

## COUPLING A STOCHASTIC OCCUPANCY MODEL TO ENERGYPLUS TO PREDICT HOURLY THERMAL DEMAND OF A NEIGHBOURHOOD

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### ABSTRACT

When designing and managing integrated renewable energy technologies at a community level, prediction of hourly thermal demand is essential. Dynamic thermal modelling, using deterministic occupancy profiles, has been widely used to predict the high-resolution temporal thermal demand of individual buildings. Only in recent years has this approach started to be applied to simulate all buildings in a neighbourhood or an entire housing stock of a region. This study explores the potential of predicting hourly thermal demand for a group of dwellings by applying a stochastic occupancy model to dynamic thermal modelling. A case study with 125 new houses demonstrates the approach. The result was a more realistic and representative hourly thermal demand profile, compared to using standard deterministic occupancy profiles.

### INTRODUCTION

The 2008 Climate Change Act requires the UK to achieve at least an 80% cut in greenhouse gas emissions by 2050, compared to the 1990s baseline (DECC, 2008). Housing is responsible for a quarter of the UK's greenhouse gas emissions, so it would be impossible to meet the 2050 objective without changing emissions from homes (DECC, 2011). With less than 1% annual growth rate of new-build homes, it is estimated that 75% of the housing stock in 2050 will have been constructed before 2014 (Ravetz, 2008). Substantially improving the energy-efficiency of the existing housing stock as well as promoting low or zero carbon emissions for new builds is expected to play an important role. However, efforts to achieve the target cannot rely solely on improving the thermal efficiency of houses. There also needs to be integration of the full suite of low-carbon technologies in homes on both a local and a regional scale (RAE, 2010).

One requirement for such integration and subsequent management of low-carbon technologies is a high-resolution temporal prediction of thermal demand of buildings in the area of interest (Orehounig et al., 2014). Dynamic building energy simulation programmes such as EnergyPlus, IES and TRNSYS have long been widely used to model temporal (e.g. hourly) thermal demand of individual buildings. The

deployment of dynamic building energy simulation programmes for the estimation of dynamic thermal demand on a local or regional scale has started to be recognized as increasingly important, especially in the context of evaluating the implications for the energy network (Simpson et al., 2014).

This work builds upon previous research on the evaluation of alternative approaches in dynamic energy modelling of UK housing (Taylor et al., 2013), and the development of a dynamic housing stock model for the evaluation of the effectiveness of various retrofitting strategies for the housing stock in the North East region of England (He et al., 2014). It is part of the Self Conserving Urban Environment (SECURE) project funded by EPSRC. In previous work, standard heating hours and temperature set points were implemented in a dynamic housing stock model. This approach is adequate in terms of predicting annual and monthly thermal demand but is not suitable for predicting hourly thermal demand because it lacks the variations in schedules and their timing that are a feature of real behaviour (Kane et al., 2015). This study aims to explore the feasibility of coupling a stochastic occupancy model with the dynamic housing stock model for the prediction of hourly thermal demand for a neighbourhood.

### HEATING PATTERNS

Demand temperatures and heating hours are recognised as the main determinants of building energy consumption in housing stock modelling (Firth et al., 2010); however, there is ongoing discussion in the research field about what values should be used for these two parameters. A version of BREDEM (Shorrock & Anderson, 1995), the Building Research Establishment's domestic energy model, assumes the default heating demand temperature in the living room to be 21 °C, with two heating periods totalling 9 hours (07:00 – 09:00 and 16:00 – 23:00) on weekdays and a single period of 16 hours (07:00 – 23:00) at weekends (Anderson et al., 2002). The Cambridge Housing Model (Hughes et al., 2013), which uses a version of BREDEM as its core calculation engine, reduces the heating demand temperature in the living room to 19 °C, but assumes the same heating hours as BREDEM. This adjustment resulted in a good fit to the electricity and gas consumption data published by DECC (Lee et al.,

2014). A recent study by Huebner et al. (2013), which analysed national survey data, suggested the heating demand temperature in the living room should be 19.5 °C, and the heating periods should be 10 hours for both weekdays and weekends. A recent study by Kane et al. (2015) analysed heating patterns in 249 dwellings in Leicester UK, highlighting the diverse heating hours and temperatures in UK homes. It was found that among all the homes with central heating, about half were heated for two periods each day for a total of 10 hours (median heating time 06:00 – 09:00 and 15:00 – 22:00). One third of them were heated for only one period per day but for a longer period of 15 hours (median heating time 07:00 – 23:00). In addition, a small proportion of homes (5%) were heated for multiple periods. A large variation in mean achieved temperatures was also observed in the study, ranging from 11.0 °C to 30.5 °C with an average mean achieved temperature of 20.9 °C (Kane et al., 2015).

## METHODS

This study uses a stochastic occupancy model to generate heating patterns, with the aim of reflecting the variability of heating patterns in UK homes described in the previous section. This is done by assuming that the heating is on and demand temperature is achieved whenever there is an active occupant (i.e. not asleep) at home. This assumption is adequate for modelling modern houses that are well insulated and of lightweight construction. Extensions to other house types will be discussed later. The demand temperatures are assumed to be 19.5 °C in the living room and 18 °C in bedrooms, in line with findings from Huebner et al. (2013). The heating periods are coincident with the actively occupied periods derived from the occupancy model. These data are fed into the dynamic housing stock model (He et al., 2014) for simulating hourly thermal demands.

### **A dynamic housing stock model**

A dynamic housing stock model was developed to estimate the baseline energy demand of the existing housing stock in the North East region of England, as well as to predict the reduction in energy demand and associated CO<sub>2</sub> emissions when applying different retrofit measures to the existing housing stock (He et al., 2014). This model has also been used in a study to identify the most cost-effective combinations of all measures across the housing stock by embedding a multi-objective optimization package into the process for making decisions on retrofit solutions (He et al., 2015). The model takes house details from the dataset used by the 2011 version of the Cambridge Housing Model (CHM) (Hughes et al, 2013). This dataset was in turn derived from English Housing Survey (EHS) (DCLG, 2010) data. The CHM dataset contains detailed information such as age band, dwelling type, floor area, window area, wall, roof, floor construction and loft insulation, etc. of 16,150

representative houses in England. However, additional information, such as width and depth, that allows the building form of the dwellings to be accurately modelled, can only be found in the EHS data. The 2011 version of the CHM was chosen because it contains an explicit link to the EHS data, thus allowing such details to be used, and this link is lacking in later versions.

The dataset so formed is coupled to EnergyPlus building simulation software (Crawley et al., 2000). EnergyPlus takes an input data file (IDF), in which a building model is specified, to run a dynamic simulation of a building. In order to automate the transformation process, an in-house program called the Building Generation Tool (BGT) was developed and implemented in programming language C#. It takes text file inputs from EHS data and generates IDFs for houses of interest. The detailed description of the model and the validation against a steady state housing stock model can be found in a previous study (He et al., 2014). A parametric tool called jEPlus (Zhang, 2009) has been used in this study to run simulations in EnergyPlus in parallel and to extract outputs. Python scripts have been written to process and visualise the outputs automatically.

### **A stochastic occupancy model**

A stochastic occupancy model developed by Richardson et al. (2008) based upon the UK 2000 Time-Use Survey (TUS) data set was used in this study. The UK 2000 TUS was a large survey conducted in the year 2000 on how people use their time (Ipsos-RSL and Office of National Statistics, 2000). It contains detailed 24-hour diaries, completed at ten-minute resolution by many thousands of participants (Richardson et al., 2008). The TUS data set was used to derive the transition probability matrices for the prediction of how likely the current stage will be changed in the next time step. The model can then apply the first-order Markov-Chain technique (Gamerman, 1997) to generate synthetic occupancy data based on these probabilities.

Households are categorised in the model by number of people. A weekday and a weekend profile are generated for a household. The aggregate weekday and weekend profiles from this model are almost identical to the TUS data (Richardson et al., 2008), showing that the model has been implemented accurately.

An implementation of the model of Richardson et al. (2008) in the form of a Microsoft Excel workbook, available for free download (Richardson and Thomson, 2008), to provide occupancy profiles for individual households is adopted in this study to generate thousands of occupancy profiles for households with different numbers of occupants. Python scripts have been used to process the occupancy profiles automatically into a format that can be interpreted by the BGT, and consequently can be written into the IDFs and simulated in EnergyPlus.

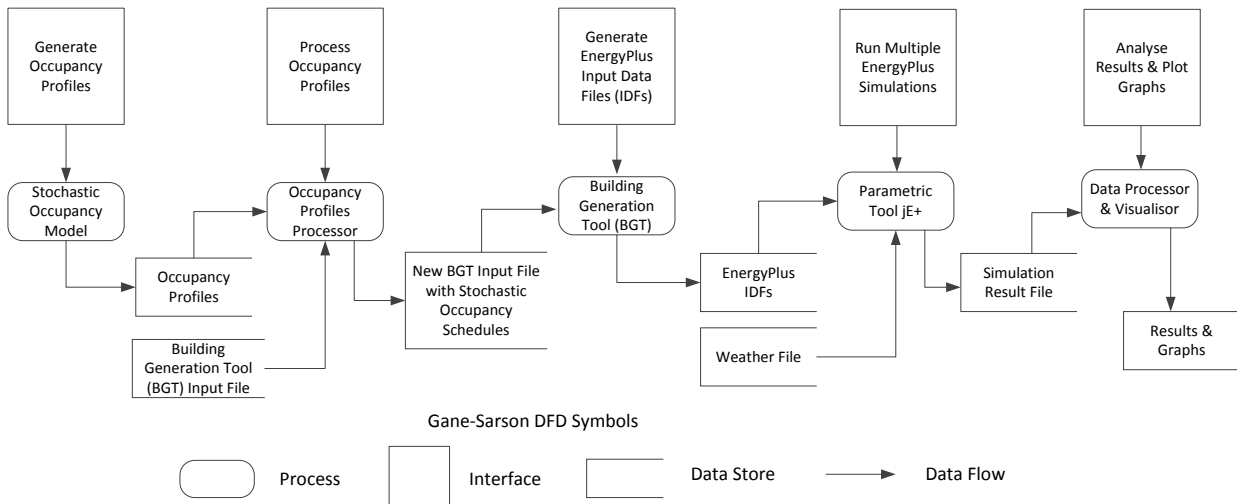


Figure 1 Gane-Sarson data flow diagram (DFD) of the integration framework.

### Integration framework

An integration framework has been developed to facilitate the coupling of the stochastic occupancy model into the dynamic housing stock model. The Gane-Sarson data flow diagram of the integration framework is shown in Figure 1.

This framework automates most parts of the process, and consequently enables large number of cases to be run and large quantities of data to be analysed efficiently and effectively.

## RESULTS AND DISCUSSION

### Number of occupancy profiles

Figure 2 and Figure 3 show 5 different occupancy profiles generated by the occupancy model for a household with 2 people for a weekday and weekend, respectively.

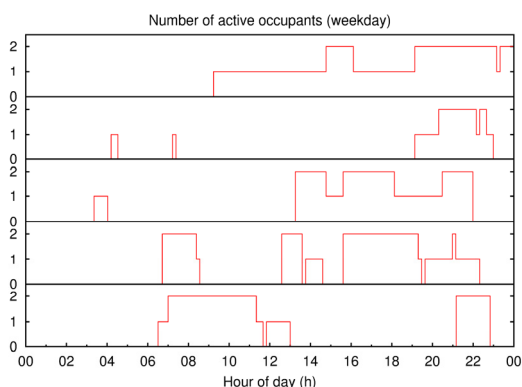


Figure 2 Occupancy profiles for a weekday.

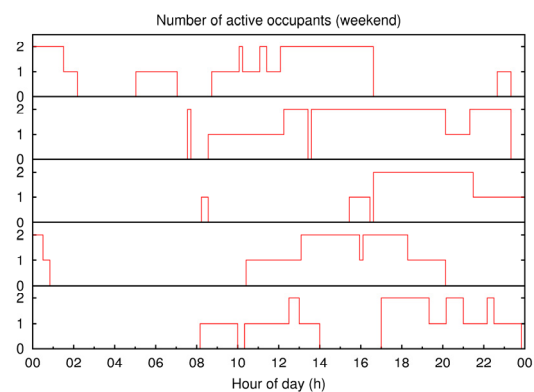


Figure 3 Occupancy profiles for a weekend.

Assuming that the heating is operating during these actively occupied periods according to the set-point temperatures described earlier, these occupancy profiles can be used to generate heating patterns that can be fed into the dynamic housing stock model. For the same dwelling, each occupancy profile results in different thermal demand when simulated in building energy simulation tool such as EnergyPlus. Figure 4 shows the thermal demand for the same house with the 5 different occupancy profiles generated above for a weekday. The thermal demand for the same house varies significantly with each of the occupancy profiles, and therefore, it is difficult to identify a typical profile. One way is to take the mean values after aggregating the thermal demands corresponding to different occupancy profiles.

Figure 5 shows the mean values of the aggregated thermal demand of the house with the same 5 different occupancy profiles as discussed above. Comparing the thermal demand in Figure 5 to Figure 4, it is clear the peak values in Figure 5 are much lower than the peak values in Figure 4, which suggests that the mean values of the aggregated thermal demand has lower peaks than the thermal

demand with individual occupancy profiles. This is a well-known phenomenon in the gas industry because pipes must be sized according to peak flows, which vary relative to the mean flow according to the number of households supplied. This effect would have a big impact when designing district/communal heating systems, especially if technologies such as heat pumps are used, where the thermal dynamics plays an important role in designing and controlling the systems (He et al., 2011).

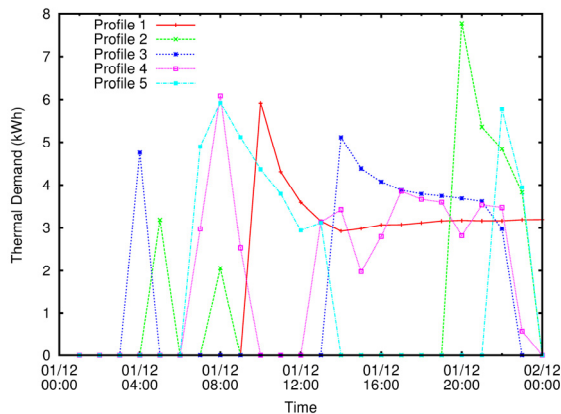


Figure 4 Thermal demand of a house with 5 different occupancy profiles.

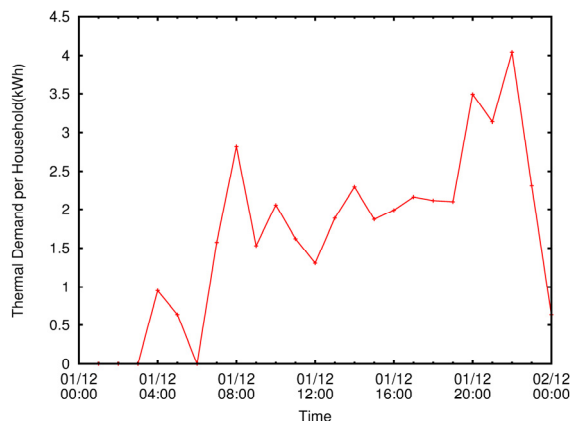


Figure 5 The mean values of the aggregated thermal demand with 5 different occupancy profiles.

Figure 6 shows the mean values of the aggregating thermal demand of the same house with 5, 10, 50, 100, and 1000 profiles for a household with 2 people. When increasing the number of occupancy profiles from 5 to 10, 50 and 100, the mean values of the thermal demand change quite significantly with some of the peak values going higher and some lower. However, the mean values change little when the number of occupancy profiles is increased from 100 to 1000.

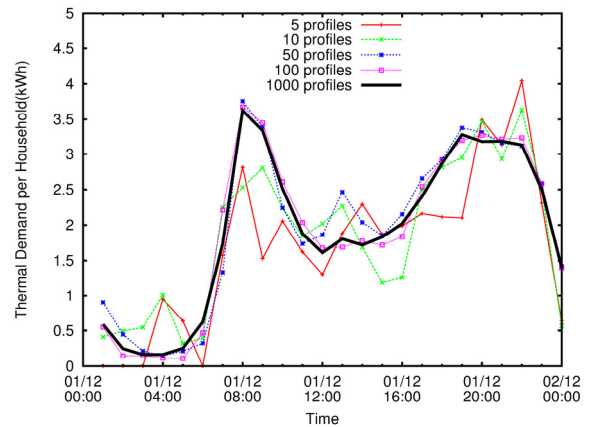


Figure 6 Mean values of the thermal demand of a house when aggregating different numbers of profiles.

### Number of people in a household

Number of people in a household is another factor that might influence the thermal demand of a house. Figure 7 shows the mean values of aggregated thermal demand of 100 profiles for household with different number of people in the same house.

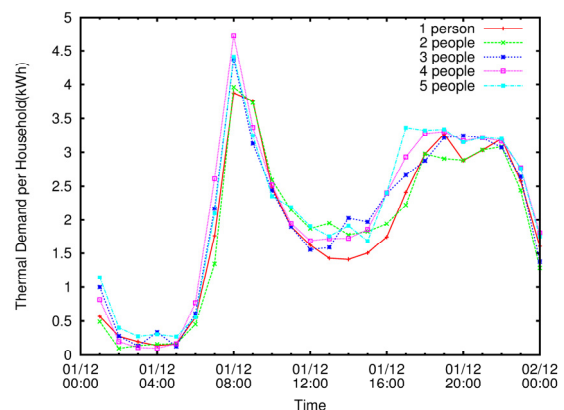


Figure 7 Mean values of aggregated thermal demand of 100 profiles for household with different number of people.

The thermal demand for a household with 1 – 5 people follow a similar pattern, i.e. minimum demand from 0:00 to 06:00; peak demand around 8:00; half of the peak demand from 11:00 to 17:00; three quarters of the peak demand from 18:00 to 23:00. However, the peak demand at around 8:00 varies slightly for the household with different number of people. Households with one and two people have similar peak demands, and so do those with three and five people. A household with 4 people has the highest peak demand. Between 12:00 to 18:00, a household that has more than one person seems to have a slightly higher demand, but the amount does not have a correlation to the number of people.



Figure 8 Plan view of the housing estate in the case study ([http://www.dwh.co.uk/new-homes/leicestershire/H550901-David-Wilson-at-Quorn/#prettyPhoto\[siteplan\]/0/](http://www.dwh.co.uk/new-homes/leicestershire/H550901-David-Wilson-at-Quorn/#prettyPhoto[siteplan]/0/)).

### A case study

A case study has been carried out to explore the potential of coupling a stochastic occupancy model to a dynamic housing stock model for the prediction of dynamic thermal demand of a neighbourhood. A housing estate with 125 new houses in a village near Loughborough, Leicestershire in the East Midlands of the UK was chosen for this case study. Figure 8 shows the plan view of the housing estate. This new development comprises 21 different styles of houses ranging from 2 to 5 bedrooms. There are 66 detached, 26 semi-detached, 17 mid-terrace and 16 end-terrace houses. All were built between 2012 and 2015 in line with the latest building regulations. The energy efficiency ratings of all houses are in band B. Table 1 shows a summary of one of the home’s energy performance related features on its Energy Performance Certificate.

Table 1 Summary of one of the homes’ energy performance related features on its Energy Performance Certificate.

ELEMENT	DESCRIPTION
Walls	Average U value = 0.25 W/m <sup>2</sup> K
Roof	Average U value = 0.14 W/m <sup>2</sup> K
Floor	Average U value = 0.16 W/m <sup>2</sup> K
Windows	High performance glazing
Main heating	Boiler and radiators, mains gas
Main heating controls	Time and temperature zone control
Hot water	From main system
Lighting	Low energy lighting in all fixed outlets
Air tightness	Air permeability 5.3 m <sup>3</sup> /h.m <sup>2</sup>

By assuming that the features in Table 1 apply to all houses and making use of data in the sales brochure, sufficient information, such as dwelling type,

dimensions and construction of walls, roof, floor and windows, can be converted into the inputs for the dynamic housing stock model. 125 occupancy profiles from the stochastic occupancy model have been used to derive the stochastic heating patterns, assuming the living room is heated to 19.5 °C and the bedrooms to 18.0 °C during actively occupied hours. Each of these heating patterns is randomly assigned to one individual dwelling. Consequently, all the dwellings with stochastic heating profiles can be simulated in EnergyPlus through the integration framework (Figure 1). For comparison purposes, another set of simulations of all dwelling with the same demand temperatures but standard heating hours (07:00 – 09:00 and 16:00 – 23:00 for weekdays; 07:00 – 23:00 for weekends) has been run. Figure 9 shows the results of hourly thermal demands predicted with stochastic heating profiles, compared to those by standard heating hours for a weekday (Friday 1 December, 01/12) followed by a weekend (02/12) in the design week.

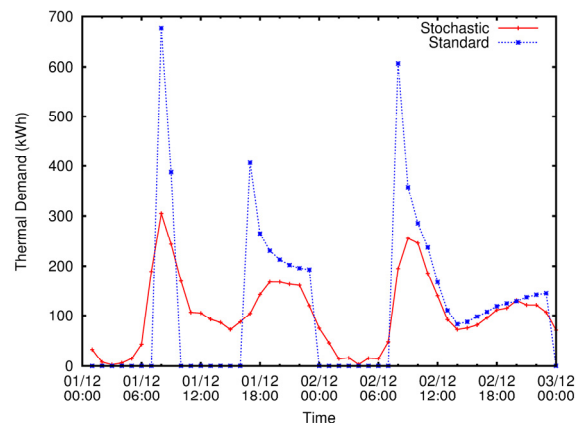


Figure 9 Hourly thermal demands for 125 houses predicted with stochastic heating hours compared to standard heating hours.

For the case with standard heating hours, due to the unified start and end times, high peaks occur at start times. This is not realistic as it is very unlikely that all 125 dwellings would be heated to 19.5 °C at the same start time. For the case with stochastic occupancy profiles, the peaks are much lower because the start times are more spread out. The thermal demand, as a result, is likely to be a more representative profile for all dwellings. More interesting perhaps is the situation at the weekend. For standard heating hours, the demand profile for a weekend is very different from that for a weekday due to the distinct heating hours assigned. For stochastic profiles, however, the thermal demand profiles for a weekday and a weekend are not that different. Both have a peak demand at about 07:00, drop to a plateau at around 12:00, and rise to a smaller peak at about 19:00. This similarity of weekday and weekend heating patterns is consistent with findings from other studies (Huebner et al, 2013; Kane et al, 2015).

Figure 10 shows the results of daily total thermal demands predicted with stochastic heating hours, compared to those by standard heating hours for the design week (01/12 – 07/12). Despite substantial differences in the hourly thermal demand profiles produced by stochastic occupancy profiles and standard heating hours as shown in Figure 9, the differences between daily total thermal demands during weekdays, i.e. 01/12, 04/12 – 07/12, are relatively small (less than 4%). Weekends, however, are different. The standard heating pattern results in about 20% higher daily total thermal demands, compared to those by stochastic heating hours (02/12 – 03/12). The finding is explained by the lengths of the heating periods. At 16 hours, the standard heating period is longer than the average period for the stochastic case.

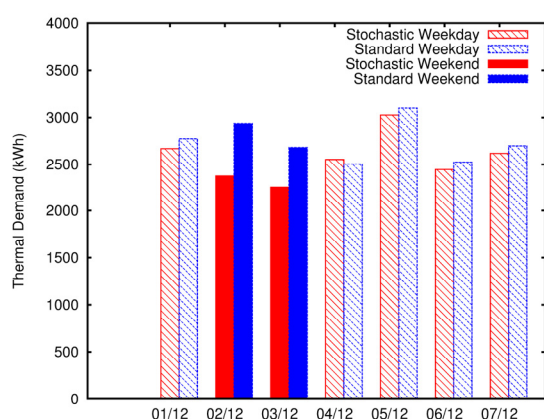


Figure 10 Daily total thermal demands predicted with stochastic heating hours compared to standard heating hours.

## CONCLUSIONS

This paper describes a novel method of coupling a stochastic occupancy model to a dynamic housing

stock model, in order to examine high-resolution temporal, e.g. hourly, thermal demands of a neighbourhood. The stochastic occupancy profiles generated by the model have been applied to derive stochastic heating hours. These, together with demand temperatures, are fed into the dynamic housing stock model that runs EnergyPlus simulations. This study concludes that the number of the stochastic occupancy profiles that are required to generate a general and perhaps more representative hourly thermal demand profile for a single dwelling is about 100. There is a small impact of the number of people in a household on hourly thermal demand profiles, mainly affecting the peak values, but all profiles for households with 1 – 5 people follow a similar pattern.

This approach has been further explored through a case study with 125 dwellings in a housing estate with new builds. It has been demonstrated that it is possible to gather enough data for a range of dwelling types through publicly available information to construct models efficiently for simulation in EnergyPlus. It has also been established that by coupling a stochastic occupancy model to generate stochastic heating hours for the dynamic housing stock model, it is possible to generate potentially more representative hourly thermal demand profiles for a neighbourhood than using standard heating hours. It was found that hourly thermal demand profiles for a weekday and a weekend are similar when incorporating stochastic heating hours, as opposed to the distinct profiles assumed by standard heating hours. This is consistent with studies carried out by other researchers. Moreover, despite the dramatic differences in hourly thermal demand profiles by stochastic and standard heating hours, the daily total thermal demands for all weekdays are similar. The larger differences in the daily total thermal demands for weekends are thought to be caused by overestimated heating hours in standard heating hours.

## FURTHER WORK

This novel approach to predict hourly thermal demands for a neighbourhood will be further explored. It has many applications, especially in the context of designing and integrating renewable/low-carbon heating technologies, as well as evaluating the implications for the energy network if in the future the thermal demands are shifted to electricity demands.

It was stated earlier that the current model assumes a heating system of infinite capacity, such that the air temperature of the heated space immediately rises to the set-point temperature. This is adequate for the modern homes that form the focus of the present work. However, it might not be accurate for simulating a large solid wall house, as it will take a long time (e.g. one or two hours) for the house to be heated to the demand temperature. The possibility

will be explored of modelling heating systems more accurately, by reducing the capacity to realistic levels, for example. This would have an impact on the energy use profile, with older houses possibly never reaching the set-point temperature during short heating periods; but more interestingly, this provides a vehicle for predicting the way users interact with the controls, e.g. setting the heating to come on earlier in order to reach to the set point temperature at the desired time.

In general, heating temperatures in UK homes vary substantially; however, it has been identified that the heated temperatures within homes differed significantly and systematically with the age of the household (Kane et al., 2015). This information can potentially be added to the current approach. Instead of having fixed heating set points for the living room and bedroom, varied set points that are linked to the age of the oldest person in the household can be further developed.

### ACKNOWLEDGEMENT

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### REFERENCES

- Anderson B.R., Chapman P.F., Cutland N.G., Dickson C.M., Doran S.M., Henderson G., Iles P.J., Kosmina L., Shorrocks L.D. 2002. BREDEM -8 Model Description: 2001 Updates, Building Research Establishment (BRE), Garston, and Department for Environment, Food and Rural Affairs (DEFRA), London.
- Crawley D.B, Lawrie L.K., Pedersen C.O., Winkelmann F.C. 2000. EnergyPlus: Energy simulation program. ASHRAE journal 42(4), pp. 49 – 56.
- Department for Communities and Local Government, 2010. English Housing Survey: Headline Report 2009-2010, Department for Communities and Local Government, London.
- Department of Energy and Climate Change, 2008. Climate Change Act 2008, The Stationary Office, London.
- Department of Energy and Climate Change, 2014. Energy Consumption in the UK. <https://www.gov.uk/government/statistics/energy-consumption-in-the-uk> (last accessed May 2015).
- Firth S.K., Lomas K., Wright A. 2010. Targeting household energy-efficiency measures using sensitivity analysis. Building Research & Information 38 (1), pp. 25 – 41.
- Gamerman D. 1997. Markov Chain Monte Carlo – Stochastic Simulation of Bayesian Inference, Chapman and Hall.
- He M., Lee T., Taylor S., Firth S.K., Lomas K. 2014. Dynamic modelling of a large scale retrofit programme for the housing stock in the North East of England. 2<sup>nd</sup> International Conference on Urban Sustainability and Resilience, London, UK.
- He M., Brownlee A., Lee T., Wright J., Taylor S. 2015. Multi-objective optimization for a large scale retrofit program for the housing stock in the North East of England. 6<sup>th</sup> International Building Physics Conference, Turin, Italy.
- He M., Rees S., Shao L. 2011. Simulation of a domestic ground source heat pump system using a three-dimensional numerical borehole heat exchanger model. Journal of Building Performance Simulation 4(2), pp. 141-155.
- Huebner G.M., McMichael M., Shipworth D., Shipworth M., Durand-Daubin M., Summerfield A. 2013. Heating patterns in English homes: Comparing results from a national survey against common model assumptions. Building and Environment. 70, pp. 298 – 305.
- Hughes M., Palmer J., Pope P. 2013. A Guide to the Cambridge Housing Model, Cambridge Architectural Research Limited.
- Ipsos-RSL and Office for National Statistics, United Kingdom Time Use Survey, 2000 (Computer File), third ed., UK Data Archive (distributor), Colchester, Essex, September 2003, SN: 4504.
- Kane T., Firth S.K., Lomas K.J. 2015. How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling. Energy and Buildings 86, pp. 817 – 832.
- Lee T., He M., Taylor S., Firth S.K., Lomas K. 2014. Developing a geographically detailed housing stock model for the North East of England. 2<sup>nd</sup> International Conference on Urban Sustainability and Resilience, London, UK.
- Natarajan S., Levermore G. J. 2007, Predicting future UK housing stock and carbon emissions, Energy Policy. 35, pp. 5719 – 5727.
- Orehounig K., Mavromatidis G., Evins R., Dorer V., and Garmeliet J. 2014. Towards an energy sustainable community: An energy system analysis for a village in Switzerland. Energy and Buildings 84, pp. 277 – 286.
- Ravetz J. 2008. State of the stock: what do we know about existing buildings and their future prospects? Energy Policy 36, pp. 4462 – 4470.
- Richardson I., Thomson M. 2008. Domestic active Occupancy Model – Simulation Example,

Loughborough University Institutional Repository, <http://hdl.handle.net/2134/3112>.

- Richardson I., Thomson M., and Infield D. 2008. A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings* 40, pp. 1560 – 1566.
- Shorrock L.D., Anderson B.R. 1995. A Guide to the Development of BREDEM, BRE Information Paper, Building Research Establishment, London.
- Simpson S., Jenkins D., and Patidar S. 2014. A local scale dynamic stock model for high resolution thermal demand. Building Simulation and Optimization Conference, UCL, London, UK.
- Taylor S., Allinson D., Lomas K. 2013. Dynamic energy modelling of UK housing: Evaluation of alternative approaches. 13<sup>th</sup> Conference of International Building Performance Simulation Association, Chambéry, France, pp. 745 – 751.
- Royal Academy of Engineering, 2010. Generating the Future: UK energy systems fit for 2050.
- Zhang Y. 2009. Parallel EnergyPlus and the development of a parametric analysis tool. Proc. Of the 11<sup>th</sup> IBPSA Conference, Glasgow, UK.