2020 Building Performance Analysis Conference and
SimBuild co-organized by ASHRAE and IBPSA-USA
Chicago, IL
August 12-14, 2020

A TWO-STATE STOCHASTIC RESIDENTIAL BUILDING OCCUPANCY MODEL BASED ON THE AMERICAN TIME-USE SURVEY DATA

Diba Malekpour Koupaei[1] and Ulrike Passe[1]
[1]Iowa State University, Ames, IA
{malek, upasse}@iastate.edu

ABSTRACT

Misrepresentative occupancy schedules cause uncertainty in building energy simulations which often results in an undesired gap between actual performance and predictions. To address this issue, stochastic building occupancy models, which commonly use time-use surveys (TUS) as their input, have been proposed as a replacement for the conventional generic static schedules. This paper describes the development of a two-state stochastic occupancy model based on the 2017 American TUS (ATUS) that takes account of differences between weekdays and weekends. In this model, survey respondents were clustered based on the number of residents in their households and a first-order Markov-Chain technique was used to generate occupancy presence schedules.

INTRODUCTION

In the U.S., residential buildings accounted for more than 21% of total energy consumption, 36% of total electricity use, and 19% of total greenhouse gas (GHG) emissions in 2018 (U.S. Energy Information Administration (EIA), 2019b). Moreover, energy consumption from residential buildings is projected to increase by a national average of 0.1% per year for the period of 2018–2050 under a business as usual scenario (U.S. Energy Information Administration (EIA), 2019a). Thus, the building energy sector, in general—and residential buildings in particular—represents a significant opportunity for accelerating the energy transition and ensuring a low-carbon future (Zhang, Bai, Mills, & Pezzey, 2018). The prediction of buildings' energy use, both current and future, plays a crucial role in the realization of this opportunity. Factors that influence a building's energy performance and are commonly utilized for making such predictions include (1) climate, (2) building envelope, (3) building energy and services systems, (4) indoor design criteria, (5) building operation and maintenance, and (6) occupant behavior (Yoshino, Hong, & Nord, 2017). Of all the factors mentioned here, occupant behavior is commonly cited as a major contributor to uncertainty in buildings' energy use predictions and simulations (Hong, Taylor-Lange, D'Oca, Yan, & Corgnati, 2016; Yan et al., 2015). This uncertainty often results in an undesired gap between actual and predicted energy consumption of buildings (Hoes, Hensen, Loomans, de Vries, & Bourgeois, 2009; Hong et al., 2016; Yan et al., 2015).

To address this misrepresentation and the resulting undesired performance gap, in recent years numerous efforts have been made to improve the accuracy of occupancy models in terms of predicting occupants' energy-related behaviors and presence schedules (Hong et al., 2016; Yan et al., 2015). Yan et al. (2015) provide an overview of these efforts and categorize them into the following four key areas of improvement: (1) occupant monitoring and data collection, (2) model development, (3) model evaluation, and (4) model implementation into building simulation tools (Yan et al., 2015).

This study focuses on the model development and implementation areas of improvement in the aforementioned occupant behavior modelling framework and this study attempts to bridge the gap between predicted and actual energy consumption of buildings by proposing an accurate yet practical stochastic modelling approach based on the 2017 American Time Use Survey (ATUS) (U.S. Bureau of Labor Statistics, 2017). The proposed model generates stochastic domestic occupancy presence data with the same characteristics as the ATUS data when given the following two input parameters: (1) type of day (weekday or weekend day) and (2) the number of people in the household. In addition to the availability of the required inputs, the main advantages of the proposed model compared to those that have been previously proposed (For a complete review of these efforts please refer to Hong et al. (2016) and Yan et al. (2015)) are

related to the compatibility of the resulting outputs' formatting for implementation in conventional energy simulation tools. In the following sections of this manuscript, first, the methodology for developing the introduced model is discussed in detail. Then, the resulting model is verified and analyzed.

METHODOLOGY

As noted in the introduction section, the proposed occupancy presence model is based on the 2017 ATUS data. ATUS is a yearly survey, sponsored by the U.S. Bureau of Labor Statistics and conducted by the U.S. Census Bureau, that measures the amount of time people spend doing various activities such as working, watching television, and sleeping (U.S. Census Bureau, 2012). Information collected by the ATUS includes the start and stop times of each activity (in minutes), where each activity occurred, and whether the activity was done for one's job. Additional information on each respondent, including age, sex, occupation, and region of residence, is also available (U.S. Bureau of Labor Statistics (BLS), 2017). It should be noted that while researchers have explored the limitations of TUSs for such application before, TUS datasets remains the sole source for occupancy and activity data with a sufficient breadth of respondents to be representative of the overall population and also smaller sub-populations and are thus used as the database in the study (Flett & Kelly, 2016; Torriti, 2014).

Overall, the development of the proposed occupancy presence model can be divided into two subsequent steps: (1) data cleaning and processing procedure and (2) model development procedure. In the following sections, these steps are described.

Step 1: Data Cleaning and Processing Procedure

The goal of this step is to prepare and process the ATUS data for use in the proposed occupancy presence model. The original data from the 2017 ATUS is organized into the following six separate files: (1) the Respondent File, (2) the Roster File, (3) the Activity File, (4) the Who File, (5) the Eldercare Roster File, and (6) the Activity Summary File (U.S. Bureau of Labor Statistics (BLS), 2017). For the specific purposes of this study, only the Respondent and Activity files have been used as input.

According to the ATUS Data Dictionary (2017), the ATUS Respondent File contains case-specific variables collected in ATUS (that is, variables for which there is one value for each Respondent). In this file, the "TUCASEID" (a 14-digit identifier) identifies each household, and "TULINENO" identifies each individual within the household (U.S. Bureau of Labor Statistics (BLS), 2017). It should be noted that while the TULINENO variable can theoretically take any value between 1 and 30, the person selected to be interviewed for ATUS is always TULINENO = 1 (U.S. Bureau of Labor Statistics (BLS), 2017). Therefore, unique respondents can be identified by their "TUCASEID" without the need for any further information.

As for the ATUS Activity file, the same document states that "it includes activity-level information collected in ATUS, including activity code, location, duration, activity start and stop times, whether respondents had a child under 13 in their care during the activity, and whether the activity was identified as eldercare" (U.S. Bureau of Labor Statistics (BLS), 2017). For each activity there is only one record available and location (or "where") information is not collected for some selected activities, such as sleeping and grooming (U.S. Bureau of Labor Statistics (BLS), 2017). In such instances, a value that indicates the activity was "out of universe" for the "where" question (-1) is attributed to those specific activities (U.S. Bureau of Labor Statistics (BLS), 2017).

In the following five upcoming sections, different sub-steps in this data cleaning procedure are discussed in detail.

Sub-Step 1-1: Creating Group Clusters Based on the Respondents' Household Size

Previous studies suggest that data on active occupancy along with household size are the most important source of information when assessing energy load profiles (Abu-Sharkh et al., 2005). Therefore, as a first step of the data cleaning process, respondents' household sizes are determined and all respondents are assigned to group clusters based on this variable. To do so, we need to identify all unique respontants (each identified by their own unique "TUCASEID" number in the 2017 ATUS Respondent File) and determine their household sizes. In the 2017 ATUS Respondent File, this information is available under the "TRNUMHOU" label which, according to the ATUS Data Dictionary (2017), is an indication of the "number of people living in respondent's household" and can have any whole numerical value between 1 and 30 (U.S. Bureau of Labor Statistics (BLS), 2017). Table 1 shows the distribution of this variable across the 2017 ATUS Respondent database.

Sub-Step 1-2: Creating Subgroups Based on the Diaries' Recording Day Type

Secondly, it is common with occupancy behavioral models to account for the differences between weekdays and weekend days. Therefore, the diaries of respondant groups created in the last sub-step (Sub-Step 1-1) were divided into subgroups based on the type of the day for which a diary was recorded. The goal of this sub-step was to reveal the variance of the occupancy over a typical week. In the 2017 ATUS Respondent File (and

Table 1 Household size based groups' distribution across the ATUS database

HOUSEHOLD SIZE	NUMBER OF CASES	% OF TOTAL
1	2766	27%
2	2943	29%
3	1643	16%
4	1707	17%
5	743	7%
6	277	3%

also the Activity Summary File), "TUDIARYDAY" is the variable that holds this information and is defined as the "day of the week of diary day (day of the week about which the respondent was interviewed)" (U.S. Bureau of Labor Statistics (BLS), 2017). Valid entries for this variable are 1 for Sunday, 2 for Monday, 3 for Tuesday, 4 for Wednesday, 5 for Thursday, 6 for Friday, and finally 7 for Saturday (U.S. Bureau of Labor Statistics (BLS), 2017). Therefore, within each group, a diary is tagged with a "weekday" lable unless its' TUDIARYDAY value is equal to either 1 or 7 which would make it a "weekend day" diary instead. Table 2 below shows the distribution of this variable within the defined groups across the 2017 ATUS database.

Sub-Step 1-3: Defining the Presence States of the Respondents for All Activities

In a third sub-step, a presence state of either 0 or 1 is allocated to each diary entry according to the respondents' presence at their house during that specific activity. A presence state equal to 0 stands for "not present" while a state equal to 1 has the connotation that the respondent is indeed "present" at their house during the activity in question (Malekpour Koupaei, Hashemi, Tabard-Fortecoëf, & Passe, 2019a, 2019b). This information is derived from the "TEWHERE" variable in the ATUS Activity File. In the ATUS Data Dictionary (2017), the TEWHERE variable is described as "where were you during the activity?" and a value equal to 1 for this variable stands for presence at the "respondent's home or yard" (U.S. Bureau of Labor Statistics (BLS), 2017).

Table 2 Day type based subgroups' distribution across the ATUS database

HOUSEHOLD SIZE	WEEK DAY		WEEKEND DAY	
	#	%	#	%
1	1355	27%	1411	27%
2	1485	29%	1458	28%
3	816	16%	827	16%
4	850	17%	857	17%
5	367	7%	376	7%
6	133	3%	144	3%

It should be noted that this variable is not collected for activities with activity codes of 0101xx (sleeping or sleeplessness), 0102xx (washing, dressing and grooming oneself), 0104xx (personal/private activities), 500105 (respondent refused to provide information/"none of your business"), or 500106 (gap/can't remember) (U.S. Bureau of Labor Statistics (BLS), 2017). In such cases, a value of -1 is assigned to the TEWHERE variable in the ATUS Activity File which indicates that the activity was "out of universe" for the "where" question (U.S. Bureau of Labor Statistics (BLS), 2017). Since most of the listed unregistered activities are most probable to be happening in one's private living space, in this study it is assumed that a value of -1 for TEWHERE is essentially no different than a value of 1 which stands for presence at home. Accordingly, for each activity diary, the presence state variable is equal to zero unless the TEWHERE variable is equal to either 1 or -1. Table 3 shows how a sample diary is interpreted by this protocol.

Sub-Step 1-4: Creating 24-Hour Diaries for All Respondents

While each respondent's entire diary input in the 2017 ATUS database is meant to capture at least a full 24-hour period (starting at 4:00 a.m.), there is no guarantee that a diary is exactly 24 hours long. In other words, the duration of the last activity recorded determines the entire length of a respondent's diary. However, for the specific purposes of this study, it was necessary to remove the extra parts of the diaries to get one exactly 24-hour long diary per respondent.

Before going into detail about explaining the procedure for the necessary modifications in this sub-step, it should be noted that for each activity recorded, two ATUS variables recorded in the ATUS Activity File are essential for this step: (1) "TUSTARTTIM" which stands for "activity start time", and (2) "TUSTOPTIME" which is defined as "activity stop time" (U.S. Bureau of Labor Statistics (BLS), 2017). According to the ATUS Data Dictionary (2017), both of these variables can take any valid time value between 00:00:00 and 24:00:00 (U.S. Bureau of Labor Statistics (BLS), 2017).

Table 3 A sample diary from the ATUS tagged with presence states

TRCODE	ACTIVITY	TEWHERE	STATE
30112	Picking up/dropping off household children	3	0
180301	Travel related to caring for & helping household children	12	0
20201	Food and drink preparation	1	1
110101	Eating and drinking	1	1
20203	Kitchen and food clean-up	1	1
10201	Waiting associated w/eating & drinking	-1	1
120303	Television and movies (not religious)	1	1
10101	Sleeping	1	1

To achieve one exactly 24-hour long diary per respondent, in each respondent's diary input the TUSTOPTIM for the last activity recorded is defined as the stop time for the entire diary. Then, the diaries that are longer than 24 hours are cut short to be no more than 24 hours long. To do so, if an activity exists that its TUSTOPTIME occurs less than 24 hours away from the defined stop time for the entire diary, then that activity is broken into two parts at exactly 24 hours before the defined stop time for the entire. Then, the first part is removed from the diary and the reduced part now takes the place of the initial activity entry.

While the longer diaries are cut short to be exactly 24 hours long, their start time is 4:00 a.m. However, it is now necessary to make sure that each diary starts at midnight and finishes at a second midnight exactly 24 hours later. This means that any activity entries that either occur on the second day or happen overnight need to be modified. To do so, any activities that start after midnight on the second day are moved to the beginning of the diary. Then, if the second midnight occurs between the TUSTARTTIM and the TUSTOPTIME of the last diary entry, that entry is broken into two parts at midnight. Then, the second part (the one that starts at the second midnight) is moved to the beginning of the diary while the first part is kept in its original spot at the end of the diary. Figure 1 shows how a sample diary (TUCASEID = 20170111162238) is processed according to the procedure described in this step.

Sub-Step 1-5: Regulating the Time Steps for All Recorded Activities

While some time-use surveys are recorded in predefined time intervals, the ATUS time steps are merely determined by the duration of activities (Centre for Time Use Research, 2017; The French National Institute of Statistics and Economic Studies (INSEE), 2010). Moreover, the temporal resolution of the diary recordings in the ATUS is in minutes (based on the "TUACTDUR" variable in the ATUS Activity File that defines the duration of an activity in minutes), while previous studies had suggested that a 10-minute temporal resolution is sufficient for the purposes of

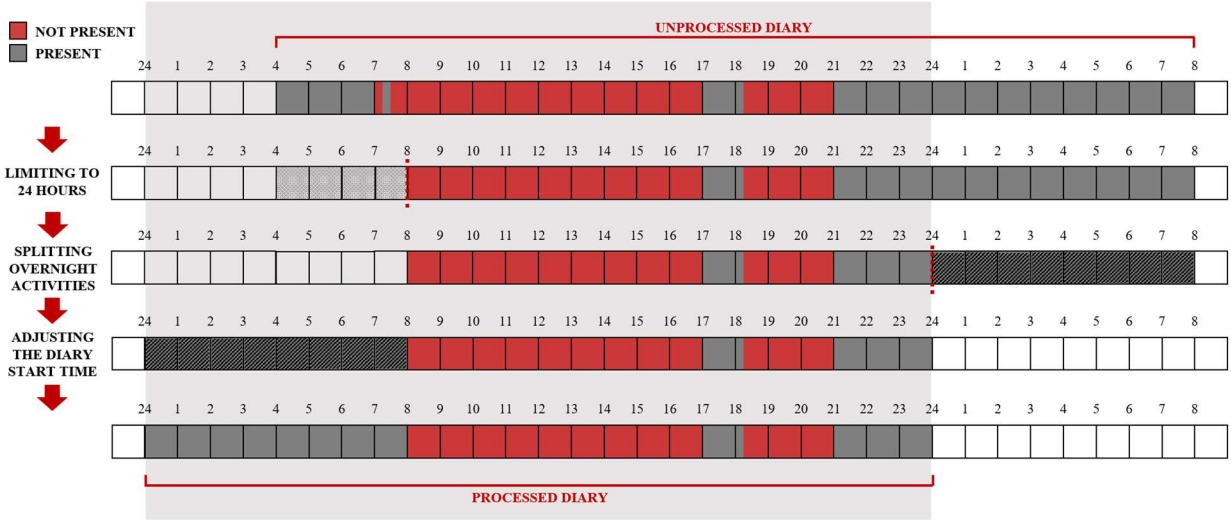


Figure 1 An example of the Sub-Step 1-4 process for modifying the respondents' diaries

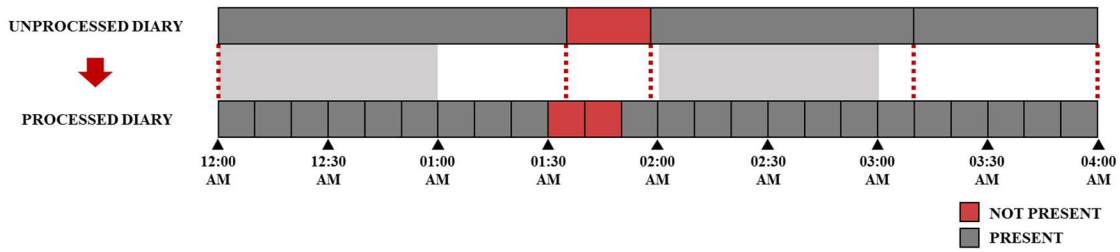


Figure 2 An example of the Sub-Step 1-5 process for modifying the respondents' diaries

building energy use studies (Mahdavi & Tahmasebi, 2016; Richardson, Thomson, & Infield, 2008; Yan et al., 2015). Therefore, in this step each activity entry is broken into one or multiple sequential 10-minute activity entries. The process begins at midnight on the first night (the beginning of each respondent's diary entry after the modifications in the last step) and the first activity's duration is modified to be exactly 10 minutes long. Next, if the original TUACTDUR for the first activity is more than 10 minutes long, a duplicate of that activity is redefined so that it starts right after the first one and ends 10 minutes later (e.g. minute 20 of the entire diary). This process is repeated until the TUSTOPTIME of the last duplicate goes beyond the TUSTOPTIME of the original activity. Then, that TUSTOPTIME marks the TUSTARTTIM of the next activity in the diary and the same process is repeated for this activity and its succeeding activities until the TUSTOPTIME for an activity marks the midnight for the second night (Figure 2).

At this stage, the 24-hour diary inputs developed in the last sub-step (Sub-Step 1-4) are divided into 10-minute time slots and are ready to be used in the occupancy presence model which is explained in the next step (Step 2). Figure 3 shows a sample diary for a specific respondent (TUCASEID = 20171212171895) that has been modified according to the explained procedure. This respondent is from a three-person household and the diary is recorded on a weekday.

Step 2: Model Development Procedure

Step 2 is the model development procedure that uses the Markov Chain technique to generate ATUS based occupancy presence schedules with the cleaned data prepared in the previous step (Step 1). As it was mentioned in the previous sections, for probabilistic models, Markov chains are one of the more common method used to stochastically model occupancy and predict occupancy profiles (Mitra, Steinmetz, Chu, & Cetin, 2020). The Markov-Chain techniques allow the occupancy status at a time, to be determined based only on the status at the previous time (Flett & Kelly, 2016). Therefore, in order to generate the synthetic data, a random number (uniform from 0 to 1) is picked at each time step and used, together with the appropriate transition probability matrix and with the state at the current time step, to determine the state at the next time step. The upcoming sub-steps describe the necessary calculations for developing both the start states probabilities and the transition probability matrices (Richardson et al., 2008).

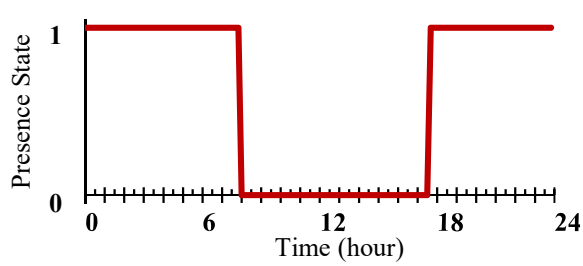


Figure 3 A sample diary from ATUS as modified by Step 1

It should be noted that the authors use a first-order Markov-Chain approach to predict changes in occupancy. While the use of higher-order models was previously shown to be slightly more effective in predicting occupancy with accuracy, the added benefits of such techniques when compared to a first-order model are not significant and given the added complexity are avoided here (Flett & Kelly, 2016).

Sub-Step 2-1: Calculating the Start Time Probability Distributions

In order to generate the Markov chain, it was necessary to provide a start state which is meant to describe how probable it is for an individual to be present at the house at midnight on the first night (beginning of a respondent's processed diary). This is, of course, random but should match the probabilities found in the original ATUS data. For instance, out of the 816 diaries filled by people coming from three-person households in the weekend days subgroup, 43 of them indicated 0 as their presence state at 00:00, while the other 773 were actually present in their homes at midnight. Accordingly, the chance of a respondent from a three-person household being present in the house at 00:00 on a weekend night was set to be 95% (773/816=0.95). This means that the chance for someone from that same subgroup not being

present in the house at that time was only 5% (43/816=0.05).

Sub-Step 2-2: Developing the Transition Probability Matrices

As mentioned before, the concept of the first-order Markov–Chain technique is that each state is dependent only on the previous state together with the probabilities of that state changing. These set of probabilities are held in "transition probability matrices" and are directly derived from the ATUS data. In each subgroup, the following 4 probability inputs are calculated for each of the 144 defined 10-minute time steps:

(1)
$$T_{00} = \frac{\text{\# of cases where start state \& end state are both=}}{\text{\# of cases where start sta}}$$
(2)
$$T_{01} = \frac{\text{\# of cases where start state is=0 \& end state is=}}{\text{\# of cases where start state is=0}}$$
(3)
$$T_{10} = \frac{\text{\# of cases where start state is= \& end state is=0}}{\text{\# of cases where start state is=}}$$
(4)
$$T_{11} = \frac{\text{\# of cases where start state \& end state are both=}}{\text{\# of cases where start state is=1}}$$

Equations 1-4 Probability inputs to be used in the transition probability matrices (based on Malekpour Koupaei et al. (2019))

For instance, going back to the previous three-person household weekend subgroup example, of all the 43 respondents absent in the house at 00:00, 3 of them reported that they were present in their houses at 00:10. This means that T01 for this subgroup was 6% (3/73=0.06) and therefore their T00 at this time step was equal to 94%.

These sets of calculations were repeated for all the subgroups and then organized into corresponding transition probability matrices.

Sub-Step 2-3: Generating the Occupancy Presence Schedules

In order to generate occupancy presence schedules, first, the start state was chosen by picking a random number of present occupants from the appropriate probability distribution as calculated in sub-step 2-1. Subsequent states in the chain were determined by picking a random number for each time step and using this number with the appropriate transition probability matrix as defined in the last sub-step (Sub-Step 2-2).

The transition probability matrices, the start state distributions and a Visual Basic implementation of the algorithm are implemented in a Microsoft Excel workbook. The authors would like to acknowledge that the source code utilized (and modified according to the specific requirements of the database) has been initially developed by Richardson et al. (2008) and used the UK TUS data instead. In the following section, multiple example runs of the model are presented, verified, and discussed.

DISCUSSION & RESULTS ANALYSIS

In the first set of validation efforts, the output from six example runs of the model, for a three-person household on both weekdays and weekends, is calculated and shown in Figure 4 and Figure 5. While each run is different due to the use of random numbers in the stochastic generation, all runs are based on the same transition probability matrices and thus exhibit similar characteristics. For readers' reference, the dotted black lines in these figures represent the commonly used static occupancy schedule proposed for residential buildings by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1 (ASHRAE, 1989).

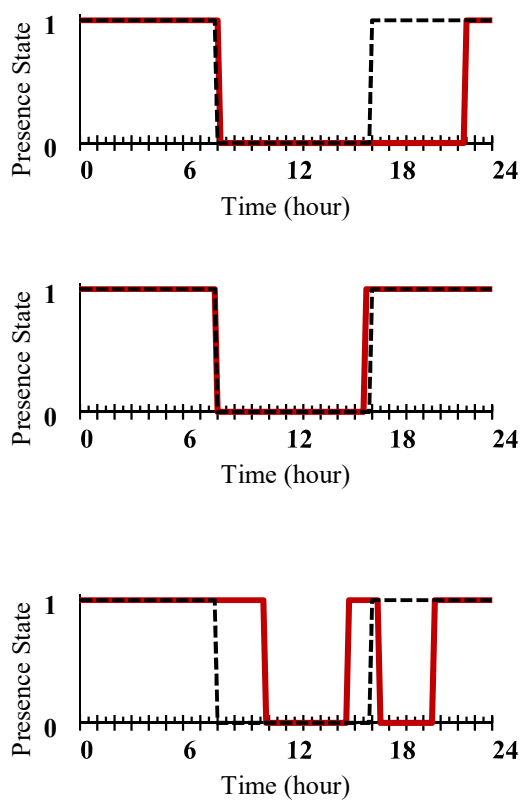


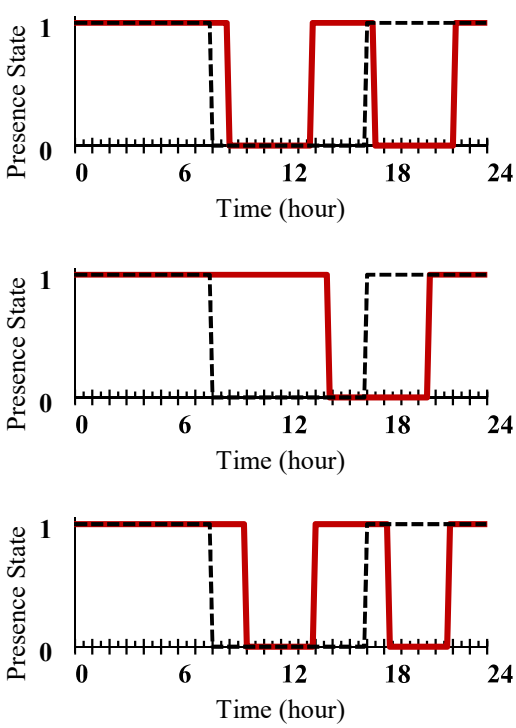
Figure 4 Three occupancy model example run results (three-person household on weekdays)

In , it can be seen that according to the model outputs, during the week, occupants typically leave the house in the morning and then return for the evening. The length of their absence period and the exact times of their departure and return, however, varies and in some cases, the occupant returns home for a brief period in between two prolonged absence periods. On the weekends, however, occupants typically spend more time at the house and usually leave the house at a later time compared to the weekdays. It can also be seen that their return time in the evenings are typically later than their return times during weekdays (Figure 5).

A comparison between the developed presence scheduled and the ASHRAE 90.1 schedules, revealed that while ASHRAE 90.1 schedules are somewhat representative of the real occupant behaviour captured by the ATUS, its applicability to weekend days needs consideration.

Comparison of the occupancy patterns developed by the model (as presented in Figure 4) to a real processed sample from the ATUS (as shown in Figure 3) provides an indication that the model is working as expected: showing low levels of presence in the mornings and evenings and low levels of absence at nighttime.

In order to validate the model more fully, it was run a very large number of times (100 times for each one of



the three-person household subgroups) and the statistics

Figure 5 Three occupancy model example run results (three-person household on weekend days)

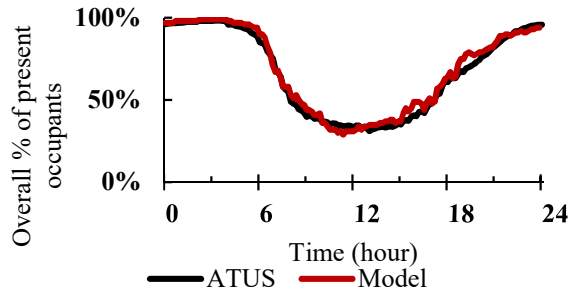


Figure 6 Comparison of simulated and surveyed data for a weekday (three-person household)

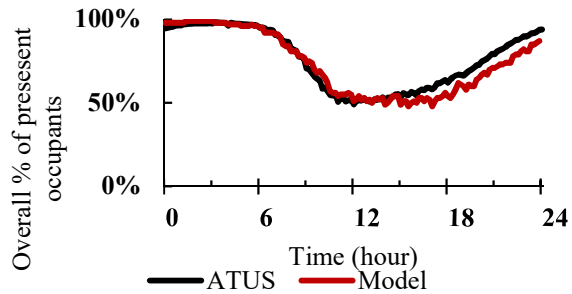


Figure 7 Comparison of simulated and surveyed data for a weekend day (three-person household)

of its output were compared against the original ATUS data. Figure 6 and Figure 7 present this data for weekdays and weekend days respectively and confirm that the simulation output is generating data with an almost identical active occupancy profile to the ATUS data. The close correlation between the model output and the ATUS data is also seen when performing comparisons for all other subgroups that represent households with other numbers of residents.

CONCLUSION

Occupancy schedules are often recognized as a leading source of uncertainty in building energy simulations and this uncertainty results in an undesired gap between actual performance and predictions. To address this issue and with the aim of increasing the reliability and accuracy of occupancy behavioral inputs of building energy models, in the recent years, many stochastic building occupancy models have been proposed as a replacement for the conventional generic static schedules. Such stochastic models commonly use time-use surveys (TUS), which are large nationally representative surveys of how people use their time, as their input. This paper describes the development of a two-state stochastic occupancy model based on the 2017 American Time-Use Survey (ATUS) data that takes account of differences between weekdays and weekends. In this stochastic occupancy model, survey respondents are clustered based on the number of residents in their

households. A first-order Markov-Chain technique is used to generate occupancy presence schedules such that it has the same overall statistics as the original ATUS data. The high-resolution representative occupancy data that this model generates can be used as input to any residential energy modelling tool that uses occupancy time-series as a base variable. The main advantages of this model compared to those that have been previously proposed are related to the simplicity and practicality of the model. The availability of the required inputs as well as the compatibility of the resulting outputs' formatting for implementation in conventional energy simulation tools make it optimal for use in future building energy modeling efforts instead of the commonly used static generic schedules proposed by standards and guidelines. Future work will include the optimization of this model for compatibility with co-simulation tools such as the Building Controls Virtual Test Bed (BCVTB).

ACKNOWLEDGEMENT

This work was funded by the 2016 Iowa State University Presidential Interdisciplinary Research Initiative (PIRI) on Data-Driven Science.

REFERENCES

Abu-Sharkh, S., Li, R., Markvart, T., Ross, N., Wilson, P., Yao, R., … Arnold, R. (2005). *Microgrids: distributed on-site generation*. Tyndall Centre for Climate Change Research.

ASHRAE. (1989). *ASHRAE Standard 90.1.1989 Energy Efficient Design of New Buildings Except Low-Rise Residential Buildings*.

Centre for Time Use Research. (2017). *United Kingdom Time Use Survey (UKTUS), 2014-2015*.

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

Hoes, P., Hensen, J. L. M., Loomans, M., de Vries, B., & Bourgeois, D. (2009). User behavior in whole building simulation. *Energy and Buildings*, *41*(3), 295–302.

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

Mahdavi, A., & Tahmasebi, F. (2016). The deployment-dependence of occupancy-related models in building performance simulation. *Energy and Buildings*, *117*, 313–320.

Malekpour Koupaei, D., Hashemi, F., Tabard-Fortecoëf, V., & Passe, U. (2019a). A Technique for Developing High-Resolution Residential Occupancy Schedules for Urban Energy Models. *The Symposium on Simulation for Architecture and Urban Design (SimAUD)*, 95–102. Retrieved from https://lib.dr.iastate.edu/ccee_conf/104/

Malekpour Koupaei, D., Hashemi, F., Tabard-Fortecoëf, V., & Passe, U. (2019b). Development Of A Modeling Framework For Refined Residential Occupancy Schedules In An Urban Energy Model. *Building Simulation 2019: 16th Conference of IBPSA*. https://doi.org/https://doi.org/10.26868/25222708.2019.210553

Mitra, D., Steinmetz, N., Chu, Y., & Cetin, K. S. (2020). Typical occupancy profiles and behaviors in residential buildings in the United States. *Energy and Buildings*, *210*, 109713.

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

The French National Institute of Statistics and Economic Studies (INSEE). (2010). *The 2009-2010 French Time Use Survey*.

Torriti, J. (2014). A review of time use models of residential electricity demand. *Renewable and Sustainable Energy Reviews*, *37*, 265–272.

U.S. Bureau of Labor Statistics. (2017). *American Time Use Survey*. Retrieved from https://www.bls.gov/tus/

U.S. Bureau of Labor Statistics (BLS). (2017). *American Time Use Survey (ATUS) Data Dictionary: 2017 Interview Data*.

U.S. Census Bureau. (2012). *American Time Use Survey User's Guide: Understanding ATUS 2003 to 2011*.

U.S. Energy Information Administration (EIA). (2019a). *Annual Energy Outlook 2019 (with projections to 2050)*.

U.S. Energy Information Administration (EIA). (2019b). *November 2019 Monthly Energy Review*.

Yan, D., O'Brien, W., Hong, T., Feng, X., Gunay, H. B., Tahmasebi, F., & Mahdavi, A. (2015). Occupant behavior modeling for building performance simulation: Current state and future challenges. *Energy and Buildings*, *107*, 264–278.

Yoshino, H., Hong, T., & Nord, N. (2017). IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods. *Energy and Buildings*, *152*, 124–136.

Zhang, Y., Bai, X., Mills, F. P., & Pezzey, J. C. V. (2018). Rethinking the role of occupant behavior in building energy performance: A review. *Energy and Buildings*, *172*, 279–294.