7th International Building Physics Conference

IBPC 2018

Proceedings

SYRACUSE, NY, USA

September 23 - 26, 2018

Healthy, Intelligent and Resilient Buildings and Urban Environments

ibpc2018.org | #ibpc2018

Energy Flexibility of Building Cluster – Part I: Occupancy Modelling

Rongling Li[1]*, Andong Wang[2], Carsten Rode[1], Shi You[3]

[1]Department of Civil Engineering, Technical University of Denmark, Denmark
[2]Department of Building Science, School of Architecture, Tsinghua University, China
[3]Department of Electrical Engineering, Technical University of Denmark, Denmark

*Corresponding email: liron@byg.dtu.dk

ABSTRACT

With the growing application of renewable energy, the stability of power systems can be seriously affected due to the fluctuations in the instantaneous generated power. As one of the potential solutions for this upcoming challenge, energy flexibility of buildings has received attention for research and technology development. Demand response and energy flexibility should be implemented at a large scale to have the accumulated energy flexibility to a magnitude, which can be meaningful for energy sectors. Studies have shown that the energy flexibility of a building is greatly influenced by both building physical characteristics and occupancy pattern of residents. To the best knowledge of authors, occupancy has not been considered in the study of building cluster. The aim of this paper is to present the modelling process of occupancy/vacancy of Danish households based on Danish Time Use Survey (DTUS) 2008/09 data. In this paper, we present a data-driven approach to generate occupancy/vacancy models for different types of household and for building cluster of different scales. As the result, vacancy profile and vacancy duration models are developed. The stochasticity of occupancy is also unveiled. The next step is to apply these models to quantify energy flexibility of building cluster and the uncertainty of energy flexibility due to the stochastic occupancy.

KEYWORDS
Occupancy; Stochastic; Building cluster; Energy demand flexibility

INTRODUCTION

The penetration of renewable energy resources is increasing rapidly. In EU countries, at least 20% of total energy demand must come from renewables by 2020 (EU, 2009). Denmark plans to be fossil-fuel free by 2050 (The Danish Government, 2013). High penetration of intermittent renewables will affect the stability of energy grid and energy flexibility in the grid will be more crucial. Buildings account for one third of total energy consumption in Denmark and most other developed countries, which amounts to considerable potential for activating flexible energy demand in buildings. In future smart cities, demand response and energy (demand) flexibility of buildings are likely to play a significant role.

Demand response and energy flexibility should be implemented at a large scale to have the accumulated energy flexibility to a magnitude, which can be meaningful for energy sectors. To the best knowledge of the authors, there are only a few publications about demand response or energy flexibility at building cluster level. Vigna et al. (2018) presented an overview of the concept of building cluster and its relevant concepts. A definition to Building Cluster was defined from the perspective of building and energy grid interaction. In this definition, the building cluster is an aggregation of buildings which can be managed by a common agent such as a utility company to exploit the energy flexibility of the building cluster.

Studies have shown that the energy flexibility of a building is greatly influenced by both building physical characteristics and occupancy pattern of residents (Masy et al., 2015), (Li et al., 2017). A review of large scale demand response estimation (Goy and Finn 2015) conducted in 2015 concluded that studies by then commonly oversimplified building models without considering different building types nor various building characteristics such as thermal characteristics and occupants behavior. There are only a few studies done after 2015 (Li et al., 2016), (Ma et al., 2016), (Georges et al., 2017), but none of the studies included the influence from occupancy and occupant behavior. The lack of data support and multidisciplinary knowledge together with the requirement on computational efficiency are among the main reasons for achieving better investigations.

In this study, we aim to model the stochastic occupancy to quantify its influence on energy flexibility of building cluster with different scales of occupants and quantify the uncertainty of flexibility. The value of the uncertainty quantification is in the planning of energy services.

METHODS

Occupancy models are developed based on data from Danish Time Use Survey (DTUS) 2008/09 (Bonke and Fallesen, 2010). The data consists of 9640 individuals and 4679 households. Individuals' daily activities were logged in two diaries, one for a weekday and another for a weekend day with 10 min time interval starting at 4:00 and ending at 3:50 the next day (Bonke and Fallesen, 2010), (Barthelmes et al., 2018). In this study, only weekday is considered, as on weekend vacancy time is much shorter for residential buildings and the pressure on the energy grids could be less in comparison with weekdays.

Based on the Statistics Denmark (2017), 84% of the households living in apartment buildings consist of no more than three members. The data of household with one to three persons from the DTUS are used in this study. The data consists of 1641 one-person households, 1980 two-person households and 448 three-person households, which is generated from the same data source presented in (Barthelmes et al., 2018).

Occupancy modelling includes three steps: 1) data resampling, 2) occupancy/vacancy profiling and 3) occupancy/vacancy duration estimation.

1) Occupancy data resampling

We resampled the data by randomly divide N households into X samples with each sample contains Y (**n, 2n, 3n …**) households using Bootstrapping method. Limited by the total number of each type of household, we predefined n=100 for one-person household, n=50 for two-person household and n=33 for three-person household. For example, in the case of 1641 one-person households, the data processing steps are as follows.

a) Sample size: 100 households.
b) Randomly divide 1641 households into 16 groups with each group contains 100 households.
c) Repeat the above process for several times (In this study, 10 times).
d) Obtain 160 samples.
e) Change sample size to 200, 300, 400 …

2) Vacancy profiling based on Normal Distribution Probability

Each data sample is a 3D matrix as shown in Equation (1) with 1 indicates occupancy and 0 indicates vacancy.

$$OccupancyData(household\ serial\ number, timeline, sample\ serial\ number) = \left(\begin{array}{cc} & timeline \\ \begin{matrix} house_1 \\ \vdots \\ house_n \end{matrix} & \begin{bmatrix} s_1^1 & \cdots & s_1^{144} \\ \vdots & \ddots & \vdots \\ s_n^1 & \cdots & s_n^{144} \end{bmatrix} (s_i^t = 1\ or\ 0), sample\ serial\ number \end{array} \right) \quad (1)$$

Taking the case of the 160 samples of 100 one-person households as an example to explain the processing in detail. The size of the 3D matrix is 100×144×160 (households: 100, the length of timeline: 144, samples: 160). As the time interval is 10 min, there are thus 144 states for one day. For every state, vacancy percentage of 100 households are calculated. As for every state, there are 160 different samples; there are thus 160 vacancy percentages. A Normality Test (95% confidence) is carried out on these 160 vacancy percentages. The result can be expressed in equation (2).

$$VacancyPercentage_t \sim N(\mu, \sigma^2) \quad (2)$$

Where μ: mean, also the mathematical expectation; $\mu + 1.96\sigma$: upper limit of 95% confidence interval, $\mu - 1.96\sigma$: lower limit of 95% confidence interval.
The result of probability distribution of vacancy is a 3×144 matrix as shown in Equation (3).

$$Probability\ distribution\ of\ vacancy = \begin{array}{cc} & timeline \\ \begin{matrix} \mu \\ \mu + 1.96\sigma \\ \mu - 1.96\sigma \end{matrix} & \begin{bmatrix} \mu_1 & \cdots & \mu_{144} \\ \vdots & \ddots & \vdots \\ (\mu - 1.96\sigma)_1 & \cdots & (\mu - 1.96\sigma)_{144} \end{bmatrix} \end{array} \quad (3)$$

The above data processing is applied to all three household types. This results with probability distribution of vacancy matrices for every sample size and every type of household.

To assign the above probability distribution of vacancy to Danish households, we used the data from Statistics Denmark (2017). Among the households living in apartment buildings, 38% are one-person household, 33.7% are two-person household and 11.9% are three-person household. Only 16% of Danish households living in apartment buildings consist of more than three residents. Therefore, households of four people and above are not included in this study. Taking these three household sizes as a whole, one-person household accounts for 45.5%, two-person household accounts for 40.3% and three-person household accounts for 14.2%. Vacancy matrices for every sample size and every type of household are aggregated according to these three percentages as shown in Equation (4).

$$Probability\ distribution\ of\ vacancy_{aggregated} = [45.5\% \quad 40.3\% \quad 14.2\%] \begin{bmatrix} Probability\ distribution\ of\ vacancy_{1\ person} \\ Probability\ distribution\ of\ vacancy_{2\ persons} \\ Probability\ distribution\ of\ vacancy_{3\ persons} \end{bmatrix} \quad (4)$$

3) Vacancy duration based on Kaplan-Meier estimator

Survival analysis (Kaplan-Meier estimator) is applied to estimate vacancy duration, which is the time duration occupants are away from home. The Kaplan-Meier estimator, also known as the product limit estimator, is a non-parametric statistic to compute probabilities of occurrence of an event from a certain moment (Goel et al. 2010). The estimator is given by:

$$S(t) = \prod_{i:t_i} \left(\frac{n_i - d_i}{n_i} \right) \quad (5)$$

Where n_i is the number of activates on-going at time t_i and d_i is the number of actions ended. The followings are the steps of survival analysis.

a) The initial matrix (InitialOccupancyData) shown in Equation (6) is used for survival analysis.

$$InitialOccupancyData(household\ serial\ number, timeline) = \begin{array}{c} \\ house_1 \\ \vdots \\ house_n \end{array} \begin{array}{c} timeline \\ \begin{bmatrix} s_1^1 & \cdots & s_1^{144} \\ \vdots & \ddots & \vdots \\ s_n^1 & \cdots & s_n^{144} \end{bmatrix} \end{array} (s_i^t = 1\ or\ 0) \tag{6}$$

b) There are 144 observation states in the timeline. For each state, all the vacant households is identified and then the vacancy duration of these households is calculate from this moment to the future. Then the matrix of SurvivalTimeLength is generated as shown in Equation (7).

$$SurvivalTimeLength = \begin{array}{c} \\ house_1 \\ \vdots \\ house_n \end{array} \begin{array}{c} timeline \\ \begin{bmatrix} d_1^1 & \cdots & d_1^{144} \\ \vdots & \ddots & \vdots \\ d_n^1 & \cdots & d_n^{144} \end{bmatrix} \end{array} \tag{7}$$

Where d_i^t is the vacancy duration at time *t* of $house_i$, $d = 0$ means occupancy.

c) For every state (1~144), Kaplan-Meier Estimator is used to estimate the probability of vacancy duration as shown in Equation (8).

$$(timelen_t, P_t) = Kaplan - Meier\left(\begin{array}{c} \\ house_1 \\ \vdots \\ house_n \end{array} \begin{array}{c} t \\ \begin{bmatrix} d_1^t \\ \vdots \\ d_n^t \end{bmatrix} \end{array} \right) \tag{8}$$

RESULTS

With the aggregation of the probability distribution of vacancy of different types of household, vacancy matrix becomes a 3D matrix where the first two dimensions are shown in Equation (3) and the third dimension is the sample size. This vacancy matrix is generated for cluster of households consisting of one person, two persons and three persons. Fig. 1 shows three different sample sizes of the matrix. With number of residents and number of households specified, sample size of occupancy model is determined and thus the occupancy model can be chosen. In the timeline of one day, there are 144 states with 10-minute interval between each state. For each state, the mathematical expectation, $\mu + 1.96\sigma$ and $\mu - 1.96\sigma$ of vacancy percentage are determined as it is shown in Fig. 1. For example, for a building cluster with 1000 residents and 643 households, the right diagram in Fig. 1 is the vacancy profile can be used.

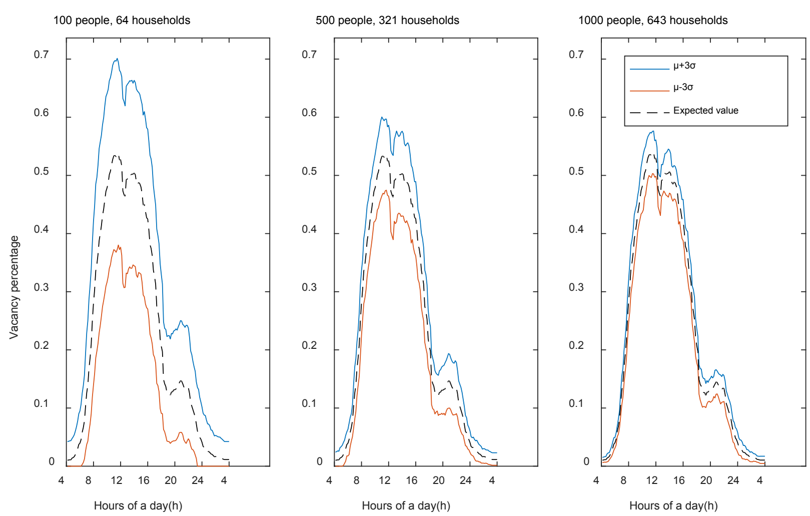

Fig. 1 Vacancy profile of clusters with different number of people and households

As it is shown in Fig.1, expected value of vacancy percentage does not change with the number of residents. However, σ becomes smaller with more residents aggregated. In other words, uncertainty of vacant percentage decreases with the size of residents increases.

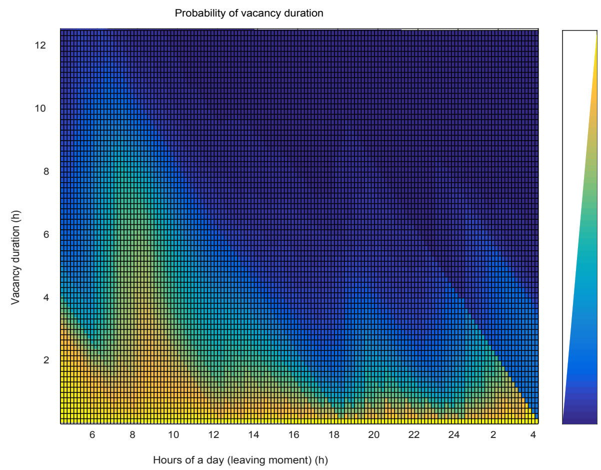

Fig. 2 Survival analysis of vacancy for all 144 states.

The probability of vacancy duration is shown in Fig. 2. It is the aggregation of results from all 144 states. This figure shows the probability a house is vacant from any states onwards. For example, if a house is unoccupied at 8:00 (see x-axis), the probability it is still unoccupied after two hours (see y-axis) is around 80% (color bar) and after six hours is around 60%.

DISCUSSIONS

In this study, using a data-driving approach, statistical occupancy models were developed for the investigation of the uncertainty of energy flexibility due to the stochastic nature of occupancy using TUS data. Some existing studies showed that TUS data was a valuable resource by validating their TUS-based approaches against field measurements. Fischer et al. (2015) modelled household electricity load profiles based on German TUS. The models were validated against measurement data from 430 households with good accuracy. Widén et al. (2009) modelled household electricity load profile based on Swedish TUS data. The profile was validated with electricity measurements in a few households. It revealed that the models captured important features of the measured data. Although there is no measured data from Danish households available for the authors now, model validation is planned for further work. Nevertheless, the models developed in our study can be a tool for the simulation of energy flexibility of buildings for district energy planning under the background of mass application of renewable energy in the future. In addition, this method can be used in other geographical areas if TUS data of these areas are available. The vacancy percentage, vacancy duration, household size, etc. might be different due to different geographical and demographical conditions. This method can also be used to capture seasonal differences in vacancy using TUS data collected during specific seasons, such as heating/winter season.

CONCLUSIONS

In this paper, we presented a data-driven approach to generate occupancy/vacancy models for different types of household and for different scales of building cluster using Danish Time User Survey 2008/09 data. Using this approach, vacancy profile and vacancy duration of any building cluster can be generated. The stochasticity of occupancy is also unveiled. The next step is to apply these models in the quantification of energy flexibility of building cluster and the uncertainty of the quantification due to the stochastic occupancy. The value of the uncertainty quantification is in the planning of energy services. A typical case is that a grid operator will have information on the reliability of deploying a certain amount of households and buildings for using demand flexibility to balance the grid.

ACKNOWLEDGEMENT
This study was made possible with the financial support of two Danish pilot projects: EnergyLab Nordhavn: New Urban Energy Infrastructures and CITIES: Centre for IT-Intelligent Energy Systems in cities. This work partially receives the support from Tsinghua University Initiative Scientific Research Program. The authors would also like to acknowledge IEA EBC Annex67 – Energy Flexible Buildings for providing excellent research networking.

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