Modelling residential building stock heating load demand - Comparison of occupancy models at large scale

Giuseppina Buttitta *Student member ASHRAE*
William Turner
Olivier Neu *Member ASHRAE*
Donal Finn *Member ASHRAE*

ABSTRACT

In the residential housing sector, a strong correlation exists between occupant behaviour and space heating energy use. In particular, the occupancy scenario (e.g., daytime absence, morning presence, etc.) has a significant influence on residential heating load profiles, as well as on cumulative heating energy consumption. In the literature, many occupancy models have been utilised to predict occupancy profiles of individual dwellings as part of larger residential building stocks. The choice of the most suitable occupancy model is a trade-off between complexity, accuracy and computational effort, as well as model integration at large scale. The current paper analyzes the combined influence of different occupancy assumptions and different occupancy models on housing heating loads for a UK building stock sample. The building stock heating loads are estimated using a dynamic thermal model based on an equivalent Resistance-Capacitance electric circuit. It is assumed that the heating periods are coincident with the actively occupied periods. The actively occupied periods are first determined using two existing consolidated occupancy models, and then by using newly developed probabilistic occupancy models. All the models are characterised by a different grade of complexity and accuracy. Comparing the results of all the presented methodologies, the advantages of the new probabilistic approaches are analyzed.

INTRODUCTION

Modelling occupant behaviour in buildings is of growing interest in the scientific community, as evidenced by IEA-EBC Annex 66 (2016). The relative impact of occupant behaviour on energy consumption, and in particular on heating load demand, is predicted to increase as the energy performance of dwellings increases (De Meester et al. 2013). Thus, the choice of the most suitable occupancy model to be integrated into residential building energy models is essential in order to estimate better building energy end-use demand. The most suitable model can be identified by comparison of available models. While there is not a standard method to objectively compare results given by different models, a few comparative studies are available (Mahadavi and Tahmasebi 2016; Tahmasebi et al. 2015). However, all previously reviewed studies focus on the effect of occupancy models on the energy simulation of a single building and do not consider the cumulative effect caused by the choice of a determined model when a large urban building stock is simulated. Recently, this aspect was analyzed by He et al. (2015), who studied the impact of the use of deterministic and stochastic models on predicting the heating demand of large building stocks. Applying both

Giuseppina Buttitta is a PhD student in School of Mechanical and Materials Engineering, University College Dublin (UCD), Dublin, Ireland. **William Turner** a senior energy systems researcher in School of Mechanical and Materials Engineering, UCD, Dublin, Ireland. **Olivier Neu** is a senior energy systems researcher in School of Mechanical and Materials Engineering, UCD, Dublin, Ireland. **Donal Finn** is a Senior Lecturer at UCD, Dublin, Ireland.

deterministic and stochastic occupancy models to generate stochastic heating hours of 125 new houses, the authors established that by adopting a stochastic occupancy model, it is possible to generate more realistic hourly thermal demand profiles for a neighbourhood than by using standard heating hours. The use of these two different models has a negligible impact on the prediction of daily total heating demand. This means that total daily energy demand is unlikely to be a sufficient indicator to describe occupancy model accuracy, especially when the model must be used to obtain high temporal resolution energy demand.

The aim of the current paper is to find the most appropriate methodology to simulate the heating demand of domestic building stock, considering the trade-off between accuracy and computational effort, in the context of model integration at large scale. A hypothetical building stock of 100 identical new flats located in London is modeled. The physical characteristics of all the flats are the same but the behaviour of the occupants is different. This choice allows for isolation of the impact of occupant behaviour on building stock heating load demand. Initially, deterministic occupancy profiles are used to determine the building stock heating demand. Next, the building stock heating demand is re-calculated considering a previously-developed stochastic occupancy model. The results of these two approaches are then compared with the results given by two newly developed probabilistic occupancy models, the subject of the current paper. These models are able to create diversified stochastic occupancy profiles for UK population subgroups characterised by different occupancy scenarios. The effect of these four different occupancy models on the estimation of building stock heating load demand is analysed by means of two case studies. In the first case study, the aggregated occupant behaviour of the modelled households exhibits the same average behaviour as for the entire population, while in the second case study the household behaviour is obtained from the combined behaviour of two particular population subgroups identified in the UK, which are characterised by different occupancy patterns. These two case studies demonstrate that in order to obtain scalable models of household groups with occupancy behaviours that differ from the national average, it is necessary to categorize the whole national population in subgroups, according to their characteristic occupancy patterns.

METODOLOGY

Building characteristics

The current study estimates the heating load demand of 100 identical new flats, located in London. The modeled flats represent a typical, modern mid-flat, built after 1991 (BRE 2014). The floor area each flat is 60 m^2 (Arababadi 2012) and the total window area is 9.27 m^2 (BRE 2014). Neigbouring flats are all assumed to have the same air temperature, therefore there is no heat transfer between the flats. As a simplification, internal heat gains are not considered in the model. It is assumed that the exclusion of internal heat gains does not generate significant contributions in the critical comparison of the different occupancy models. Moreover, this assumption allows the isolation of the impact of occupancy behaviour on the heating demand profiles. The main data for new UK houses is based on both surveyed and standard information available from (i) the housing survey 2013 (DCLG 2016), (ii) the Standard Assessment Procedure (BRE 2014) and (iii) the data collected by the University of West of England (University of the West of England 2009). From the analysis of the data, it is assumed that the external wall of the modeled flat is an insulated cavity with a U-value = 0.45 [W/(m^2K)] and the window is a double pane window with a 6 mm air gap, with a total U-value = 3.12 [W/(m^2K)].

Building model

Buildings are simulated using a dynamic building equivalent Resistance-Capacitance (RC) model, as described in Good et al. (2015). The calibration of the parameters which characterise this model is conducted using the data obtained from detailed building models in EnergyPlus (E+). The RC model is calibrated by varying the values of the thermal resistances and capacitances of the RC model in order to minimise the discrepancy between the building internal temperature given by E+ and the RC model. Once the RC model is calibrated, it is used to model the heating

demand at one-minute resolution considering different heating periods. This study is based on the assumption that the heating periods are coincident with the actively occupied periods. This assumption is adequate for modelling modern houses that are well insulated and for lightweight construction (He et al. 2015). Heating set-points are assumed to be 19.5 °C during the actively occupied hours, based on the observations of Shipworth et al. (2010) and Jevons et al. (2016). In the model, the heat produced by the heating unit is added directly to the indoor environment, such as the case with direct electric heating systems. The environmental conditions are obtained from the International Weather for Energy Calculations (IWEC) weather file from ASHRAE (2001) for London Gatwick.

Occupancy models

Flats in the considered building stock are occupied by households having different behaviours, reflecting the data collected in the UK Time Use Survey 2000 (UK 2000 TUS) (Ipsos-RSL and Office for National Statistics 2003). The UK 2000 TUS is a survey which recorded the everyday routines of 11,700 UK citizens belonging to 6,500 households. One household is defined as a person or group of people who have specified the accommodation as their only or main residence and share the living accommodation. The routine of survey respondents is described in detailed 24-hour diaries (household diaries), completed at ten-minute intervals. In order to investigate how different occupancy models influence domestic heating loads, four different models are considered to generate different heating patterns.

Model 1: Fixed deterministic profiles. The fixed deterministic profiles are obtained from the data mining clustering technique presented in Buttitta et al. (2016). This technique is applied to the UK 2000 TUS data. First, household diaries are grouped according to the day type (weekday or weekend). Then, household daily occupancy profiles are obtained considering the daily sequence of these three household occupancy states: Absent (Abs), in the case where there are no occupants in the dwelling; Active (Act), in the case where at least one of the dwelling occupants is home and awake; Non-Active (Non-Act), in the case where all the dwelling occupants are home and asleep. These three states do not identify the number of occupants in the house in each state. However, energy load profiles are mainly influenced by the occupancy pattern (the unoccupied period frequency) and the household size (Yao and Steemers 2015; Famuyibo et al. 2012, He et al. 2015). For this reason, it is assumed that these states are sufficient to model the heating demand of the flats. For each day type, similar household daily occupancy profiles are grouped together applying the k-mode clustering technique (Jain et al. 1999). This technique is used to obtain clusters of similar household daily occupancy profiles. Each cluster is characterized by a mode and the number of households which are associated with each cluster. The modes for each cluster represent the fixed deterministic household daily occupancy profiles which are used to model the building stock heating load demand. The modes for the clusters obtained from weekday household daily occupancy profiles are reported in Figure 1, where the y-axis indicates the time of day and the x-axis the percentage of households that have an occupancy pattern which can be associated with the mode of the cluster.

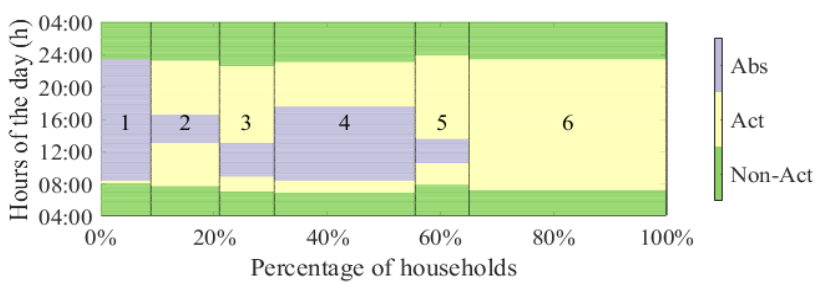

Figure 1 Weekday household daily occupancy mode profiles for each cluster (1 to 6).

Model 2: Stochastic profiles generated using an existing occupancy model. The stochastic profiles in this case are generated using the CREST occupancy model developed by Richardson et al. (2008), based on UK 2000 TUS data. In this model, the household diaries are divided in multiple categories according to the number of occupants

(from 1 to 6) and the day type, obtaining 6 different categories for each day type. For each category the synthetic occupancy profiles are generated using a first-order Markov-Chain model. The Markov-Chain model is a stochastic process in which each state only depends on the state of the previous time step, according to the probabilities of a state change (Weisstein 2016). In this case, in each state, the number of active occupants in the house is defined, and it depends on the number of active occupants in the previous state. The probabilities to pass from one state to another, for each category, are determined by transition probabilities matrices which have *(n+1)-by-(n+1)* dimensions, where *n* is the number of occupants in the house.

Model 3: Stochastic profiles generated using a new occupancy model based on Markov-Chain Monte Carlo technique. In this model, synthetic occupancy profiles are obtained using first-order Markov Chain model. However, in this case the household diaries are categorised according to the day type and the daily occupancy profiles, using the clustering technique described for Model 1. In this way 6 different categories for each day type are obtained. For Model 3, each state defines the household state using the same three household states: Abs, Act and Non-Act. Transition probability matrices with dimensions of 3x3 are then generated independently from the number of occupants in the house. This reduces the computational time compared to Model 2, but this also reduces the obtained information because the number of occupants in each time step is lost. Nevertheless, this model has a good ability to create differentiate occupancy profiles for each cluster.

Model 4: Stochastic profiles generated using a new occupancy model based on an inverse function method. In this model the household diaries are categorised according to the day type and the occupancy profiles. The stochastic profiles are obtained using the inverse function method (Devroye. 1986), that can generate a sample (in this case the daily time series of household states) of events from a given probability distribution function (PDF). The PDFs describe the probability of transitioning from one state to another as a function of the time of the day, and they are called Transition Proclivity Functions (TPFs). TPFs are obtained by calculating the number of households of each category which change their state during each time step, and then dividing this data for the number of households in each category. The TPF is defined from 04:00 to 04:00 of the successive day. The initial state of the household at 04:00 is non-active. The time of the state transitions are obtained by generating random numbers in the interval [0,1], using a flat distribution random number generator. This method is described in more details in Buttitta, et al. 2017.

For comparison purposes, standard heating schedules (07:00 – 09:00 and 16:00 – 23:00 for weekdays) indicated by the SAP 2012 (BRE. 2014) could have been considered. However, it was already proved that the aggregate demand curve which is obtained using the standard schedule is not realistic because it is very unlikely that all the buildings commence and end their associated heating period at the same time (He et al. 2015).

Case studies

Two case studies are analysed: Case Study 1, where it is assumed that the aggregate occupancy profile reflects the behaviour of the whole UK population, without considering any specific population subgroup; Case Study 2 where the building stock households do not have the same behaviour as the whole UK population, but specific UK population subgroups are considered, characterised by specific occupancy patterns. The comparison of these case studies demonstrates that the categorisation of the national population according to the occupancy patterns is necessary to avoid biased results when a group of households with an occupant behaviour different from the national average is modeled.

When Model 1 is applied in Case Study 1, the percentage of households with a determined occupancy profile respects the percentages indicated in Figure 1. This means that there are 9, 12, 10, 25, 9 and 35 households associated with clusters 1 to 6, respectively. Model 2 generates 100 stochastic occupancy profiles which are then randomly associated to the modeled dwellings. In order to apply Model 3 and Model 4, the households are first associated to a determined cluster, respecting again the percentages indicated in Figure 1. Then, in both cases, 100 occupancy profiles are generated using the indicated methods: Markov Chain Monte Carlo and Inverse function method for Model 3 and Model 4, respectively and then they are associated with the dwellings modeled. The validity of Model 2 has already

been proved (Richardson et al. 2008), so it is used as the baseline reference.

In Case Study 2 it is assumed that the households can be associated to Clusters 4 and 6 only, because these two clusters together represent more than 50% of UK household occupancy profiles during weekdays. In particular, the following cases are analysed: 100% households are associated to cluster 6; 75% of households are associated to cluster 6, 25% to cluster 4; 50% of households are associate to cluster 6, 50% to cluster 4; 25% of households are associate to cluster 6, 75% to cluster 4; 100% households are associated to cluster 4. In this case study, Model 2 cannot be used because it categorises the UK population according to the number of occupants and not according to the occupancy patterns. However, real profiles are extracted from TUS household diaries belonging to each cluster and then they are used to produce realistic building stock load profiles, which are used as benchmarks.

The indicators which are used to compare the four different models are the daily heating load demand profiles and the daily cumulative energy consumption during the heating season.

RESULTS

Case Study 1: Households with same occupancy behaviour as the whole UK population

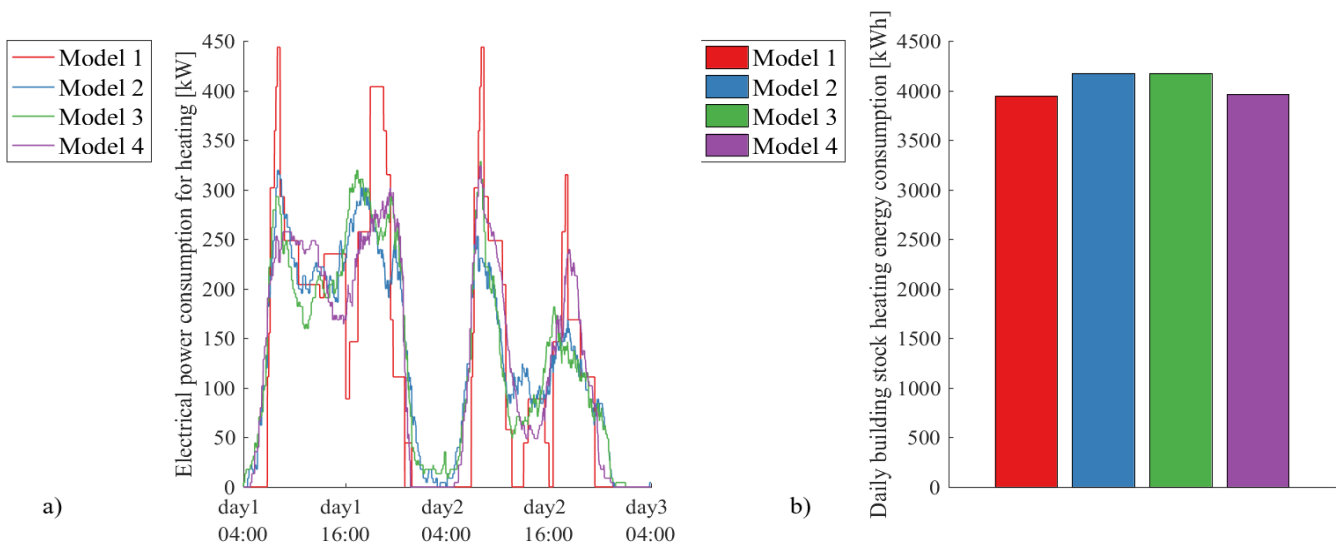

Figure 2 (a) Building stock heating power consumption and (b) Daily building stock energy consumption during working days.

Fig 2(a) shows the housing stock heating load profiles for two consecutive winter days. Model 1, which considers deterministic profiles, is the simplest model to use. However, it produces unrealistic power peak demand due to the fact that all houses with the same occupancy profile require the heating to be on at the same time. The other two models, based on probabilistic approaches, produce similar results to Model 2, which is used as baseline. The heating load demand is at the lowest during the night, followed by an initial peak at breakfast time. Then, the demand is quite constant during the day, until the late afternoon, when it rises towards an evening peak after which it decreases during the night. Comparing results obtained from Model 3 and Model 4 against the Model 2 results gives Pearson correlation coefficients of 0.97 and 0.92, respectively (Table 1). It is interesting to note that, the Pearson Correlation Coefficient is still acceptable for the Model 1. It means that the use of deterministic occupancy profiles, obtained through the clustering technique of household occupancy profiles, is able to closely reflect the real national behaviour. The average daily energy consumption is similar for all four models (Figure 2(b)), indeed, comparing results obtained from Models 1, 3 and 4 against Model 2, the mean absolute percentage error is always lower than 5%. Once again, it is proved that daily energy consumption is not a reliable indicator for the model accuracy.

Case Study 2: Households belonging to specific UK population subgroups

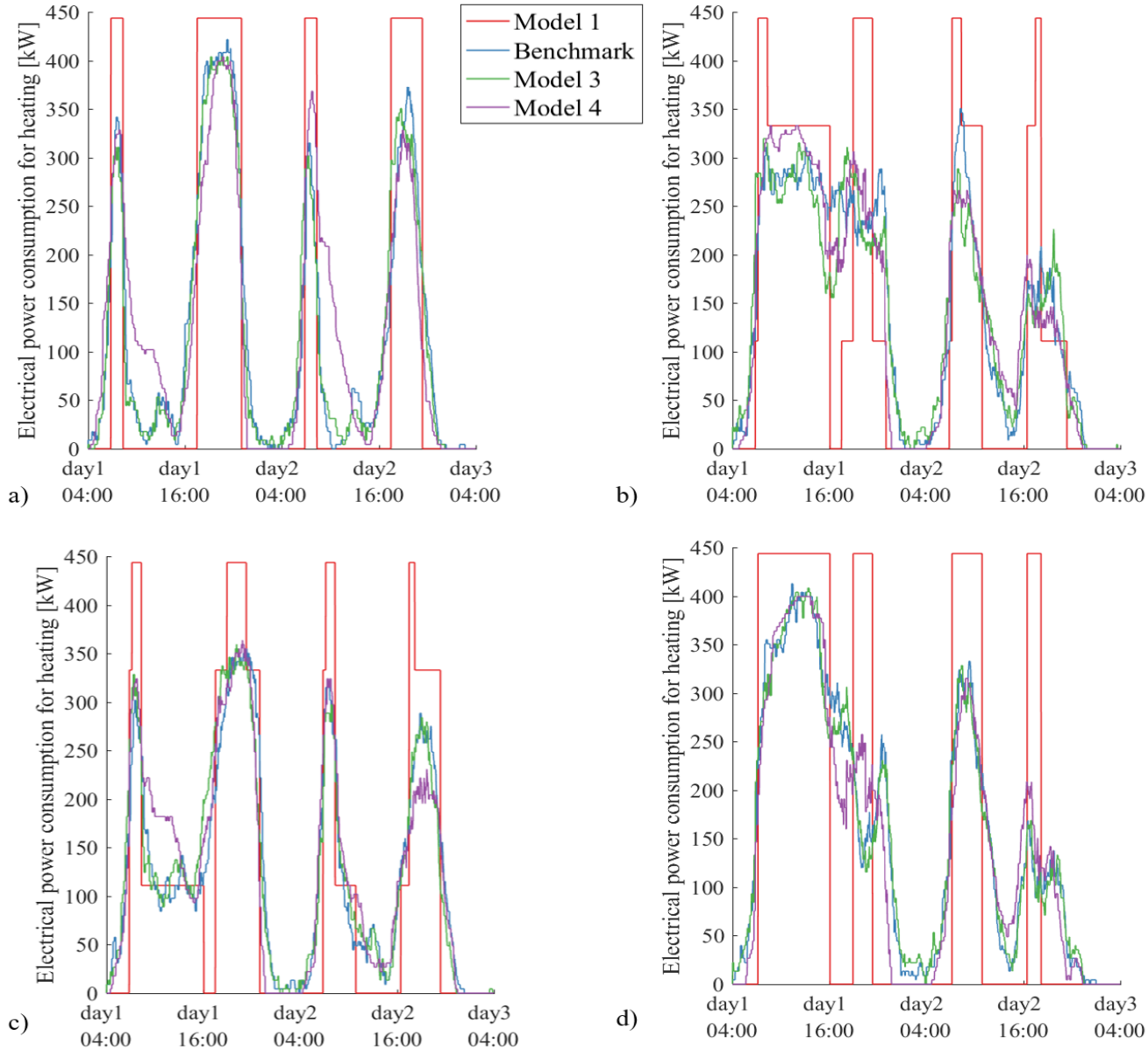

Figure 3 Building stock electric power consumption for heating in the following cases: (a) 100% Cluster 4, (b) 75% Cluster 4/25% Cluster 6, (c) 25% Cluster 4/75% Cluster 6, (d) 100% Cluster 6.

In this case study, different occupant behaviour assumption are analysed, and it is clear that the consideration of different UK population subgroups leads to different building stock heating load demand curves (Figure 3). The benchmark curve is obtained using the real occupancy profiles extracted from TUS diaries, and it used to test the accuracy of the Models 1, 3 and 4. Also in this Case Study Model 3 performs better than the others models. Indeed, Model 3 produces load profiles which are very similar to the benchmark (Figure 3) and it has the highest Perason Correlation Coefficient (Table 1) when it is compared to benchmark data. Model 4 is still an accurate model, however Model 4 accuracy is lower than Model 3 because Model 4 is not able to predict unexpected deviation of the occupancy behaviour from the occupancy profiles described by the modes.

Table 1. Pearson Correlation Coefficients

Case studies		Model 1	Model 3	Model 4
Case Study 1		0.85	0.97	0.92
	100% cl. 4	0.73	0.99	0.96
	75% cl. 4/25% cl. 6	0.79	0.95	0.94
Case Study 2	50% cl4/50% cl. 6	0.83	0.98	0.96
	25% cl. 4/75% cl. 6	0.89	0.97	0.94
	100% cl. 6	0.89	0.99	0.92

Figure 4 compares the cumulative daily heating energy demand consumption required by the building stock considering the presented models and the different household occupancy behaviour. In this case it is clear that each assumption on occupant behaviour has a strong impact of the final result of the model. Moreover, the comparison of Figure 4 and Figure 2(b) shows that the consideration of the average national household occupancy behaviour leads to underestimation or overestimation of the heating energy required when particular national subgroups are considered.

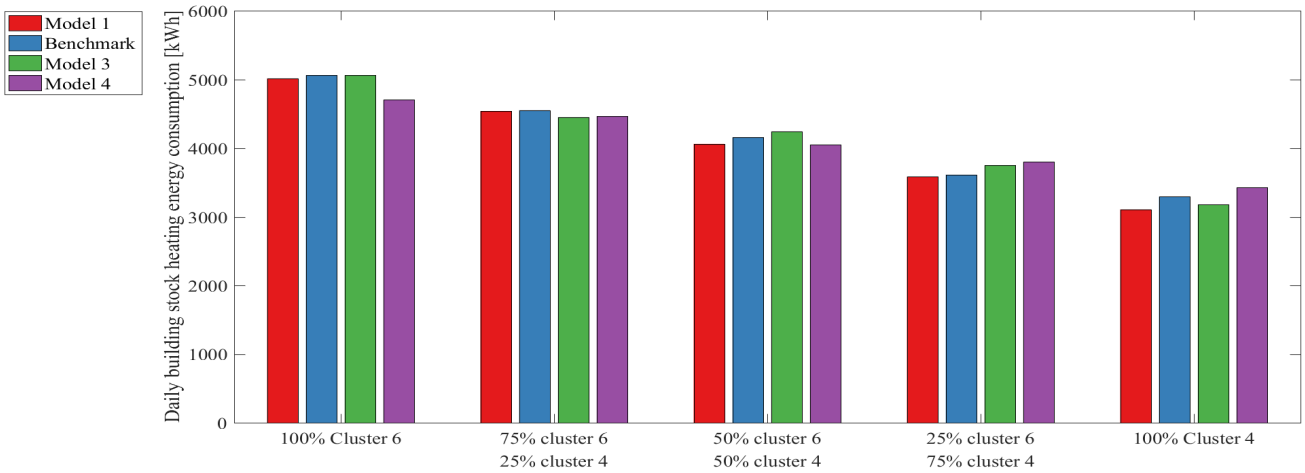

Figure 4 Daily building stock energy consumption

Analysing these results, it is clear that the Model 1 cannot accurately represent reality, although it has the advantage of simplicity. Model 2 is less suitable when particular population subgroups are considered. Model 3 is the most accurate and it is also computationally less demanding than Model 2. Model 4 is the most efficient model from the computational point of view, but it is less accurate than the Model 3. However, the computational difference between the models is overall negligible, so it is not determinant in the choice of the occupancy model.

CONCLUSIONS

The current paper analysed the effect of four different occupancy modelling approaches on the estimation of building stock heating load demands. The occupancy profiles generated by the models are coincident with the heating hours, which are then applied to the RC model of 100 identical flats having the characteristics of new UK flats. Two case studies are considered: (i) the housing stock occupancy behaviour reflects the average national behaviour; (ii) the house stock occupancy behaviour is different from the average national behaviour. From the analysis of the building stock heating load profiles, it is clear that Model 1 generates unrealistic peak electricity demand profiles. For this reason, this approach should be avoided when the aim of the simulation is to generate high temporal resolution building stock heating load demand profiles. Both Model 2 and Model 3, based on the Markov Chain modeling approach are capable of replicating the duration and transition of occupant behaviour. However, Model 2 cannot be applied if particular population subgroups are considered. On the other hand, Model 4 showed weakness in replicating

occupancy behaviour which are not similar to the deterministic occupancy profiles considered. However, the model was observed to be computationally faster. In conclusion, Model 3 and Model 4 perform better than the others model, and the choice between the two is determined by the required accuracy in the building stock heating load profiles.

This paper is based on the assumption that heating hours are coincident with occupied hours and that the heat produced by the heating unit is added directly to the indoor environment. However, these assumptions are not always realistic when different dwelling types and heating systems are considered. Further possibilities will be explored in future work, extending the presented approach to different heating systems and different dwellings.

AKNOWLEDGEMENT

This work is part of the RealValue project. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 646116.

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