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Profiling Occupant Behaviour in Danish Dwellings using Time Use Survey Data - Part II: Time-related Factors and Occupancy

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SUMMARY

Occupant behaviour has been shown to be one of the key driving factors of uncertainty in prediction of energy consumption in buildings. Building occupants affect building energy use directly and indirectly by interacting with building energy systems such as adjusting temperature set-points, switching lights on/off, using electrical devices and opening/closing windows. Furthermore, building inhabitants' daily activity profiles clearly shape the timing of energy demand in households. Modelling energy-related human activities throughout the day, therefore, is crucial to defining more realistic occupant profiles for prediction of energy use to reduce the gap between predicted and real building energy consumptions.

In this study, we exploit diary-based Danish Time Use Surveys for understanding and modelling occupant behaviour in the residential sector in Denmark. This paper is a continuation of "Profiling occupant behaviour in Danish Dwellings using Time Use Survey Data: Part I" that focuses on time-related and time-specific aspects of occupants' activity profiles. Each activity was analysed in terms of daily time duration and starting/ending times. In detail, a Kaplan-Meier Survival analysis is performed in order to create an estimator of the survival function of the various activities. Finally, this study provides representative occupancy profiles in Danish households during weekdays and weekends.

INTRODUCTION

Building energy simulations (BES) have become indispensable tools for accurately predicting building energy use and valuable design-support tools for energy experts in the building sector. However, a major challenge in simulation tool development and application is how to deal with difficulties associated with a large variety of parameters and complexity of factors such as non-linearity, discreteness, and uncertainty (Hopfe et al. 2011). Although the modelling options within BES tools are constantly improved and updated, they are still subject to great uncertainty when predicting the absolute energy performance of buildings (Gaetani et al. 2016). Indeed, the key sources of uncertainty are strictly related to occupancy and building operation according to ASHRAE (2007). In line with this, extended literature reviews confirm that the stochastic nature of the human interaction with the building is a key driving factor of uncertainty in the prediction of residential buildings' energy demand (Janda 2011, Peng et al. 2012). The occupant influences building energy use and the indoor environment by

not only presence and actions in the building, but also through interaction with the controls of building systems designed to adjust indoor environment variables. Many studies have shown that there is an urgent need for comprehensive and validated stochastic models for predicting residential occupancy and activities, including their variations between individuals and households (Andersen et al. 2007, Mahdavi 2011, Masoso and Grobler 2013). In particular, Larsen et al. (2010) carried out an in-depth analysis on how occupants influence the energy consumptions of Danish residential buildings and highlighted how the new demand for sustainability will inevitably increase the influence of the occupants' presence and interaction on energy use. Therefore, detailed modelling of these processes is necessary to predict energy use, indoor climate and in particular peak loads of heating, ventilation and air conditioning for system dimensioning.

Occupants' activities evidently shape the timing of building energy use throughout the day. More specifically, the timing of energy use, particularly electricity, is highly dependent on the timing of the occupants' activities. This is important, for example, in the context of designing and assessing demand-side management systems including load shifting. In order to model domestic demand profiles with high temporal resolution, it is necessary to take account of residents' behaviour in terms of when they are likely to be at home and carry out specific energy-related activities. Diary-based surveys on how occupants spend their time during the day can help to define occupancy profiles and energy-related activities. In this environment, Time Use Survey (TUS) data is becoming an essential data source for energy-related occupant behaviour modelling.

Richardson et al. (2008) presented a thorough and detailed method for generating realistic occupancy data for UK households, based upon surveyed time-use data describing what people do and when. The approach presented generates statistical occupancy time-series data at a ten-minute resolution and takes account of differences between weekdays and weekends. The model also indicates the number of occupants that were active within a house at a given time. Wilke (2013) developed stochastic models based on the French TUS to predict time-dependent residential occupancy and activities, relating the use of electrical appliances to the activities performed. Yu et al. (2013) used data collected in a household TUS in Beijing to develop a household time-use and energy-consumption model that incorporates multiple behavioural interactions. Torriti (2016) used the British TUS to assess how dependent energy-related social practices in the household are in relation to the time of the day. They analysed the 2005 UK TUS and made use of

statistically derived time dependence metrics for six social practices, including preparing food, washing, cleaning, washing clothes, watching TV and computer usage. The main findings show that washing has the highest value for the time dependence metric and using computers is the least time-dependent practice; Tuesdays, Wednesdays and Thursdays have the highest time dependence for all practices and certain energy-related practices have higher seasonal dependence than others.

In this paper, the latest diary-based Danish TUS is used to understand and analyse time-related factors linked to the daily practices of the occupants to define (i) survival curves of the daily time durations of the activities, (ii) typical starting/ending times of the activities and (iii) representative occupancy profiles during weekdays and weekends.

METHODOLOGY

Danish Time Use Data

The Danish TUS 2008/2009 surveyed randomly selected 18 to 74-year-olds in Danish households (Bonke, 2016). Besides answering 50 questions related to general demographic information (family background, incomes, and labour market attachment) and the compilation of a booklet keeping track of household expenditures, respondents were asked to complete two forms for daily time use – one for a weekday and one for a weekend day. These diary-based forms included a pre-coding system for different types of activities for enabling the respondents to easily compile the time use survey and to facilitate data analysis. In particular, the day was divided into 10-minute intervals (in total 144 intervals). The time required for a given activity in the course of a day therefore becomes the sum of 10-minute sequences, where these activities occur. A detailed description of the survey can be found in Bonke (2002) and Bonke and Fallesen (2010) where the response rates among others are specified.

Since the Danish TUS 2008/09 framework pre-coded and included more than 35 preliminary activities, Barthelmes et al. (2018) clustered these activities into a number of activities that were considered energy- and occupancy-related and therefore valuable for occupant behaviour analysis in the residential sector (Table 1).

Table 1. Clustered activities

No.	Activities
1	Sleeping
2	Toilette
3	Eating
4	Cooking/Washing dishes
5	Cleaning/Washing clothes
6	Practical Work
7	Family care/Free time
8	Relaxing/TV/IT
9	Not at home
10	Others

(i) Kaplan Meier Survival Curve

The first step of analysis is aimed at understanding and analysing typical time durations of the several activities throughout the day. The Kaplan-Meier estimate is one of the best methods for describing the fraction of subjects living or persisting for a certain amount of time. The Kaplan-Meier estimate is also called a "product limit estimate" (Goel et al. 2010). It involves computing of probabilities of occurrence of event at a certain point of time. We multiply these successive probabilities by any earlier computed probabilities to get the final estimate. The survival probability at any particular time for the several activities is calculated by the Equation 1:

$$S(t) = \frac{Number\ of\ activities\ started - Number\ of\ activities\ finished}{Number\ of\ activities\ started} \quad (1)$$

where S(t) is the probability that the individual activities survive beyond a certain amount of time t.

(ii) Transition states

The second step of analysis is focused on outlining starting and ending times of the activities during weekdays and weekends. For this, transition states (activity started/activity ended) were defined for eight activities and then accumulated on an hourly basis. Table 2 shows an example of transition states related to activity 3; in this case, a survey respondent performed activity 3 for half an hour; the starting and the ending time of this activity are described by the transition states "activity started" and "activity ended", respectively. Activity 9 ("not at home") is analysed separately in step (iii) regarding the definition of occupancy profiles and activity 10 ("others") is not considered relevant for the analysis.

Table 2. Example: Transitions states of activity 3

Time	Activity state (survey response)	Transition state "activity started"	Transition state "activity ended"
00:00	0	0	0
00:10	3	1	0
00:20	3	0	0
00:30	3	0	1
00:40	0	0	0

(iii) Occupancy patterns

The third step of analysis addresses the definition of representative occupancy profiles for the Danish residential sector during weekdays and weekends. For this analysis, the clustered activity 9 ("not at home") provides information on when occupants are absent from home, while all the other activities take place in the domestic environment. A departure event therefore takes place when activity 9 is started. On the other hand, a returning event takes place when activity 9 is ended. In detail, activity 9 includes activities performed elsewhere such as work, transportation, education, shopping, errands, visiting public offices, association activities, voluntary work, sport, and time spent for leisure, entertainment outside the house, and restaurants/cafés.

The probability of leaving (LH) and returning home (RH) in the next 10 minutes at a given time step t is calculated according to Equations 2 and 3, respectively:

$$P(LH)(t) = \frac{Number\ of\ departure\ events}{Number\ of\ responses\ at\ time\ step\ t} \quad (2)$$

$$P(RH)(t) = \frac{Number\ of\ returning\ events}{Number\ of\ responses\ at\ time\ step\ t} \quad (3)$$

RESULTS

(i) Survival curves of activities' daily time durations

Figure 1 depicts the survival functions based on the Kaplan-Meier procedure for daily occupants' activities. The graph shows the cumulative distribution of the duration of nine activities. The graph clearly shows that the longest time durations are linked to the sleeping activity. Around 90% of the respondents sleep at least six hours, then the survival curve

gradually decreases and after ten hours, 10% of the survey respondents have ceased their sleeping activity. The second longest daily time durations are linked to activities away from home ("not at home"), this survival curve is less steep with respect to others, which reflects the large variety of time durations of this activity throughout the day. The second longest activity performed at home, after sleeping, is relaxing and TV/IT usage. The shortest time durations are linked to time spent for toilette, cooking/washing dishes, cleaning/washing clothes, and eating.
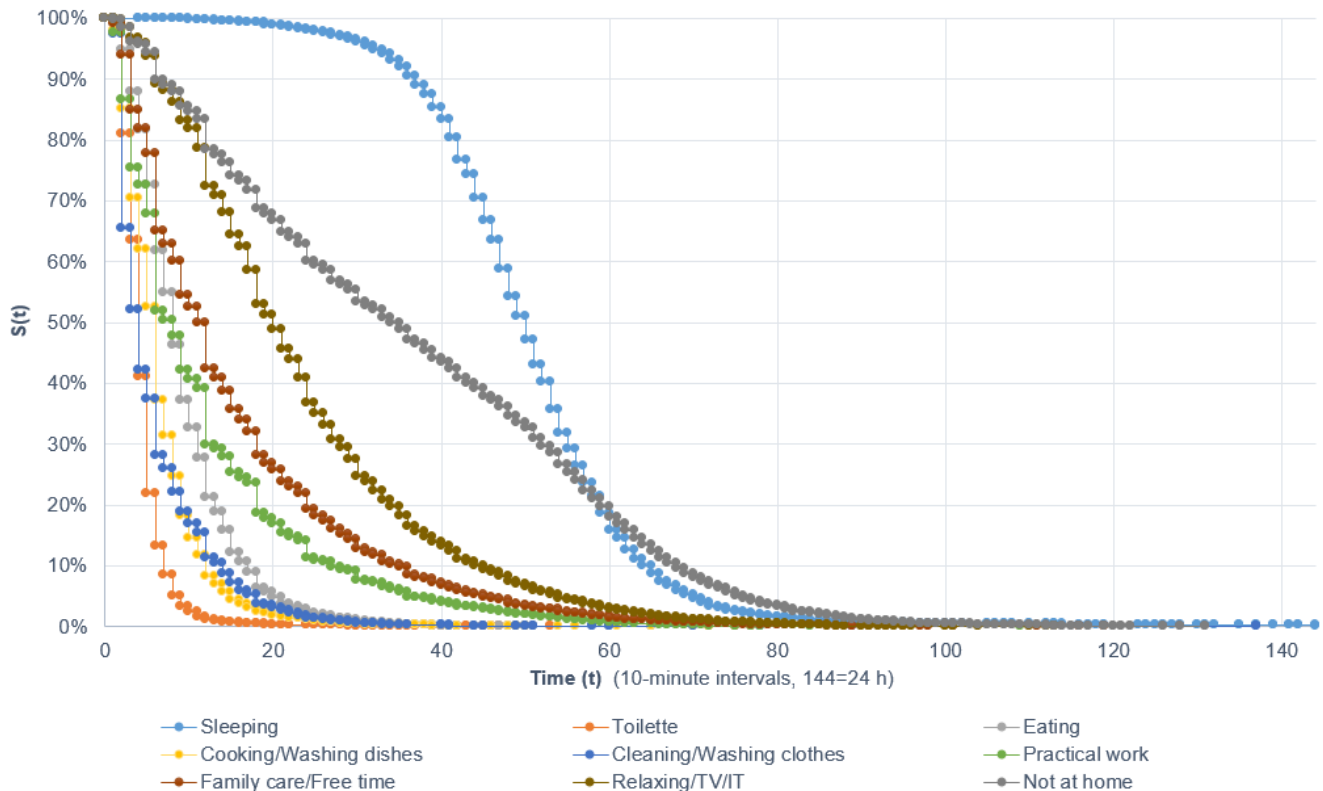

Figure 1. Kaplan-Meier procedure: Survival functions for daily occupants' activities

(ii) Starting/ending times of activities

The number of activities started throughout the day is shown on an hourly basis in Figures 2a and 2b for a typical weekday and weekend day, respectively. Figure 3 depicts when the same activities end on a typical weekday (Figure 3a) and weekend day (Figure 3b). These graphs provide insights into the time dependency of the several activities and highlight the following key aspects:

- generally, there are three peak times for initiation of activities: morning hours (7am-9am), the late afternoon/early evening hours (6pm-8pm) and finally at bedtime (23pm);

- most survey respondents start their sleeping activity between 10pm and 12am and cease the latter between 6am and 10am. In line with Part I (Barthelmes et al. 2017), the sleeping activity is shifted and terminated later during weekend days;

- clear peak values for toilette use can be observed in the morning and evening hours in correspondence of the starting and ending time of the sleeping activity;

- as expected, the highest number of eating activities start and end during breakfast (7am-10am), lunch (12pm-2pm) and dinnertime (6pm-8pm); cooking and washing dishes are also linked to these starting and ending times;

- activities related to relaxing and TV/IT usage begin during the afternoon hours and reach the highest number of started activities in the evening hours (7pm-9pm); these activities mostly end during the late evening hours (9pm-1am);

- activities related to practical work and family care show a low time dependency on the time of the day and starting/ending times are equally distributed throughout different hours of the day
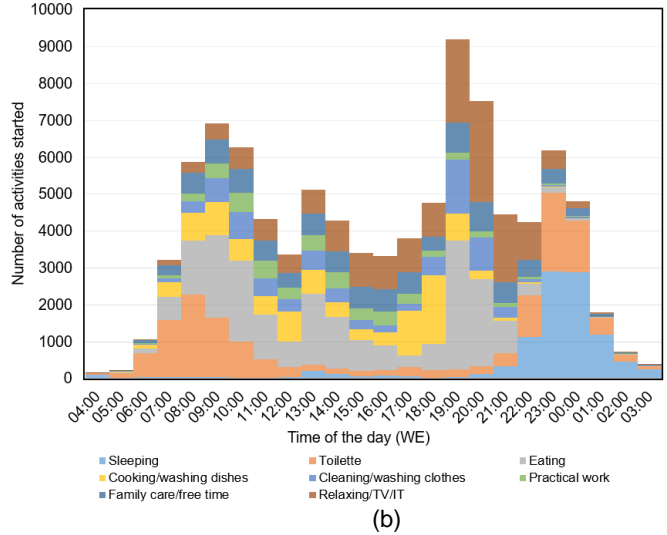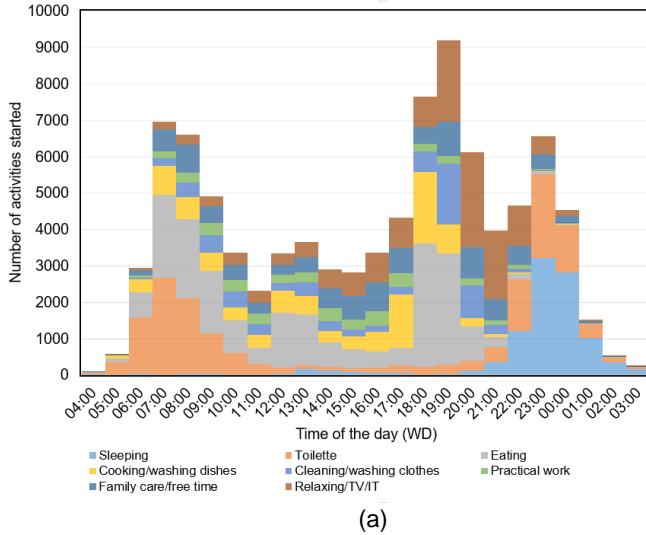
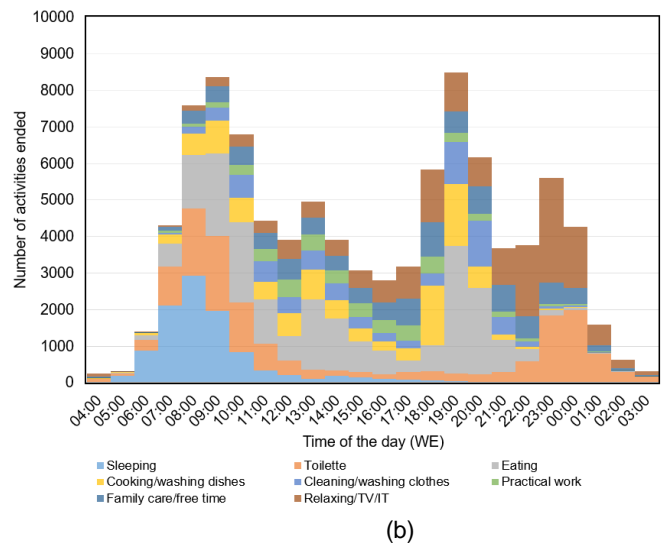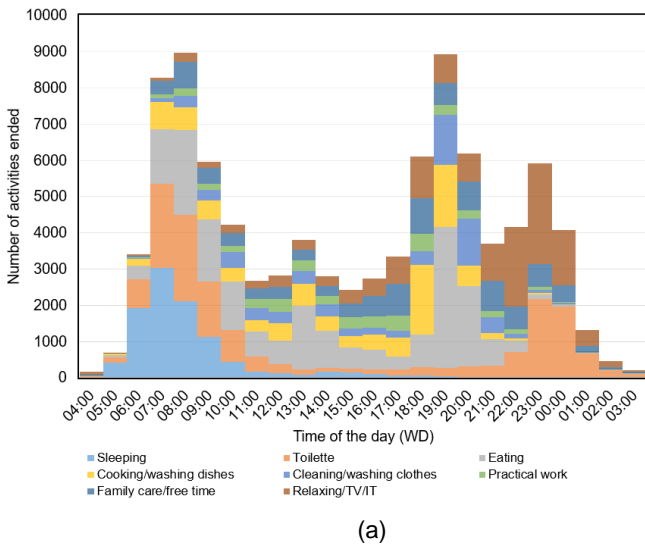*Figure 2. Number of activities started during (a) weekdays and (b) weekends*

Figure 3. Number of activities ended during (a) weekdays and (b) weekends

(iii) Occupancy profiling

A further step of analysis consisted in defining typical occupancy patterns in Danish households based on the Danish TUS 2008/09. Figure 4 depicts the percentage of survey respondents at home throughout the day during weekends and weekdays. In particular, the graph highlights that the highest percentage of respondents is out of home in the late morning hours, a rather smaller portion tends to return home for lunch, while most of the respondents come home during the late afternoon/evening hours. Furthermore, the graph clearly shows that a larger fraction of the survey respondents is at home during the weekend. Figure 5 and 6 depict the probability of leaving and returning to the home within the next 10 minutes during weekdays and weekend days, respectively. As highlighted in Figure 5, the probability of leaving home is highest in the morning hours (8am) and during the early afternoon hours (1pm). Figure 6 clearly shows that the probability of returning home is highest during lunchtime (12am) and dinnertime (6pm).
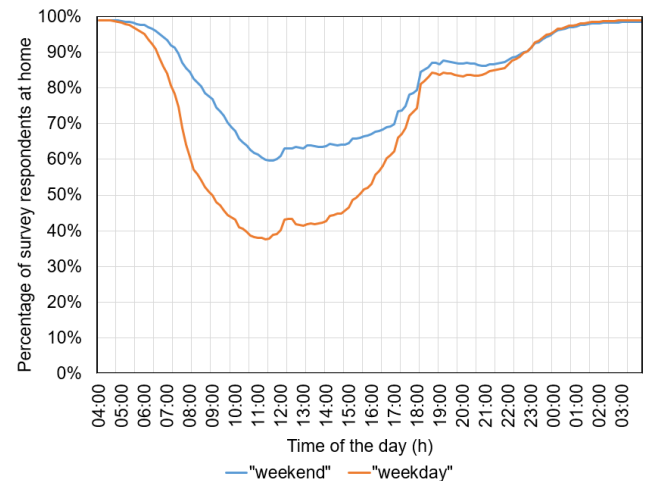

Figure 4. Occupancy patterns during weekdays and weekends

Furthermore, the curve showing the probability of leaving home is characterised by less evident peak values during weekends than during weekdays (Figure 5), while peaks for the returning hours match during both weekdays and weekends (Figure 6). It is worth highlighting that the sawtooth patterns of the curves are likely due to the fact that survey respondents tend to register new activities at the full hour or half hour.
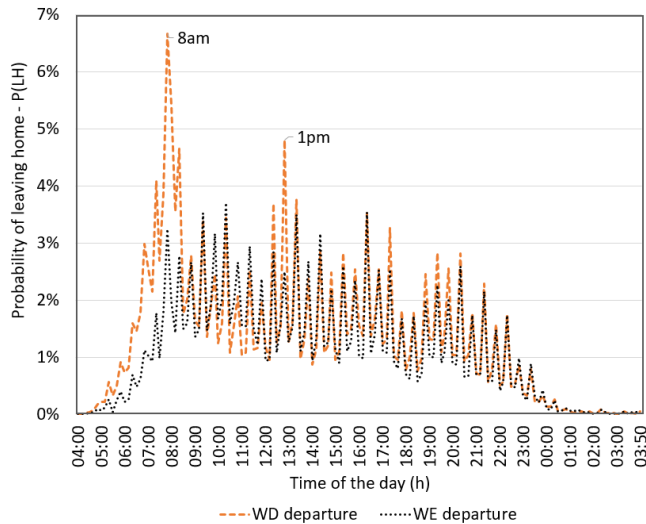

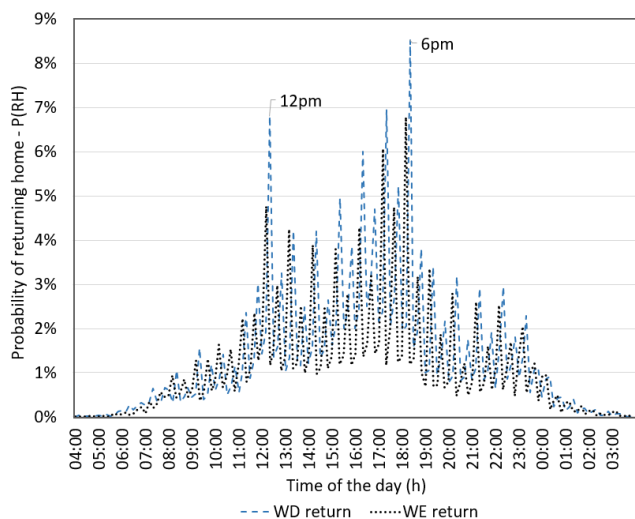*Figure 5. Probability of leaving home within the next 10 minutes on weekdays and weekends*

Figure 6. Probability of returning home within the next 10 minutes on weekdays and weekends

DISCUSSION

As mentioned previously, the definition of accurate occupancy profiles and their implementation in BES programs is crucial in order to predict building energy use more reliably. Developers of such tools tend to provide fixed predefined schedules that can be implemented when running simulations for other case studies. The U.S Department of Energy (DOE), for instance, developed reference buildings with predefined schedules for the EnergyPlus software (U.S. DOE a 2017), such as schedules for occupancy, lighting use, equipment use, ventilation rates or heating and cooling set-points.

To the best knowledge of the authors, no existing studies present tailored approaches for modelling building occupants' presence in Danish households. Therefore, the DTUS-based occupancy profile is compared with the occupancy profile provided by DOE. Figure 7 depicts their proposed occupancy profile for weekdays of a mid-rise apartment house (U.S. DOE b 2017), which is compared with the occupancy profile obtained from this study. The DTUS-based occupancy profile, while not identical qualitatively mirrors the simplified DOE occupancy profile. Hence, this graph confirms that the elaboration of the Danish TUS data might represent an adequate source for defining occupancy profiles for Danish households and a solid basis for developing further stochastic occupancy models. The latter can be implemented in energy simulation software, especially for the Danish context, in which there is still a lack of accurate occupancy profiles for residential buildings.
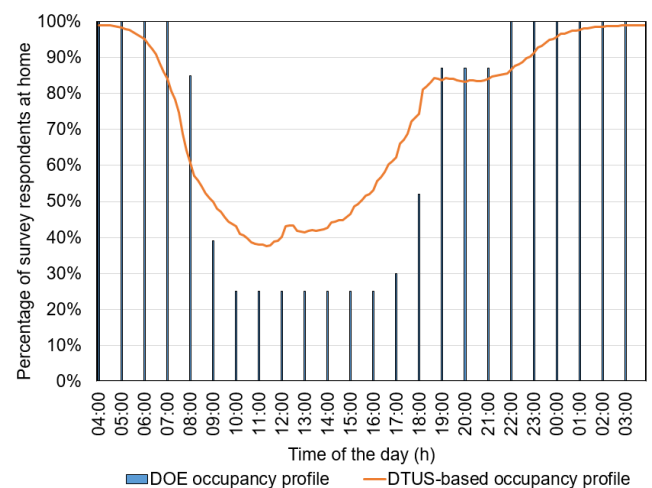

Figure 7. Comparison between the simplified DOE occupancy profile and the DTUS-based week day occupancy profile

CONCLUSIONS

In this study, the latest diary-based Danish TUS (2008/2009) was used to understand and analyse time-related factors linked to the daily practices of the occupants. In particular, this paper provides (i) survival curves of the daily time durations of the activities, (ii) typical starting/ending times of each activity and (iii) representative occupancy profiles during weekdays and weekends. Furthermore, a first stochastic approach concerned defining probabilities of leaving and returning home within the next 10 minutes, showing that during weekdays occupants are more likely to leave their home at 8am or 1pm and tend to return at noon or in the late afternoon/early evening hours (6pm). A comparison with an existing simplified occupancy profile developed by the U.S DOE showed that the Danish TUS data provides similar occupancy patterns with respect to the DOE profile. Danish TUS data might provide valuable information for further developing stochastic occupancy models in the Danish residential sector.

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