Proceedings of BS2015:
14th Conference of International Building Performance Simulation Association, Hyderabad, India, Dec. 7-9, 2015.

A NOVEL METHODOLOGY FOR GENERATING RESIDENTIAL BUILDINGS ELECTRICITY DEMAND PROFILES

Selin Yilmaz[1], Steven K. Firth[1] and David Allinson[1]
[1]London-Loughborough Centre for Doctoral Research in Energy Demand.
School of Civil and Building Engineering,
Loughborough University, Loughborough, Leicestershire. UK

ABSTRACT

This paper presents the initial development of a novel modelling framework of bottom-up stochastic model that is able to generate realistic electricity demand profiles for domestic appliance use that are based on measured data. Three appliances (washing machine, tumble dryer and dishwasher) are used to explain the model development. 100 homes are simulated for a month. The results of the model were analysed to address the key findings and challenges in modelling high-resolution electricity demand from measured data. It is shown that the model realistically reproduces electricity demand profiles for a large number of households.

INTRODUCTION

Background

This paper introduces a novel methodology on modelling high-resolution electricity demand profiles for domestic appliance use in residential buildings that are based on measured data. Due to the growth of electric end-uses, the estimates of the residential electricity demand profile is of great interest and has become essential issue for several reasons.

Firstly, the electricity demand profiles of houses or regions are important in the study of local energy systems and emerging technologies as the performance of these systems depends on these profiles. For example, the operation and optimum capacity of combined heat and power depends on the electricity demand (Wright and Firth, 2007). Household or region demand profiles are important in sizing and planning the design of renewable energy system (Yao and Steemers, 2005). Moreover, the performance of renewable energy systems such as on-site photovoltaic (PV) system highly depends on the household demand profile (Widén and Karlsson 2010). Secondly, the power demand profiles are also explored to better predict time variations of the demand and the peak power demand. This is important for analysing the impact of energy efficiency schemes or demand response to modify the network load flows after integration of renewable energy sources (Yamaguchi et al. 2011, Paatero and Lund, 2010). Another example is the application of an electric storage battery that absorbs the fluctuation in the electricity generated by photovoltaic cells that exceeds electricity demand (Fujimoto et al., 2011). Thirdly, the appliance usage profiles also become more influential on the building performance for low-carbon buildings due to heat gains from the appliances (Shimoda et al., 2004). Several models have been developed for modelling the electricity demand of households.

Existing electricity demand profile models

Two modelling approaches for household electricity consumption can be identified: top-down and bottom-up (Swan and Ugursal, 2009). The top-down modelling approaches regress or apply factors that affect consumption to attribute energy consumption characteristics of the residential sector (Baltagi, 2002; Muratori et al. 2013). These models are not concerned with individual end-uses. On the contrary, the bottom-up approach uses individual appliances and their power demand characteristic as basic for composing the energy consumption of an individual or group of households (Richardson et al., 2010). Modelling demand on a bottom-up basis allows user to modify and extend the simulations using the components of the model to evaluate the impact of different appliances, future technologies and different usage patterns as high level of detail (Capasso et al., 1994; Richardson et al., 2010; Widén et al. 2011).

Principally, a stochastic approach is taken to model the electricity demand profiles in order to include the randomness linked to the differences in occupant behaviour among households and the variation in time of each behaviour. Such energy patterns are represented in the models as probability distributions. The first work on stochastic domestic electricity demand model was made by Walker and Pokoski (1985) where they introduced availability functions and proclivity functions. A simple time-dependent home-activity model is presented by Capasso et al. (1994). Generally, stochastic process is created by either Markov-chain process with transition probabilities for switching between different states (Tanimoto and Hagishima, 2005; Widén and Wäckelgård. 2010) or fixed time steps where the initiation of the operational cycle of each domestic appliance are tested in Monte-Carlo style against hourly or minutely probability (Paatero and Lund, 2006; Gottwalt et al., 2011). For the latter, different distribution model such as Poisson, Gaussian mixed models are used to build the probability distributions. Studies that are based on first-order Markov-chains such as the work of Widén and Wäckelgård (2010) are not able to model coherently the duration distribution of activities as the transition probabilities do not depend on the time the activity was started (Wilké et al. 2012). Paatero and Lund (2006) and Gottwalt et al. (2011) used distribution that are based on Gaussian based to model the switching on of the appliances however, they selected fixed and predefined load cycles for different types of appliances. Therefore, these models lack of time-dependence of duration of appliance usage and different power demand for each appliance usage.

Both processes generate synthetic sequences of selected activities with parameters determined from different datasets. Modellers used different inputs to construct their models such as i) available statistical data, ii) measured appliance usage data and iii) Time Use datasets based on diaries reporting households' daily activities. Firstly, Capasso et al. (1994) employed distributions based on demographic surveys over family types and appliance ownership to generate appliance use profile. Gottwalt et al. (2011) used the corresponding statistical appliance data for Germany as input parameter to develop a bottom–up model to investigate the impact of smart appliances and variable prices on electricity bills of a household. Secondly, Paatero and Lund (2006) develop a bottom-up tool to artificially generate domestic electricity consumption time series that are well correlated with empirically measured reference data. Thirdly, there is a significant interest in activity-oriented electricity demand modelling where the overall electricity demand profiles are constructed by using Time Use datasets (Tanimoto et al., 2008; Richardson et al., 2010; Widén et al., 2012). The major drawback of the activity oriented approaches is that participants have to write down their daily activities each 10 or 15 minutes; therefore the switch on times cannot be identified precisely.

Purpose of the paper

The aim of this paper is to introduce a preliminary study on a household appliance usage model to simulate a high-resolution electricity demand profile of a household based on monitored electrical power demand data for a period.
The dataset used to develop modelling framework is the measurements carried out at the appliance level during The Household Electricity Use Survey", a large-scale national study of domestic appliance use funded by the UK Government in 2011 (DECC, 2013). Individual appliances monitoring also provides power demand characteristics of the appliances such as cycles, stand-by power which cannot be derived from time-use diaries. In this paper, first the probability distributions for the simulation model are introduced by discussing the three following points:
1) Determination of starting times of the appliances
2) Determination of distributions of the duration
3) Determination of power curves of the appliances
Secondly, stochastic generation method is used to simulate residential building electricity profiles. The model will simulate the appliance usage as a function of time. Thirdly, the simulation results of electricity demand calculated are compared on appliance level for validating the simulation. Based on these results, the efficiency of the model for the stochastic behaviour of aggregate electricity demand profiles is discussed. Finally, the application of this model for demand response studies is discussed.

METHODOLOGY

Overview of the model

Figure 1 shows the simulation procedure of the residential buildings electricity demand model. The model is implemented as a MATLAB script. The inputs of the model are i) probabilities of switching on of the appliances ($p_s(t)$) depending on the time of day, ii) frequency of usage of the appliance iii) the distributions of the duration and iv) the distribution of power curve of the appliance use. These data are obtained from "The Household Electricity Use Survey" funded by the UK Government based on their measurements carried out at the appliance level. The study monitored electrical power demand of over 5,000 individual appliances in 250 homes from May 2010 to July 2011.
The model first determines the switch-on times of the appliances by using the measured appliance database. The switch-on times represent the beginning of use of an appliance. The event occurs in time according to a Poisson process with parameter λ, derived from the empirical data. A modelling approach has been formulated where the switching on of each domestic appliance is tested against 2 minutely-adjusted probabilities. For simulating the switching on events of an appliance, the probability of "switch on" is used for each time step of the day, i.e. to each time step is associated a value between 0 and 1 corresponding to the probability of switching that appliance on at that time of day. A uniform random number in each time step is generated with the help of Matlab and the Poisson cumulative distribution function is used to deduce a value depending on the random variable. The appliance is switched on if the generated value is higher or equal to the given a set of 2-minute probabilities. If the appliance is switched on, the duration of its usage and the power at which the appliance is used are deduced from the corresponding distributions entered as an input. The next test is done only after completion of the usage of this appliance. If the appliance is not switched on, the test is again performed on each 2 minute time step.

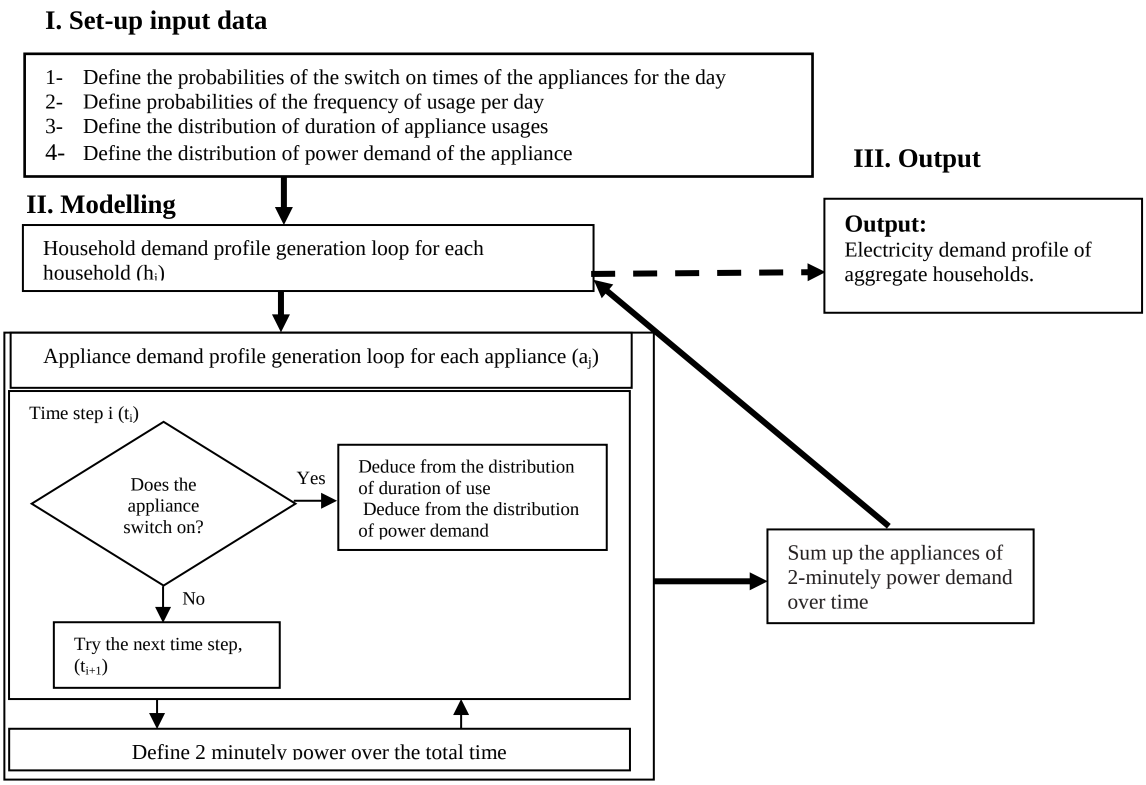

Figure 1 Diagram for the residential building electricity demand model

Preparation of probability distributions

Several surveys such as French time-use survey (February 1998 to February 1999) and United Kingdom Time Use Survey (from June 2000 to September 2001) that were used to develop the daily probabilities of switch on of appliances were only based one day or one weekday/weekend (two days in total) surveys (Richardson et al. 2010; Wilké et al. 2013). Therefore, these studies defined the probabilities of switch on of appliances on average daily profiles rather than weekly or monthly. For this study, weekly probability profiles are defined for each appliance as the monitoring was done at least a month.

For each time step, the input value would be the sum of measured "switches on" observed divided by the total number of time steps of days. Each time step of a day is associated a value between 0 and 1 corresponding to the probability of switching that appliance on at that time of day. Probability at time step (i) is calculated as such:

$$p = \frac{number\ of\ events\ that\ the\ appliance\ was\ switched\ on}{number\ of\ observations * total\ time\ steps\ of\ the\ week} \quad (1)$$

Weekly probability profiles of switch-on times for appliances with cycles (washing machines, tumble dryers and dishwashers) are shown in Figure 2.

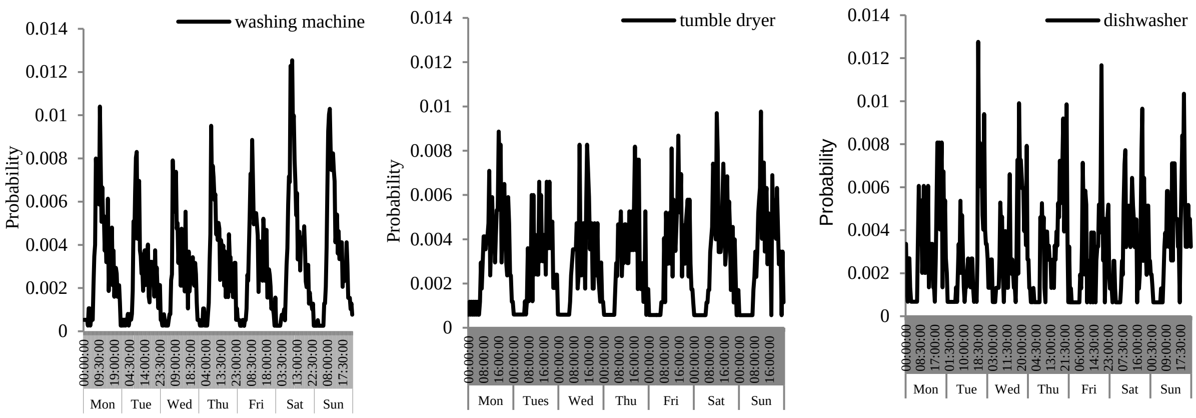

Figure 2 Weekly probability profiles of switch-on times for washing machines, tumble dryers and dishwashers

The switch on probabilities are developed for half-hourly averages to reduce the scarcity issues (especially for night times since the probabilities are sometimes zero). However, the resolution of the model is 2 minutes. For several appliances such as washing machines or dishwashers, it is possible that these appliances are not used for some days and on other days it is used twice or even three times. The frequency of the usage (event rate) is determined by the parameter λ of Poisson process, derived from the empirical data. Table 1 shows the analysis of the frequency of usage of appliances with cycles of the HEUS data.

Table 1 Analysis of the frequency of appliance usage for households monitored in the Household Electricity Use Survey

	WEEKLY CYCLE FREQUENCY (CYCLES/WEEK)		
Appliance	**Mean**	**Min**	**Max**
Washing machines	5.6	0	24.5
Tumble dryers	4.2	0	23.1
Dishwasher	4.2	0	11.2

Once the switch-on times are determined and the appliance starts, the corresponding duration of the appliance cycle or the activity is deduced from the distribution of durations determined for the appliance. Commonly used life distributions include the Poisson, lognormal and Weibull distributions. However, the goodness-of-fit tests (chi-square) show that the distribution of duration of the HEUS dataset does not fit into these parametric distributions. A kernel distribution is used to produce a non-parametric probability density function that adapts itself to the data, rather than selecting a density with a particular parametric form and estimating the parameters (Figure 3). Duration of the cycles or the activity is simulated at each usage. For activities such as TV watching, ironing, the duration depends on the occupant's behaviour therefore this could change any usage. For cycles, the duration of the cycle could also be different for each usage because different programmes can be used affecting the duration of the washing machine cycle.

To define the distribution of durations, the appliances are categorized as i) duration of the activity/cycle that do not depend on time of the day and ii) duration of the activity that depends on the time of the day. Appliances with cycles such as washing machines, tumble dryers etc. belongs to the first categorisation. Two sample t-test is performed for these appliances and found that the difference between the durations of the cycle switched on different hours on the day is not statistically significant (t-test, $p<0.05$). For these appliances, one distribution function is fitted based on the empirical durations.

Figure 4 shows the distribution of TV duration for different hours. From the data set, it was observed that the duration varies depending on the times of the day. Again, two sample t-test is performed to see difference between durations of TV started at different hours of the day.

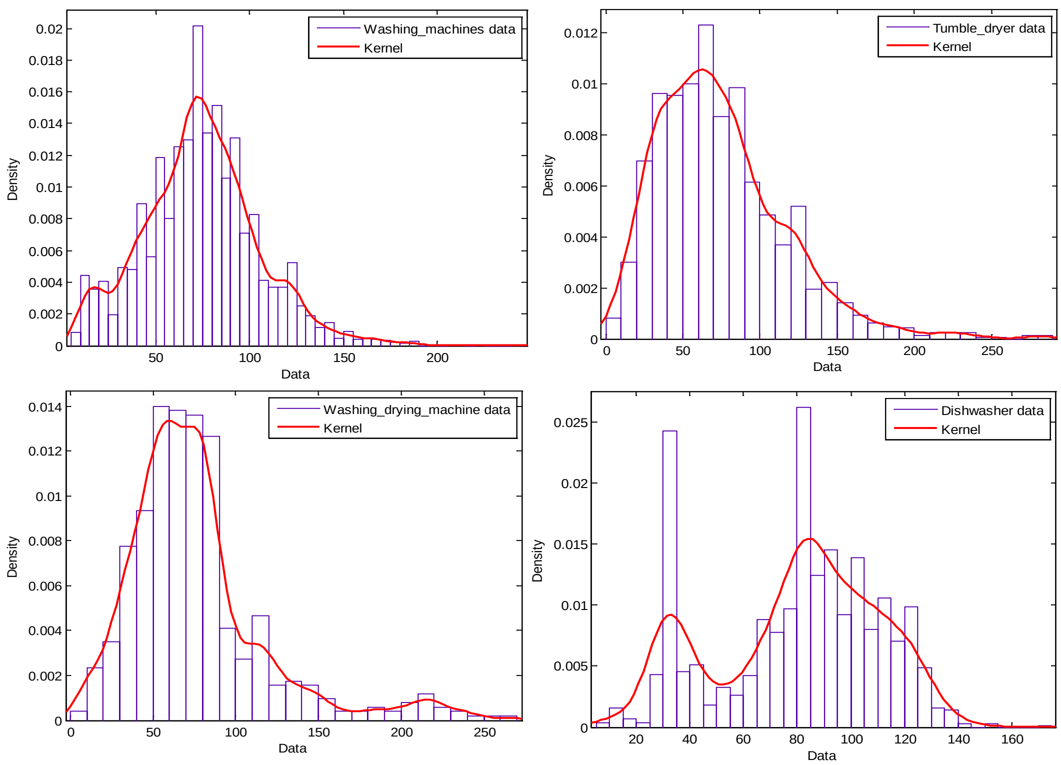

Figure 3 The empirical PDFs of durations of appliances with cycles with the fitted Kernel distribution

Two sample t-test shows that the difference between the durations for morning, afternoon and evening hours is statistically significant ($p<0.05$). Therefore for simulating the TV duration, three PDF have been fitted, based on the empirical duration distributions of all events where TV is switched on in the corresponding time interval.

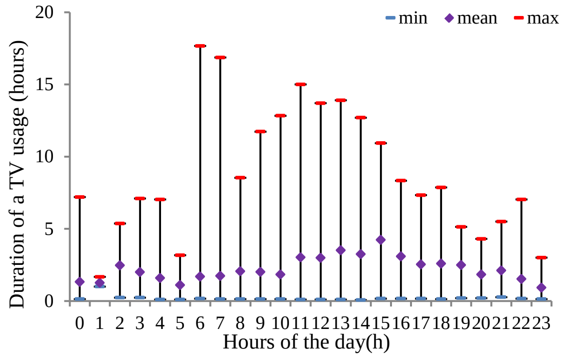

Figure 4 Durations of TV usages (minimum, mean and maximum values) that are started in the time interval (on the x-axis) (n=225 household, 12,738 observed TV usage)

Once the activity starts, another quantity to deduce from the distributions is the power demand of the appliance. The appliances are categorized into two: i) power demand of the appliance usage is simulated at each usage and ii) power demand of the appliance is simulated only once for the household. The first category includes the washing machines, tumble dryers as the power demand of the usage may differ depending on the programmes that the occupant may choose or the amount of clothes. However, for the second category which includes TVs, DVD player and other ICT equipment, power demand of the appliance is same for each usage, therefore it is simulated once for each household.

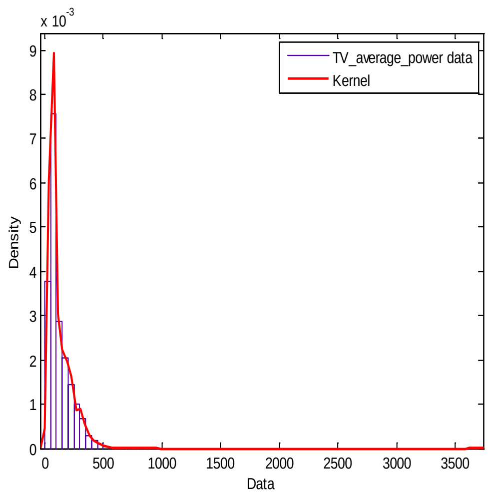

Figure 5 The empirical PDFs of average power of TVs with the fitted Kernel distribution

Validation of the model

The performance of the model is validated through a comparison analysis. Often, the performance of the models were compared on the building level or for aggregate populations (Paaetero and Lund, 2006; Wilké et al. 2013). The performance of existing models has not been evaluated in appliance level which is crucial for a robust bottom-up approach. In this paper, the performance is compared at an individual appliance level. Two comparisons are shown; the first compares the estimated probability profile of switch on appliances (dishwasher as an example) with the measured profile and second compares the estimated electricity demand with a time series of actual electricity demand.

RESULT AND DISCUSSIONS

Using the model described above, electricity demand profiles of 100 households with appliances with cycles have been generated for continuous 28 days (4 weeks) by applying the procedure in Figure 1. The simulation results have been generated by taking the average values of 100 simulation runs. The probabilities of switching of the dishwashers of simulated and measured dishwasher usage are compared in Figure 6. The probability of switch on of dishwashers are more or less evenly scattered over the time steps of an average day.

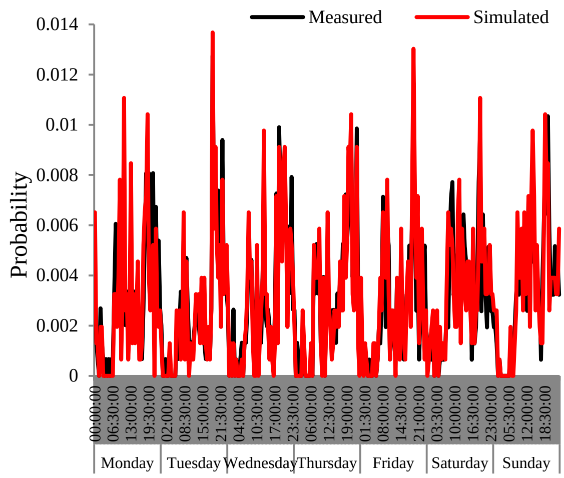

Figure 6 Half hourly (30 minutes) probability of switching on a dishwasher of a week (in black the measured profile entered, in red the profile resulting from 100 simulated homes for 28 days)

Figure 7 shows the box plots of weekly number of usages of dishwashers of 100 homes simulated for a month versus the measured value of HEUS dataset. As can be seen from Figure 7, the number of usages of the simulated houses were in the range of the measured values.

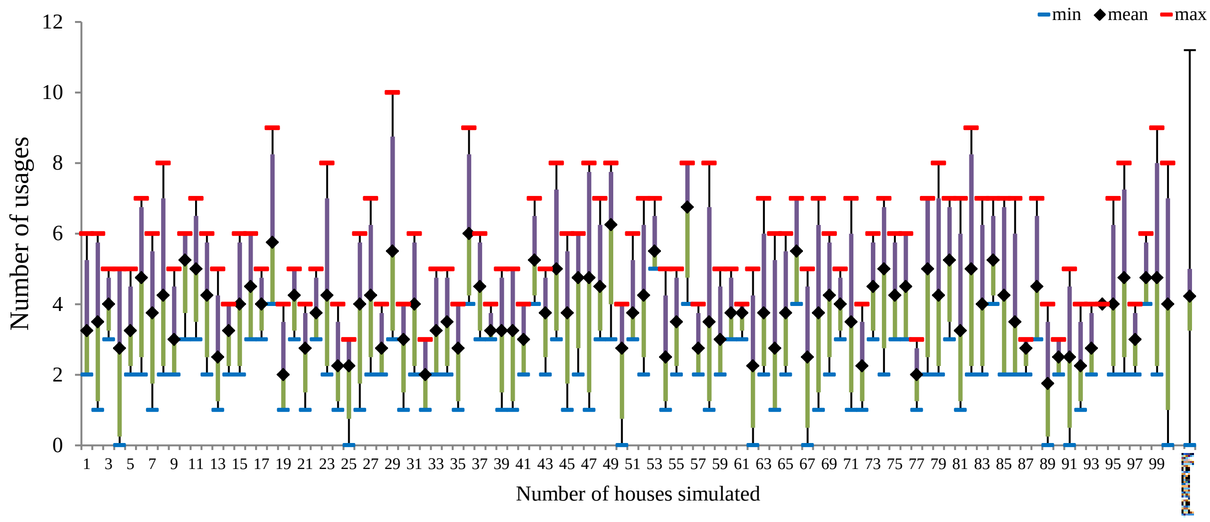

Figure 7 Box plot of number of usage of dishwashers in a week simulated for 100 homes and the measured value (HEUS data)

Table 2 shows the number of usage of the appliances with cycles in a week for the 100 simulated homes.

Table 2 Analysis of the weekly number of usages of appliances with cycles for 100 homes simulated

	SIMULATED WEEKLY CYCLE FREQUENCY (CYCLES/WEEK)		
Appliance	**Mean**	**Min**	**Max**
Washing machines	5.3	0	12
Tumble dryers	4	0	11
Dishwasher	3.4	0	10

When the simulation results are compared with the actual data presented in Table 1, it was found that model predicted closely to the minimum and the maximum number of usages per week. However, maximum values for washing machines and tumble dryers were predicted significantly less than the actual data. The reason for this is, in the HEUS dataset one of the monitored houses have used the washing machine and the tumble dryer extremely high compared to other 225 homes.

Figure 9 compares the mean half hourly power demand of the dishwashers for 86 households (HEUS dataset) and 100 simulated households versus times of the day. The peak demand values were estimated reasonably well; however there are variations between the power peak demands in the mornings.

One of the drawbacks of the model is that it does not account for the seasonality factor as the 2-minutely measured households were monitored only for a month. To solve this issue, the authors are analysing the yearly measurements of appliance electricity consumption of 26 homes at 10-min intervals to integrate the seasonality factor. However, dishwasher data of 26 homes were analysed and showed no seasonality factor therefore the only results of dishwasher are presented in this paper.

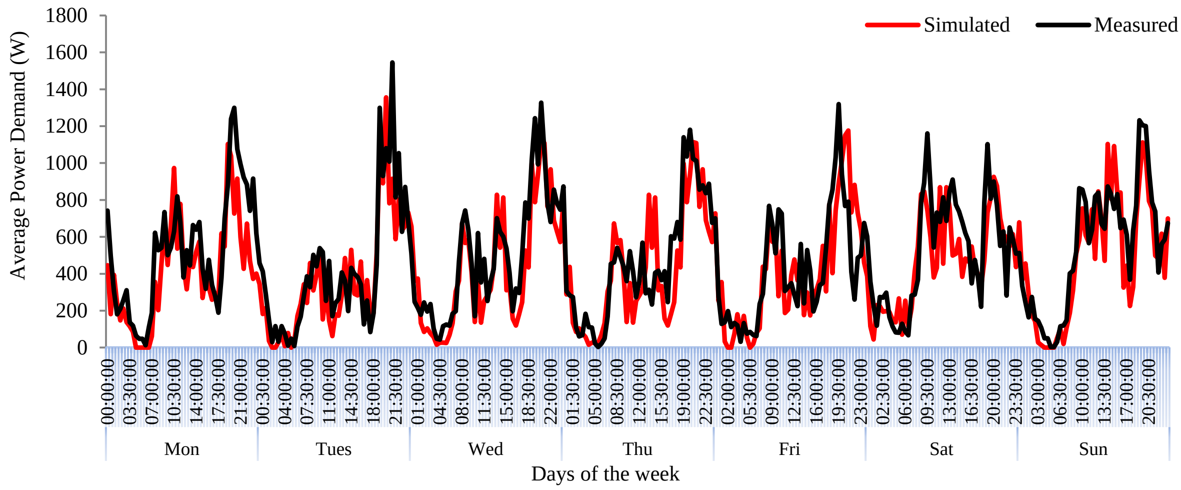

Figure 8 Comparison of the mean half hourly power demand of the dishwashers for 86 households(HEUS dataset) and 100 simulated households versus times of the day (Mean power demand for each half hour time is calculated by dividing the sum of power demand by the count the number of records of that time in the dataset)

The model that is presented in this paper can be used to study demand response. Stochastic approach has the strength compared to other models by allowing the representation of random variation in individual dwellings. For demand response studies, since not every household would respond to the price signals, only some portion of that might respond and it has to be determined stochastically. For instance, when modelling the demand shifting stochastically, as it is the probabilities that change, the chance of action that the dishwasher or washing machine is switched on for the cheap time or the expensive time slot according to the price signals is increased or decreased. This approach gives a diverse demand response which again ensures a realistic stochastic behaviour of the model. The model that is presented in this paper can be integrated into dynamic building simulation tools to study heat gains from the appliances which could help studies for zero energy buildings.

CONCLUSION

This paper introduces a preliminary study on a household appliance usage model to simulate a high-resolution electricity demand profile of a household based on monitored electrical power demand data for a period. Defining the probabilities of the appliances with cycles (washing machines, tumble dryers, washing drying machines and dishwashers) as examples from the Household Electricity Use Survey (HEUS) dataset is presented in terms of switch-on times, duration, power curve and frequency of usage for the stochastic model.

The analysis shows:

- The probability of appliance switch-on events depends on the time of the day. Therefore, the time-dependent switch on probabilities are considered. The switch on times of the appliance and the frequency of the usage depend on the days of the week.
- Due to data scarcity (less observations of events happening in the night time), the switch on times had to be calculated for average half hourly.
- The duration of the appliances with cycles (washing machines, tumble dryers and dishwashers) does not differ greatly depending on the time it is started whereas the duration of TV usage strongly depend on the times of the day it is started. For TVs, PDFs have been fitted in the corresponding time interval. For the appliances with cycles PDFs have been fitted based on the empirical duration distributions regardless of the time interval.
- The power consumption of washing machine cycles could be different each time it is used; however there is much less difference in the power demand of TV and dishwasher each time it is used.

The modelling framework demonstrates accounts for all of observations above. Electricity demand profiles of 100 households with appliance with cycles have been generated for continuous 28 days (4 weeks). The comparisons between the switch on probabilities and the electricity demand profiles of the measured data (HEUS) and 100 simulated homes show that model does reasonably well. The application of this method to other home appliances such as cooking appliances and ICT equipment and improvement of the appliance model are our future work.

ACKNOWLEDGMENTS

This research was made possible by Engineering and Physical Sciences Research Council (EPSRC) support for the London-Loughborough Centre for Doctoral Research in Energy Demand (Grant EP/H009612/1). Household Electricity Use Survey data acquisition was coordinated by the Department of Energy and Climate Change of United Kingdom.

NOMENCLATURE

p= The switch on probability of an appliance at the time step.

REFERENCES

Baltagi, B. (2002). Comparison of forecast performance for homogeneous, heterogeneous and shrinkage estimators: Some empirical evidence from US electricity and natural-gas consumption. Economics Letters. Vol. 76(3), pp. 375–382.

Capasso, A., Grattier, W., Lamedica, R., Prudenzi, A. (1994). A bottom-up approach to residential load modelling. *IEEE Transactions on Power Systems*. Vol. 9(2), pp. 957–964.

DECC (2013). Household Electricity Survey. Department of Energy and Climate Change. Available from: http://goo.gl/n0MH0A. Accessed on the 5th October 2014.

European Communities (2005), Comparable time use statistics: National tables from 10 European countries. Available from: http://goo.gl/jW33Eo. Accessed on the 24th April 2015.

Fujimoto, T., Yamaguchi, Y., Shimoda, Y. (2011). Household Electricity Simulation : Demand , the Electricity Generation and Demand-Supply Control Methods. In: Proceedings of 12th Conference of International Building Performance Simulation Association, Sydney, Australia, pp.996-1003.

Gottwalt, S., Ketter W., Block, C., Collins J., Weinhardt, C. (2011). Demand side management—A simulation of household behavior under variable prices. *Energy Policy*. Vol. 39, pp. 8163–8174.

Muratori, M., Roberts, M.C., Sioshansi, R., Marano, V., Rizzoni, G. (2013). A Highly Resolved Modeling Technique to Simulate Residential Power Demand. *Applied Energy Volume.* Vol 107, pp. 465–473.

Paatero, J.V., Lund, P.D. (2006). A model for generating household electricity load profiles. International Journal of Energy Research. Vol. 30 (5), pp. 273–290

Richardson, I, Thomson, M., Infield, D., Clifford, C. (2010). Domestic electricity use: A high-resolution energy demand model," Energy and Buildings. Vol. 42(10), pp. 1878-1887.

Shimoda, Y., Fujii, T., Morikawa, T., Mizuno, M. (2004). Residential end-use energy simulation at city scale. Build Environment. Vol. 39(8), pp. 959-967

Swan, L. G., Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modelling techniques. *Renewable and Sustainable Energy Reviews*. Vol. 13, pp. 1819–1835.

Tanimoto, J., Hagishima, A. (2005). State transition probability for the Markov Model dealing with on/off cooling schedule in dwellings. Energy and Buildings. Vol. (37), pp. 181–187.

Tanimoto, J., Hagishima, A., Sagara, A. (2008). Total utility demand prediction system for dwellings based on stochastic processes of actual inhabitants. Journal of Building Performance Simulation. Vol. 3(2), pp. 155-167.

Walker, C.F., Pokoski, J.L. (1985). Residential load shape modeling based on customer behavior. IEEE Transaction on Power Apparatus and Systems. Vol. 104(7), pp. 1703–1711.

Widén, J., Wäckelgård, E., (2010). A high-resolution stochastic model of domestic activity patterns and electricity demand. Applied Energy. Vol. 87(6), pp. 1880-1892.

Widén, J., Karlsson, B. (2010). End-user value of on-site domestic photovoltaic generation with different metering options in Sweden. In: Proceedings of Eurosun, Graz, Austria. pp.1-6.

Widén, J., Molin, A., Ellegård, K. (2011). Models of domestic occupancy, activities and energy use based on time-use data: deterministic and stochastic approaches with application to various building-related simulations. Journal of Building Performance Simulation. Vol. 5(1), pp.27-44.

Widén, J., Molin, A., Ellegård, K. (2012). Models of domestic occupancy, activities and energy use based on time-use data: deterministic and stochastic approaches with application to various building-related simulations. Journal of Building Performance Simulation. Vol. 5(1), pp. 27-44.

Wilké, U., Haldi, F., Scartezzini, J.L, Robinson, D. (2013). A bottom-up stochastic model to predict building occupants' time-dependent activities. Building and Environment. Vol. 60, pp. 254-264.

Wright, A., Firth, S. (2007). The nature of domestic electricity-loads and effects of time averaging on statistics and on-site generation calculations. *Applied Energy*. Vol. 84(4), pp. 389-403.

Yamaguchi, Y., Fujimoto, T., Shimoda, Y. (2011). Occupant behavior model for households to estimate high-temporal resolution residential electricity demand profile. In: Proceedings of 12th Conference of International Building Performance Simulation Association, Sydney, Australia, pp.1548-1555.

Yao, R., Steemers, K. (2005). A method of formulating energy load profile for domestic buildings in the UK. Energy and Buildings. Vol. 37(6), pp. 663–671.