. and Dong, B. (2017). A new modeling approach for short-term prediction of occupancy in residential buildings. Building and Environment, 121, pp.277-290.

Lutzenhiser, L. (1993). Social and Behavioral Aspects of Energy Use. Annual Review of Energy and the Environment, 18(1), pp.247-289.

McKenna, E., Krawczynski, M. and Thomson, M. (2015). Four-state domestic building occupancy model for energy demand simulations. Energy and Buildings, 96, pp.30-39.

Menezes, A., Cripps, A., Bouchlaghem, D. and Buswell, R. (2012). Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap. Applied Energy, 97, pp.355-364.

Page, J., Robinson, D., Morel, N. and Scartezzini, J. (2008). A generalised stochastic model for the simulation of occupant presence. Energy and Buildings, 40(2), pp.83-98.

S.K. Firth, T. Kane, V. Dimitriou, T. Hassan, F. Fouchal, M. Coleman, L. Webb (2016). REFIT Smart Home Dataset. Loughborough University Data Repository – figshare, 10.17028/rd.lboro.2070091

Richardson, I., Thomson, M. and Infield, D. (2008). A high-resolution domestic building occupancy model for energy demand simulations. Energy and Buildings, 40(8), pp.1560-1566.

Wang, C., Yan, D. and Jiang, Y. (2011). A novel approach for building occupancy simulation. Building Simulation, 4(2), pp.149-167.

Yilmaz, S., Firth, S. and Allinson, D. (2017). Occupant behaviour modelling in domestic buildings: the case of household electrical appliances. Journal of Building Performance Simulation, 10(5-6), pp.582-600