Investigating an Adequate Level of Modelling for Energy Analysis of Domestic Buildings

Yeonsook Heo[1,*], Guangying Ren[1] and Minna Sunikka-Blank[1]

[1]Architecture Department, University of Cambridge, 1-5 Scroope Terrace, Cambridge, CB2 1PX, United Kingdom

ABSTRACT
This paper investigates what level of modelling is required to appropriately support energy analysis of domestic buildings. The paper analyses the effect of simplications made in thermal zoning and internal loads scheduling through a case study of a UK domestic building. The case study provides quantified effects of common simplications made in practice on the accuracy of energy predictions by making simplications in the model incrementally and estimating the effect of individual simplications on electricity and heating demand predictions.

KEYWORDS
Level of Modelling, Thermal Zoning, Internal Loads Scheduling, Energy Analysis, Domestic Buildings

INTRODUCTION
Building energy simulation plays a significant role in predicting the energy performance of design options for domestic buildings. A modelling process often involves modellers' subjective judgement in making modelling assumptions in order to cost-effectively create the simulation model that reasonably represents actual building behaviour. Typical assumptions include reducing the number of thermal zones by combining rooms with similar activities into one zone and using the typical schedules specified in national standards depending on the space type instead of collecting information about actual schedules. These simplifications made in the model, however, unavoidably impact the accuracy of model outputs, which may possibly bias design decisions. On the other hand, the most detailed model with the minimal simplifications may yield reliable model outputs, but the cost associated with data collection and model creation is considerably high.

Several studies have investigated the effect of modelling assumptions on energy predictions. Korolija and Zhang (2013) compared annual energy use intensities (EUIs) predicted by detailed simulation models (i.e., modelling every room as a zone) with those predicted by simplified simulation models (i.e., modelling each floor as a single zone) for domestic buildings. They found that the simplications in thermal

[*] Corresponding author email: yh30@cam.ac.uk

zoning reduced the simulation time by 30% on average and resulted in the mean absolute relative error of 10.6% for predicting annual heating demands. Brandemuehl and Field (2011) investigated the importance of occupancy-related parameters in predicting energy consumption for a typical house and a zero-energy house. It was found that cooling set-points and lighting power have the most influence on energy predictions for the typical house whereas plug loads and schedule randomization have more impact on energy predictions for the zero-energy house. Martinaitis et al. (2015) analysed the effect of domestic occupancy profiles on energy predictions through the simulation study of an energy efficient house and found that the use of different occupancy profiles correlates with the total energy performance. The simulation study suggests that collecting occupancy information for creation of actual occupancy profiles will improve the accuracy of model predictions.

This paper examines the effect of simplifications commonly made in the modelling practice on the accuracy of model predictions for energy analysis of domestic buildings. The paper evaluates the effect of simplifications in terms of the change in the model outcomes incrementally through a case study of a semi-detached house. For evaluating the effect of simplifications in thermal zoning, we compare the model outputs predicted by the most detailed model with those by the simplified models with incremental reduction in the number of thermal zones until the two-floor house is modelled as a single zone. Regarding the effect of simplifications in modelling occupancy-related schedules, we use the time-of-use electricity data from 6061 households in UK and approximate actual internal load profiles into a set of representative profiles with use of cluster analyses. A set of representative profiles derived by cluster analyses are used to examine the value of using actual internal load schedules in terms of the added contribution to improve the prediction accuracy in comparison to using the standard schedules.

THERMAL ZONING

This section investigates the effect of reducing the number of thermal zones in modelling a domestic building on prediction accuracy. We selected a semi-detached house in Cambridge, UK as the case building. The house consists of a lounge, dining room, kitchen and bathroom on the ground floor and bedrooms and a bathroom on the first floor. We used DesignBuilder and EnergyPlus to create the energy model of a typical UK domestic building on the basis of the actual building layout and standard construction materials and standard schedules specified in BRE National Calculation Method (BRE 2015).

Figure 1 shows the original layout of the house and incremental simplifications made in thermal zoning. In Step 1, the minimal simplications are made by combining two rooms into one zone depending on the similarity in space use and operation schedules. Then, in Step 2, all spaces on the same floor are combined into one zone, and in Step 3 the entire house is modelled as one zone.

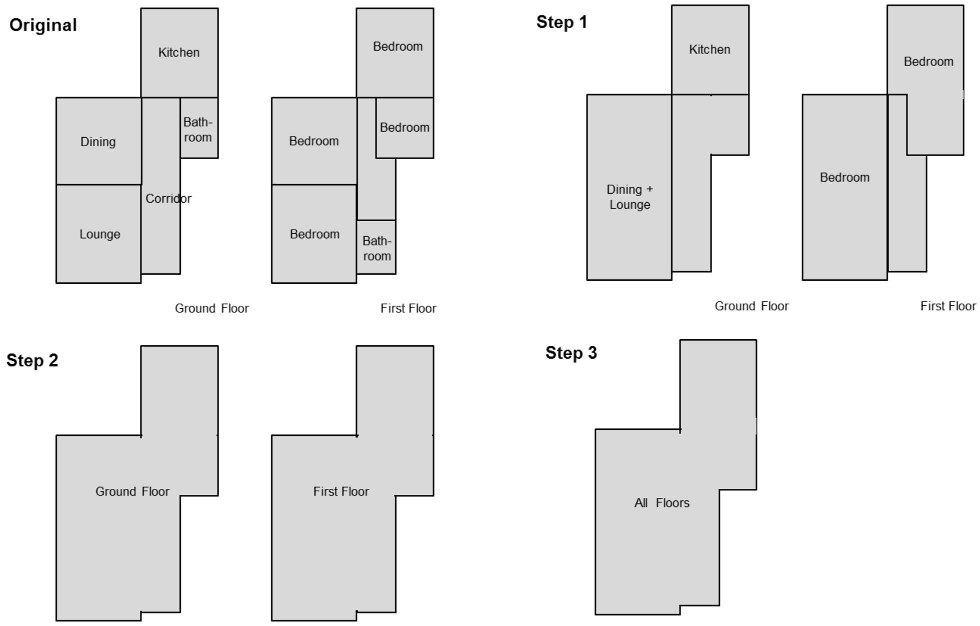

Figure 1. *Sequential simplifications in thermal zoning*

Table 1 presents standard internal heat gain values from occupants, lighting, and equipment specified in the national calculation method (NCM) (BRE 2015). With the standard density values and associated schedules, daily heat gains schedules from occupants, lighting, and equipment were created as shown in Figure 2. As the occupant densities are quite low consistently across all the space types, the magnitude of heat gains from occupants is negligible in comparison to those from lighting and equipment. Regarding lighting and equipment heat gains, the kitchen has much higher lighting and equipment power densities than the other rooms. Particularly, peak equipment heat gains in the kitchen are dominantly much higher (roughly ten times higher than the other rooms). As domestic buildings in UK are typically equipped with a boiler for heating and rely on natural ventilation for cooling, this study considers only set-point temperatures for heating that impact the energy consumption. During occupied hours, the lounge has a higher heating set-point temperature (21°C) than the other rooms that are set at 18°C. All the rooms are set back at 12°C during non-occupied hours. In addition, the system operation schedule varies per the room type; the system is in operation from 8pm to 8am for the bedroom, from 2pm to 10pm for the lounge, and for the two intermittent periods (morning and evening) for the other rooms.

Table 1. *Standard values for internal loads and heating set-point temperatures*

Room	*Occupancy (m^2/person)*	*Light (W/m^2)*	*Equipment (W/m^2)*	$T_{heating\_occ}$ *(°C)*	$T_{heating\_unocc}$ *(°C)*
Lounge	53.3	7.5	3.9	21	12
Dining	59.1	7.5	3.1	18	12
Bathroom	53.4	7.5	1.7	18	12
Kitchen	42.2	15.0	30.3	18	12
Bedroom	43.6	5.0	3.6	18	12
Corridor	64.5	5.0	1.6	18	12

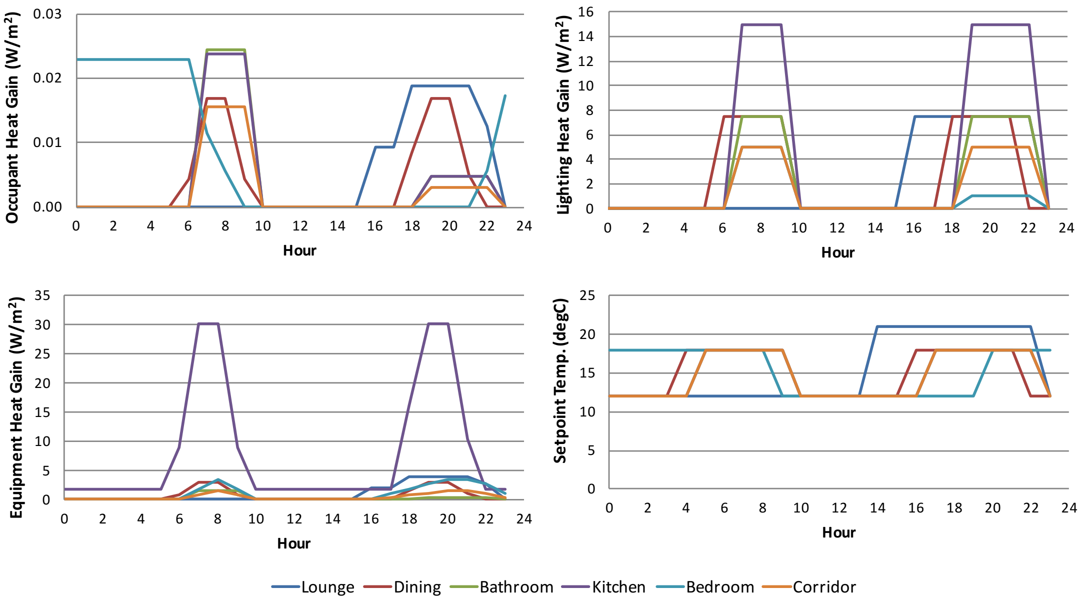

Figure 2. *Standard heat gains and heating set-point temperatures schedules*

For steps 1-3 in which different space types are combined into one zone, all density values and schedules of different spaces are weighted by the floor area of each space type to compute average density values and associated schedules per zone. Table 2 summarises the simulation results of annual electricity and heating demand predictions with different numbers of thermal zones and prediction accuracy in comparison with using the detailed original layout. Overall, the simplification steps have a minor effect on the lighting electricity consumption. However, they resulted in much larger differences in the equipment electricity consumption prediction, particularly in Step 2 when all the rooms on one floor are combined into one zone. This disparity mainly arises from the dominantly large proportion of electricity consumed by the kitchen equipment in the small area in combination of different schedules between the kitchen and the other rooms. The other rooms have a longer period of higher diversity factors than the kitchen that has the maximum diversity value (1) for two hours in the morning and in the evening. When the schedule of a zone is calculated with weighting the area of each room type in Step 2, it has higher values than the original schedule for the kitchen. As the result of multiplying the higher area-weighted schedule with the average density value, Steps 2 and 3 over-predict the annual equipment electricity consumption by roughly 21%.

In addition, as the number of thermal zones is reduced, the annual heating demand is under-estimated. This under-estimation is expected as modelling rooms into one thermal zone assumes identical heat demands across the rooms when in reality they may have uneven heat transfer conditions. Step 1 under-predicted the heating demand by 7% with minor changes in internal load predictions. When the number of thermal zones is further reduced to the two zones (Step 2) and the single zone (Step 3), the annual heating demand is under-estimated by 17% and 26%, respectively. As the increase in the electricity consumption can potentially reduce the heating demand, we created Step 3-b in which the total lighting and equipment electricity consumptions are set the same as the original case. This step suggests that modelling a single zone model for the entire house underestimates the annual heating demand by 24% in comparison to modelling every room as a separate zone.

Table 2. *Comparison of annual electricity and heating demand predictions*

	Electricity (kWh)		*Heating (kWh)*	*Electricity (%)*		*Heating (%)*
	Lighting	*Equipment*		*Lighting*	*Equipment*	
Original	1567	1388	6199	-	-	-
Step 1	1572	1382	5774	0.3 %	- 0.4 %	- 6.9 %
Step 2	1604	1688	5143	2.4 %	21.6 %	- 17.1 %
Step 3	1505	1679	4581	- 4.0 %	21.0 %	- 26.1 %
Step 3b	1567	1388	4694	0.0 %	0.0 %	- 24.3 %

INTERNAL LOADS SCHEDULING

This section compares actual internal load profiles with the standard ones and examines whether using actual internal load profiles is necessary to ensure the reliability of energy predictions. We used the electricity consumption interval data from 9200 domestic customers in London collected during May 2011 - September 2013 (Anonymity A 2016). In order to generate a representative average profile per household, we selected 6061 households that have more than 200 days of interval data and calculated an average daily profile per household used for analysis. Statistical summary of the dataset in relation to demographic variables is summarized in the Customer-Led Network Revolution report (Barteczko-Hibbert et al. 2015).

In order to effectively capture variability in the actual internal load profile, we performed a k-means cluster analysis using SPSS software with differing number of clusters. K-means clustering algorithm has been applied to compute a set of representative electricity load profiles from a large number of electricity consumption data collected from domestic buildings in UK and Ireland (McLoughlin et al. 2015; Rhodes et al. 2014). Figure 3 (left-side) shows the coefficients of variation of the root mean square error (CVRMSE) depending on the number of clusters (representative profiles). CVRMSE has been commonly used to measure the accuracy of model predictions in a normalized manner, which allows for comparing the prediction accuracy across various models. CVRMSE is obtained by computing the square root of the mean square error between actual average profiles and corresponding centroid ones and normalizing it to the mean of the observed value. When the number of cluster increases from 1 to 10, the CVRMSE value drops dramatically from 0.65 to 0.35. When the number increases further to 20 clusters, the CVRMSE is marginally reduced from 0.35 to 0.30. Thus, we selected 10 centroid profiles to manageably analyse variability across the actual profiles.

Figure 3 (right-side) shows 10 centroid profiles with the number of samples included in each cluster (in the legend) in comparison to the average profile of the entire dataset. Three distinctive profiles (C1, C2 and C7) are observed, but they can be regarded as outliers because the samples within each cluster are quite small (2, 1, and 9 for C1, C2 and C7, respectively). Except the outliers, the other centroid profiles show a similar pattern of electricity consumptions during the weekdays. The electricity consumption rises from 5am, continuously increases until 8am, and remains the same until 2pm. Then, it increases until reaching the peak value at 6pm and gradually decreases until the midnight. A major difference across the centroid profiles is the magnitude of electricity consumption. There is a need to mention that the average profile is very similar to the C6 profile and the C6 and C9 profiles present 77% of the entire households.

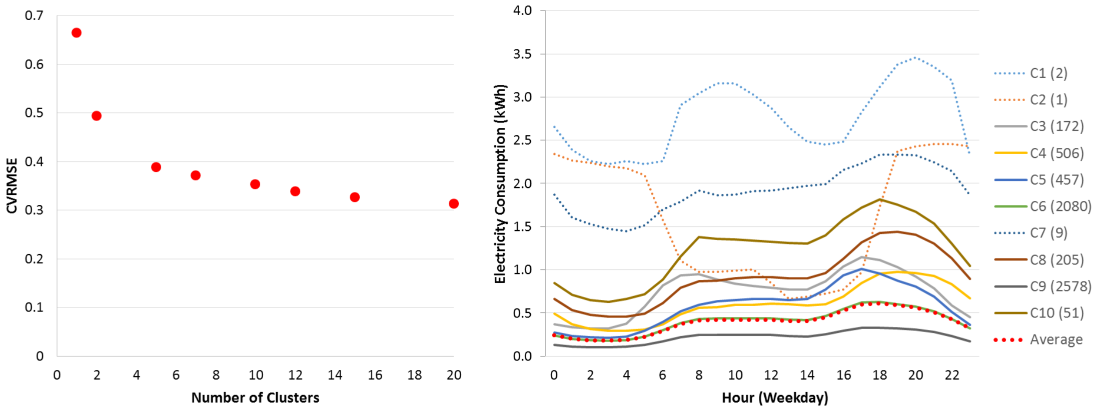

***Figure 3**. CVRMSE values of predicting electricity profiles with different number of clusters (left) and centroid profiles with 10 clusters (right)*

Figure 4 presents actual electricity profiles of 50 households randomly selected from all the households that fall into each cluster. Overall, the trend and magnitude of individual profiles are similar within each cluster although variation in the individual profiles still exists. Some peak values of individual profiles, however, were smoothed by the cluster analysis and not captured by the resulting cluster centroid profiles. We believe that missing information about peak values of individual profiles is acceptable to accomplish the purpose of this study – generating a set of profiles that capture the major variation of the entire households and evaluate the effect of the variation on annual and monthly energy consumptions. Apart from C1, C2, and C7 clusters consisting of very small number of households, the other seven centroid profiles are used in the simulation study to evaluate the relevance of using actual profiles in predicting the energy performance.

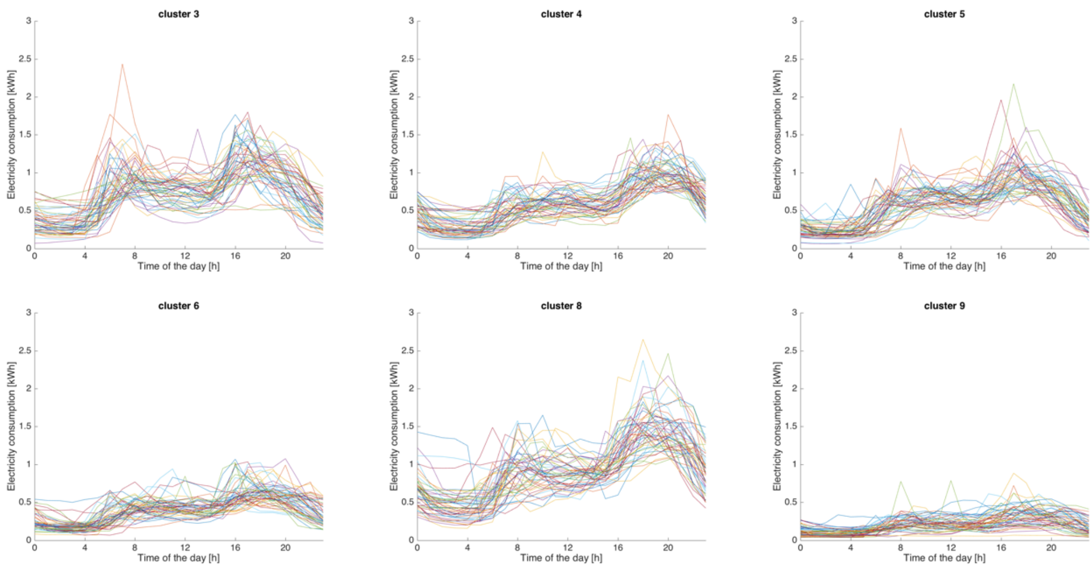

***Figure 4**. Electricity profiles of all households for different clusters*

We used the step 3 model of the case building (a single zone for a two-storey house) to analyse the effect of internal load schedules on electricity and heating demand predictions. Seven centroid electricity profiles are used as the model input for hourly internal loads from lighting and equipment. The simulation study does not present variability in the occupancy schedule due to lack of data available about occupancy, but internal heat gains from occupants are regarded as negligible in comparison to the other heat gains as also shown in Figure 2. Figure 5 shows annual electricity predictions (left) and heating demand predictions (right) with use of the standard, the average, and the 7 centroid schedules. The simulation results with the standard schedule are in good agreement with those with the average schedule. When a major variation in the actual profile is incorporated in predictions, annual electricity and heating demands substantially vary between 2,000-11,000 kWh and 5,500 kWh, respectively.

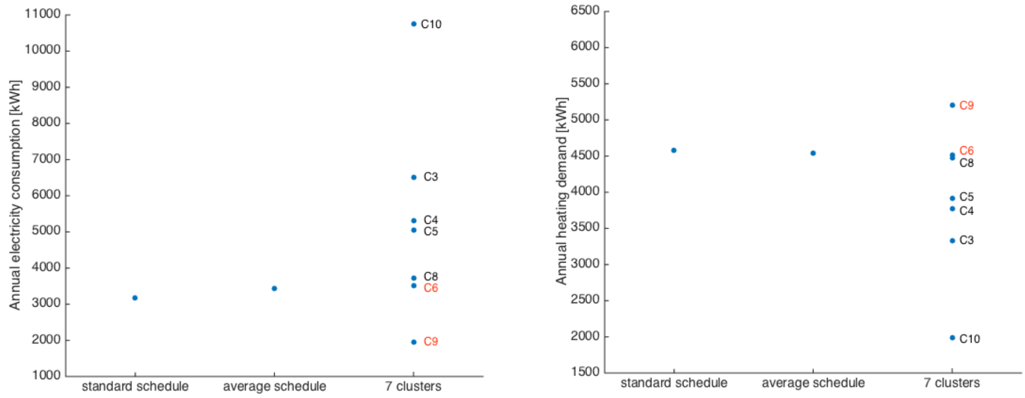

Figure 5*. Annual demand predictions with standard, average, and cluster-centroid schedules for electricity (left) and heating demand (right)*

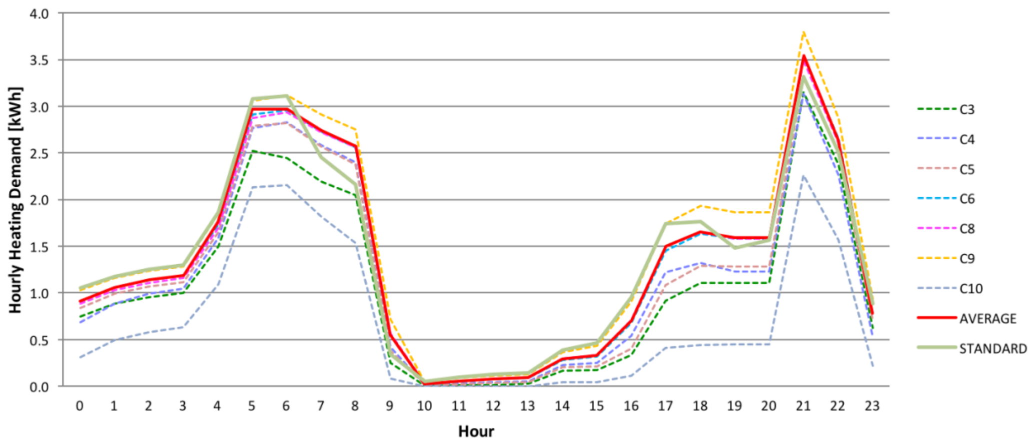

Figure 6*. Average hourly heating demands for January*

In addition to annual predictions, we further evaluated the effect of using different internal load profiles on hourly heating demand predictions as presented Figure 6. Overall, the standard profile predicted average hourly heating demands for January that closely match those predicted with the average profile derived from the dataset. Hourly predictions Moreover, the seven different profiles resulted in the similar pattern of hourly demand predictions that has low demands during 10am –

1pm and two peak demands during the same period, with the varying magnitude of peak demands.

CONCLUSION

This paper investigated an appropriate level of modelling to adequately support energy analysis of domestic buildings. A case study of a UK domestic building was performed to examine the effect of simplications commonly made in thermal zoning and internal loads scheduling in terms of the effect on model outcomes. When the number of thermal zones is more reduced to one thermal zone per floor (step 2) and one single zone for the entire house (step 3), the annual heating demand is under-estimated by 17% and 26%, respectively. In order to evaluate the value of using actual internal loads schedules, time-of-use electricity consumption data from 6061 UK households was used for cluster analysis to generate a set of representative occupancy-related profiles that effectively capture variability in the actual profiles. A majority of variations in the profile are represented by 7 cluster centroid profiles and with using the different centroid profiles the annual heating demand prediction substantially varies between 2,000 – 5,500 kWh whereas the prediction with the average schedule shows a good agreement with that with the standard schedule. The analysis results will be useful for modellers to determine thermal zoning and scheduling strategies in the modelling process depending on the level of confidence expected for energy efficiency projects.

ACKNOWLEDGEMENTS

This work is supported by Cambridge Humanities Research grant: the role of occupants and their thermal comfort perception on building energy efficiency.

REFERENCES

Anonymity A. 2016. http://www.networkrevolution.co.uk/resources/project-data/, last accessed on 20 June 2016.

Barteczko-Hibbert C, Whitaker G, Slater S, Groizard J. 2015. Insight Report: Baseline Domestic Profile: Test Cell 1a Customer Subgroup Analysis.

Brandemuehl MJ, Field KM. 2011. Effects of variations of occupant behavior on residential building net zero energy performance.*The IBPSA 2011 Conference*, Sydney, Australia.

BRE. 2015. National Calculation Methodology Database. [Online] Available at: http://www.uk-ncm.org.uk/download.jsp?id=13

Korolija I, Zhang Y. 2013. Impact of model simplification on energy and comfort analysis for dwellings. *The IBPSA 2013 Conference*, Chambery, France.

Martinaitis V, Zavadskas EK, Motuzienė V, Vilutienė T. 2015. Importance of occupancy information when simulating energy demand of energy efficient house: A case study. *Energy and Buildings*, 101:64–75.

McLoughlin F, Duffy A, Conlon M. 2015. A clustering approach to domestic electricity load profile characterisation using smart metering data. *Applied Energy*, 141:190-199.

Rhodes JD, Cole W J, Upshaw CR, Edgar TF, Webber ME. 2014. Clustering analysis of residential electricity demand profiles. *Applied Energy*, 135:461–471.