HIGH RESOLUTION SPACE - TIME DATA:
METHODOLOGY FOR RESIDENTIAL BUILDING SIMULATION MODELLING

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ABSTRACT

A bottom-up approach is developed for the specification of operational data with a high space-time resolution, to be used as inputs in multi-zone residential building models. These archetype models will be used to analyse demand modulation of total domestic electricity consumption, thus requiring a detailed knowledge of domestic loads. The approach is based on national Time-Use Survey (TUS) resident activity data. To illustrate the approach, the EnergyPlus simulation platform is used to model a multi-zone case study building. Occupancy profiles, lighting load and disaggregated electrical appliance load profiles, as well as their associated heat gains, are generated and spatially mapped within the building. A good match is seen between synthesised and measured profiles. A greater sharing of electrical appliances, as the household size increases, is also seen. Fifteen-minute resolution of the model outputs is found to be sensible in the context of the current project, due to aggregation.

INTRODUCTION

Recent advances in control, communications, and metering technologies are key factors in the on-going evolution of the "smart-grid" and, as acknowledged by Strbac (2008), are key drivers to the introduction of demand modulation strategies. The U.S. DOE (2011) recognizes that the integration of renewable energy sources, particularly wind and solar generation, with their variable and uncertain nature, require more flexibility from the power system. One possible strategy is to utilize the flexibility offered by the electrical demand side. However, quantification of this potential, especially for residential buildings, leads to several challenging issues: the wide range of electricity usage patterns, the variability of electrical loads and the uncertainty regarding human behaviour. Furthermore, stricter energy efficiency regulations, the integration of new load types and the increasing electrification of space and water heating loads, challenge the assessment of the associated flexible load resource capacity.

In such a complex context, Richardson et al. (2008) note that analysis of the demand modulation of domestic electricity consumption requires detailed and "accurate knowledge of household consumer loads". Dineen and Ó Gallachóir (2011) classify building electricity demand models according to two approaches: "top-down" and "bottom-up" models. Paatero and Lund (2006) argue that top-down models are more suitable for demand forecasting at a utility level, as they require less detail about the electricity demand at the building level. On the other hand, by aggregating individual end-use loads or groups of end-use loads, bottom-up approaches are capable of generating very detailed electricity demand profiles. However, these models are complex and data intensive, while the quality and resolution of the outputs are highly dependent on the level of detail and the quality of the supportive datasets used to develop the inputs (Paatero and Lund, 2006). In recent years, several bottom-up building energy models have been developed to study domestic loads at a high time resolution. These models allow stochastic individual daily occupancy patterns (e.g. Richardson et al., 2008; Widén et al., 2009b), daily lighting demand profiles (e.g. Richardson et al., 2009; Widén et al., 2009a), and daily electricity demand profiles (e.g. Richardson et al., 2010; Widén and Wäckelgård, 2010) to be generated at the building level. Most approaches utilise TUS data, as a starting point, to extract the behavioural patterns of household members.

The present paper contributes to the literature by extending energy models to physical building energy simulation (BES) models in order to estimate the potential resource and the impact of any demand modulation scheme, while considering the thermal behaviour of buildings and occupant comfort as the main operational constraints. These novel constraints increase the space resolution requirement of the model inputs but are necessary when modulating domestic loads. Building simulation offers the opportunity to integrate all the required parameters: building physical properties, internal heat gains, natural ventilation, space and water heating systems, weather, control systems and control strategies.

Hence, a bottom-up approach is developed for the specification of operational data with a high space-time resolution, to be used as inputs in multi-zone residential building models. Each individual building model has been designed as being representative of a group of similar buildings. Focus is placed on the modelling challenges, the required space-time
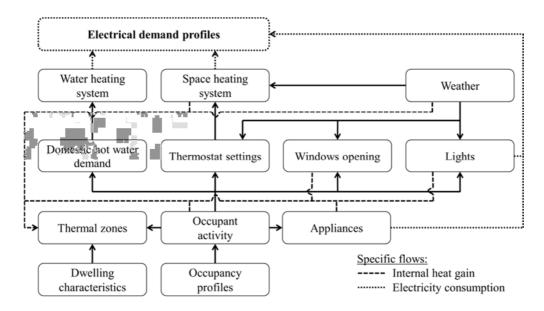
Figure 1: Bottom-up structure of building model

resolution of the model outputs, and a suitable methodology is then presented. The support TUS resident activity data and the reference real metered data are detailed. To illustrate the approach, a multi-zone case-study building model is developed, based on Irish data. Occupancy profiles are generated at fifteen-minute time resolution and disaggregated electrical appliance load and lighting load profiles at one-minute time resolution. The associated heat gains are determined and spatially mapped within the case-study building model. The synthesised data is discussed and compared with real data.

METHODOLOGY

Modelling approach overview

Figure 1 gives an overview of the full bottom-up structure of the model utilised. Electrical loads within a dwelling are assumed to be time-space dependent and are coupled with detailed TUS resident activity, depending on the day of the week (weekday or weekend) and the household size. To illustrate the approach, the EnergyPlus simulation platform is used to model a multi-zone single-storey detached building. Markov Chain Monte Carlo (MCMC) techniques are applied to develop high time resolution and disaggregated residential appliance electricity use profiles, based on TUS data. Daily power consumption profiles, for different household sizes and for different day types, are quantitatively and qualitatively validated against metered data. Appliances and associated internal heat gains are spatially distributed within the different thermal zones of the model. Internal heat gains generated by the occupants are specified by extracting occupancy and activity profiles from the TUS dataset, and are combined with the metabolic rate associated with each activity. The spatial distribution of these heat gains is mapped by attributing one or several thermal zones to each possible activity. Finally, lighting

internal heat gains associated with each activity are specified by considering several variables: bulb efficacy, illuminance requirement, surface area of thermal zones, occupancy rates and daylight.

Support data

- Time-use dataset:

In 2005, a national Time-Use Survey (TUS) was conducted in Ireland by the ESRI (ESRI, 2005a). The released dataset (ESRI, 2005b) is based on results from analysis of 1,089 representative adult participants, distributed over 567 households. Surveyed household members completed two diaries, each over a 24-hour period, at a fifteen-minute time resolution: one diary for weekdays and the other for weekend days. Each participant detailed the activity undertaken, at home or away from home, for each time-step by choosing the most appropriate activity code from a list of 26 codes. Each surveyed resident could record up to four activities undertaken for the same time-step. Two main quality issues were observed in the original dataset: about a fifth of the diaries were missing (households with less diaries than the number of eligible residents); more than half of the diaries were incomplete. Consequently, all households for which some diaries were missing are excluded from the original dataset, thus reducing the number of available diaries to 843, as part of 397 different households, as detailed in Table 1.

Table 1: Dwelling categories from Irish TUS dataset

Residents per household	No. dwellings	No. diaries	Average no. adults
1	73	73	1.00
2	140	273	1.95
3	76	195	2.57
≥4	108	302	2.80
Total	**397**	**843**	**2.12**

- Smart metering electricity data:

In 2007, the Irish energy regulator CER, initiated the Smart Metering Project (SMP). As part of this project, the Electricity Customer Behaviour Trials (ECBTs) took place from January 2009 to December 2010, involving both residential (4,225) and commercial (485) buildings. The objective was to perform a representative analysis of the economic, technological and behavioural issues, benefits and impacts associated with the rollout of smart meters in Ireland. The electrical power (kW) was measured, at a thirty-minute time resolution, and collected, at a building level, during two distinct periods: a benchmark period during which business-as-usual electricity tariff and billing frequency conditions were applied (6 months); a test period during which different electricity tariff and billing frequency stimuli were applied to defined groups of buildings (1 year). The dataset was made publicly available in 2012 (CER, 2012) together with the survey results (pre-trial and post-trial) with socioeconomic, demographic, building characteristics and appliance use information for most participants. The power consumption data collected from domestic participants during the six-month benchmark period, as well as the pre-trial survey results, are selected to validate, quantitatively and qualitatively, the appliance electricity demand profiles generated synthetically.

Space-time resolution

Fifteen-minute resolution data is usually appropriate in power systems for supply-demand balance management and electricity trading. However, for the residential sector in particular, the electricity demand may vary significantly over shorter time horizons,
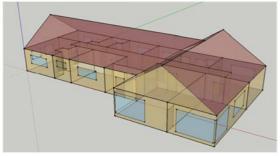

Figure 2: Single-storey detached house and thermal zones

one-minute, or even less, due to the low base load consumption. Wright and Firth (2007) concluded that one-minute or two-minute time resolution data is necessary to capture all the details and the inherent volatility of domestic load patterns.

However, an appreciation of minute-to-minute load variations are not necessary in the context of the current project, as the model will be used to study demand modulation strategies characterized by time constants of the order of tens of minutes, for an individual dwelling. Furthermore, from a power system perspective, it seems more appropriate to aggregate the potential of individual dwellings. Accordingly, the strategy applied is for each individual building model to be a "representative archetype" (Famuyibo et al., 2012) of a group of similar buildings, both in terms of inputs and outputs (electricity demand, thermal comfort), at a time resolution not higher than fifteen minutes.

Case study dwelling

The case study building, is a single-storey detached house with approximately 200 m^2 total floor area divided into thirteen thermal zones, as detailed in Figure 2. In 1999 it was representative of about 30% of the Irish national dwelling stock (Energy Research Group & Environmental Institute, 1999). It is occupied by a single family household with the number of residents equal to or greater than four, as per Table 1. The dwelling's envelope characteristics are adapted to current Irish building regulations (ECLG, 2011), and two versions of the model are created: a "new construction" version and a "retrofitted" version. It is assumed that when demand modulation strategies are applied at scale to the Irish residential sector, most of the dwelling stock would be in accordance with current building regulations. Except for the household size, building properties are not related to other socioeconomic or demographic characteristics of occupants, as it might be in reality. This is mainly due to the size of the TUS dataset used (Table 1) which does not allow a further subdivision of the dataset based on a particular characteristic, such as the household income level.

Occupancy

A method for generating high space-time resolution occupancy profiles and the associated internal heat gains is discussed in the following sections.

- Occupancy profiles:

Two types of occupancy are investigated: normal and active occupancy. An active occupant is defined as a normal occupant who is not sleeping, and is thus willing to use, or to share the use of, one or more electrical appliances, depending on the level of active occupancy and on the activities performed. It is also necessary to distribute the normal occupants, and the associated internal heat gains, within the different thermal zones, and to evaluate the thermal comfort of residents, even when they are at home but inactive.

In order to produce realistic active occupancy profiles for different categories of dwelling and for different day types, the high time resolution domestic building occupancy model developed by Richardson et al. (2008) has been adapted. It is based on TUS data, initially from a survey conducted in 2000 in the UK. The model generates stochastic active occupancy profiles that are statistically representative of the initial TUS dataset, with the same time resolution. The two main variables are the household size (1 to 6 residents) and the day type (weekday or weekend day). Both variables are adapted to the Irish TUS dataset: the time-step is changed from ten-minute resolution to fifteen-minute resolution, while the initial six dwelling categories (by household size) are decreased to four, from "1 resident" households to "4 or more residents" households. The MCMC technique utilised by Richardson et al. (2008) is also adapted and applied to the Irish TUS dataset. First, the activity grids, for each adult participant and for each day type, are transformed into active occupancy grids for each household category and day type. These are used to create the "start state" matrices and the "transition probability" matrices necessary to apply the MCMC technique.

Normal occupancy profiles are directly derived from the Irish TUS dataset. For each adult and for each day type, the activity grids are transformed into normal occupancy grids and averaged at each fifteen-minute time-step.

- Occupant internal heat gains:

The internal heat gains associated with occupants, HG_{OCC}, are activity specific, and are calculated as per (1) (LBNL, 2012):

$$HG_{OCC} = MET_{RATE} * OCC_{MAX} * OCC_{RATE} \quad (1)$$

where:

$$OCC_{RATE} = OCC_{PROP} * ACT_{PDF} \quad (2)$$

$$ACT_{PDF} = OCC_{1act} / OCC_{ACT} \quad (3)$$

The metabolic rate of occupants, MET_{RATE}, is obtained from ASHRAE HOF (ASHRAE, 2005), while the maximum occupancy level, OCC_{MAX}, depends on the household size, Table 1, and on the floor area of the thermal zone or group of thermal zones concerned. The activity specific occupancy rate, OCC_{RATE}, varies with the proportion of occupants, OCC_{PROP}, which is given by the normal occupancy profiles derived previously for each category of dwelling and day type, and with the probability distribution function, ACT_{PDF}, which is derived from the Irish TUS activity grids for each activity according to (3).

Electrical appliances

A method for generating high space-time resolution load profiles for domestic electrical appliances, and the associated internal heat gains, is described in the following sections.

- Load model:

In order to produce realistic domestic electrical appliance load profiles for different categories of dwelling and for different types of day, the one-minute time resolution model developed by Richardson et al. (2010) has been adapted. The process consists of adjusting variables and model parameters to Irish "standards", and modifying the model to produce load profiles for domestic electrical appliances only. The adjustment to Irish "standards" consists of:

1. Integration of the adapted occupancy model.

2. Construction of time-dependent activity profiles associated with electrical appliances whose use is dependent upon a specific activity.

3. Appliance parameters, such as the penetration within the Irish national dwelling stock (CSO, 2009; Leahy and Lyons, 2010). The model is calibrated to represent the annual mean electricity consumption of domestic electrical appliances and lighting in Irish households (SEI, 2008; CER, 2012).

Modification of the model mainly consists of:

1. Adjustment of the electrical load types, in order to model electrical appliances only. The model originally accounted for HVAC, DHW heating and lighting loads, which in the current work are modelled using EnergyPlus.

2. Inclusion of a "warm-up period" variable in order to better represent appliances which are turned on at the beginning of the day. The duration of the warm-up period is defined by the longest mean cycle duration of the electrical appliances modelled. A side consequence of this change is that additional day types of Monday (post-weekend) and Friday (pre-weekend) need to be defined.

- Appliances internal heat gains:

The internal heat gains associated with electrical appliances, $HG_{APP,x}$, are activity specific by nature, since their operating schedules (power consumption profile) are generated by the appliance model. The heat gains are calculated at each simulation time-step, for each electrical appliance by considering the fraction of electrical power consumed which is converted into latent heat, radiant heat, heat convected inside the thermal zone and heat lost to the outdoor environment, as per (4) (LBNL, 2012).

$$HG_{APP,x} = APP_{RATED} * APP_{SCH} * f_{APP,x} \quad (4)$$

$$x \in \{latent; radiant; convected; lost\}$$

$$f_{APP,latent} + f_{APP,radiant} + f_{APP,convected} + f_{APP,lost} = 1$$

The proportion of rated power consumed, APP_{SCH}, is given at a one-minute time resolution by the power consumption profiles for each appliance, each category of dwelling, and for each day type. The fraction of heat transfer, $f_{APP,x}$, is based on ASHRAE HOF for each appliance category.

Space-time distribution of occupants and electrical appliances

Occupants and electrical appliances are spatially mapped at room level, by attributing a unique thermal zone, or group of thermal zones, to each activity detailed in the TUS dataset and to each electrical appliance modelled. The space distribution is subjective, based on user judgement, and unique for each building model, depending on the particular activity, appliance and room types.

Lighting

- Lighting internal heat gains:

The internal heat gains associated with lighting, HG_{LIG}, are also activity specific, since the illuminance requirement is defined for each activity according to IESNA standards (IESNA, 2000). Heat gains are updated at each simulation time-step by considering the fraction of input electrical power consumed by lights which is converted into visible radiation, radiant heat and heat convected inside the thermal zone, as per (5) (LBNL, 2012).

$$HG_{LIG} = ILL_{RQT} * f_{daylight} * OCC_{RATE} * f_{APP,x} \quad (5)$$

$$x \epsilon \{radiant; convected; visible\}$$

$$f_{APP,visible} + f_{APP,radiant} + f_{APP,convected} = 1$$

The illuminance requirement, ILL_{RQT}, associated with each activity takes into account the light bulb efficacy, which is defined according to IESNA standards, depending on the light bulb technology installed. In the case study building, the compact fluorescent bulb technology is chosen for all the thermal zones. The activity specific occupancy rate, OCC_{RATE}, is calculated according to (2). The fraction of heat transfer, $f_{APP,x}$, either visible, radiant or convected, is compliant with IESNA standards, depending on the light configuration and the light bulb technology. The daylight factor, $f_{daylight}$, varies from zero to one, depending on the daylight level in a thermal zone.

- Space-time distribution:

Lights and the associated heat gains are spatially mapped at room level, by attributing a unique lighting requirement level to each activity detailed in the TUS dataset. As a result, the lighting requirement level in a thermal zone will depend on the activities taking place, the occupancy level and the daylight level inside that thermal zone.

RESULTS AND DISCUSSION

Occupancy

The domestic building active occupancy model implemented here is validated on the basis of aggregated behaviour, transitions (from active to inactive and vice-versa) and correlated occupancy changes. A comparison of the simulated average active occupancy and the surveyed average normal occupancy is shown in Figure 3 for households with

four or more residents, during both weekdays and weekend days. The occupancy profiles drawn represent the proportion of adult occupants only with respect to the total number of residents (adults/resident). For the same day type, the gap between the active occupancy profile and the normal occupancy profile represents the proportion of residents who are sleeping. For weekdays, the peaks in activity level are clear in the morning, at lunchtime and in the evening. For weekend days there is no clear peak after the initial morning period, and the active occupancy level remains at a high level until a smaller lunchtime and evening peak. For both weekdays and weekend days, the correlation between the normal and active occupancy profiles is as expected, with a large gap between the two profiles at night time and an almost perfect superposition of them during the day time when residents are at home and active.

It can also be seen, at night time in particular, that the active and normal occupancy levels introduced in Figure 3 are quite low. One might expect values closer to unity at night time. However, the occupancy profiles drawn represent the proportion of adult occupants with respect to the total number of residents. As the household size increases, the proportion of adult occupants will reduce. This is confirmed by the profiles generated for households with one or two residents only, for which the normal occupancy level reaches a maximum value during the night time. As a result, there is an obvious overall underestimation of the internal heat gains, which will grow as the household size increases. Also, it is important to emphasize one of the consequences that excluding children has on the space-time distribution of internal heat gains. Namely, it may be difficult to map all the thermal zones of the building model and the distribution of adults may as a result be unrealistic.

Electrical appliances and lighting

The synthesised data, produced with a one-minute resolution, is compared with SMP - ECBTs data collected during the 6-month benchmark period from 2009, with a thirty-minute resolution.

The synthetic average annual electricity consumption of electrical appliances is generated for the set of dwellings surveyed in the SMP-ECBTs project, as detailed in Table 2. The model has been calibrated to generate an average annual electricity consumption of 2,018 kWh for electrical appliances, representing 45% of the average annual electricity end use in Irish households (SEI, 2008). There is only a 0.6% difference between the objective average annual electricity consumption of electrical appliances for all the household sizes and the synthetic value of 2,005 kWh, generated by the model. According to the model, as detailed in Table 2, electrical appliances are responsible for about 44.7% of the average annual electricity consumption of all households

surveyed, but this figure varies from 60.4% for one-resident households to 37.5% for households with four or more residents. This result suggests a greater sharing of electrical appliances, within the same dwelling, as the household size increases. No disaggregated data was found in the literature to support these proportions, with respect to the household size.

In terms of profile, it is not trivial to validate the synthetic average daily load profiles for appliances against the surveyed total household average daily load profiles based on the 2009 SMP-ECBTs data. It is simplistic to compare load profiles for two different load categories with different time scales, i.e. thirty-minute resolution for the total household load against one-minute for the appliances load. In addition, the sets of households surveyed are different within each dataset, both in terms of number (Table 1 and Table 2) and characteristics. Indeed, the two datasets are representative of the Irish national household stock at two different periods, 2005 for the Irish TUS and 2009-2010 for the SMP-ECBTs, each with different prevailing economic conditions, which are likely to affect household behaviour.

However, some comparison can be made. In Figure 4, the average daily load profile for appliances and the surveyed total household average daily load profiles based on the 2009 SMP-ECBTs data are shown for households with four or more residents, for weekdays in September. The general patterns are similar and well correlated, with a morning rise and peak, followed by a midday peak and an evening peak. The correlation is even better when the lighting load is also considered, calibrated to match the average annual electricity consumption in Irish households. In such a case, the correlation factor between the surveyed and synthetic profiles is greater than 95%. However, a general underestimation of power consumption, especially during the night time, and a delay of approximately 1 hour between the peak times, are evident. The peak time delay issue was also observed by Richardson et al. (2010). These issues will require further validation and calibration when the building model includes space and DHW heating loads, circulation pump load, as well as the lighting load. Possible explanations are the fact that the Irish TUS dataset did not survey child activity within Irish households, and that buildings with electrical space and DHW heating systems are included in the SMP-ECBTs dataset.

It is interesting to observe that the simulation warm-up period of 300 minutes, added as a variable to the appliance model (but not to the lighting model), ensures that the load levels at the beginning and at the end of the simulation day are not noticeably different. As detailed in Figure 4, this gap is significant (about 0.24 kW) for lighting and appliances load profile, but insignificant (about 0.04 kW) for the appliances load profile only.

CONCLUSION AND FURTHER WORK

High space-time resolution operational data inputs for residential building simulation, modelled through the EnergyPlus platform, have been successfully developed for different day types and different household sizes, for Irish households. A bottom-up approach, based on TUS activity data, is used for generating, at an individual room level for a representative multi-zone domestic building: occupancy profiles at a fifteen-minute time resolution, and disaggregated electrical appliance load and lighting load profiles at a one-minute time resolution. Associated heat gains are determined and spatially mapped within the building model. The methodology is applied to a single-storey detached dwelling with thirteen thermal zones and validated against metered data. A good match is seen between synthesised and measured load profiles but further validation is required once the building models include all domestic loads (space and DHW heating). It is believed that a global underestimation of internal heat gains results from the quality of the Irish TUS dataset which did not include children activity within Irish households. According to the appliance model, electrical appliances account for a varying proportion of the average annual electricity consumption of households surveyed, from 60.4% for one-resident households to 37.5% for households with four or more residents. This suggests a greater sharing of electrical appliances as the household size increases.

As expected, the complexity of each building model is high, resulting from the choice of a bottom-up approach to develop inputs, but also from the intended purpose of the model, which requires the development of high space-time resolution operational data for a wide range of inputs, as detailed in Figure 1.

Regarding the required time resolution of the model outputs, it could be concluded that a one-minute load variation may not be necessary. Instead, the archetype building models will be used to study demand modulation strategies characterized by time constants of the order of fifteen minutes, for an individual dwelling. In addition, from a power system perspective, it may be more beneficial to aggregate the potential of individual dwellings, thus lowering the time-resolution requirement.

Further features of the building models may include the development of high space-time resolution operational data for DHW consumption, natural ventilation, the inclusion of space and DHW heating systems, the inclusion of a detailed cold appliance model, as well as the assessment of occupant thermal comfort within domestic buildings. The archetypes modelled will be key to address the issue of scaling up the potential flexibility resource from individual representative buildings up to a national scale.

NOMENCLATURE

ACT_{PDF} = activity probability distribution function
APP_{RATED} = rated power of appliances (W)
APP_{SCH} = proportion of rated power consumed
$f_{APP,x}$ = fraction of heat transfer
$f_{daylight}$ = EnergyPlus daylight factor
$HG_{APP,x}$ = heat gains from appliances (W)
HG_{LIG} = heat gains from lights (W/m^2)
HG_{OCC} = heat gains from occupants (W/m^2)
ILL_{RQT} = illuminance requirement (lm/m^2)
MET_{RATE} = metabolic rate (W/resident)
OCC_{Iact} = no. adults performing a specific activity
OCC_{ACT} = no. adults performing any activity
OCC_{MAX} = maximum occupancy level (resident/m^2)
OCC_{PROP} = proportion of adult occupants
OCC_{RATE} = activity specific occupancy rate
x = type of heat transfer

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REFERENCES

ASHRAE, 2005. 2005 ASHRAE HOF – Handbook Of Fundamentals SI, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., Atlanta, USA.

CER, 2012. Smart Metering Electricity Customer Behaviour Trial: Dataset (revised version March 2012), Commission For Energy Regulation, Dublin, Ireland.

CSO, 2009. Household Budget Survey 2004-2005, Central Statistics Office, Dublin, Ireland.

Dineen, D., Ó Gallachóir, B.P. 2011. Modelling the impacts of building regulations and a property bubble on residential space and water heating, Energy and Buildings 43 (2011) 753-768.

ECLG, 2011. Building Regulations 2011 - Technical Guidance Document L, Environment, Community and Local Government of Ireland, Dublin, Ireland.

Energy Research Group & Environmental Institute, University College Dublin, 1999. Homes for the 21st Century: The Costs & Benefits of Comfortable Housing for Ireland, Energy Action Ltd., Dublin, Ireland.

ESRI, 2005a. Time-Use In Ireland 2005: Survey Report, The Economic and Social Research Institute, Dublin, Ireland.

ESRI, 2005b. Time-Use In Ireland 2005: Survey Dataset, The Economic and Social Research Institute, Dublin, Ireland.

Famuyibo A. A., et al., 2012. Developing archetypes for domestic dwellings – an Irish case study, Energy and Buildings 50 (2012) 150-157.

IESNA, 2000. The IESNA Lighting Handbook, 9th Edition - Reference & Application, Illuminating Engineering Society of North America, New York, USA

LBNL, 2012. EnergyPlus Documentation Version 7.2, Ernest Orlando Lawrence Berkeley National Laboratory, University of California, USA.

Leahy, E., Lyons, S. 2010. Energy use and appliance ownership in Ireland, Energy Policy 38 (2010) 4265-4279.

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

Richardson, I., et al. 2008. A high-resolution domestic building occupancy model for energy demand simulations, Energy and Buildings 40 (2008) 1560-1566.

Richardson, I., et al. 2009. Domestic lighting: a high-resolution energy demand model, Energy and Buildings 41 (2009) 781-789.

Richardson, I., et al. 2010. Domestic electricity use: a high-resolution energy demand model, Energy and Buildings 42 (2010) 1878-1887.

SEI, 2008. Energy in the Residential Sector - 2008 Report, Sustainable Energy Ireland, Dublin, Ireland.

Strbac, G., 2008. Demand side management: benefits and challenges, Energy Policy 36 (2008) 4419-4426.

U.S. DOE, 2011. Load Participation in Ancillary Services – Workshop report, U.S. Department of Energy, Washington, DC, USA.

Widén, J., et al. 2009a. A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand, Energy and Buildings 41 (2009) 1001-1012.

Widén, J., et al. 2009b. Constructing load profiles for household electricity and hot water from time-use data – modelling approach and validation, Energy and Buildings 41 (2009) 753-768.

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

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

Table 2: Dwelling categories from SMP-ECBTs datasets

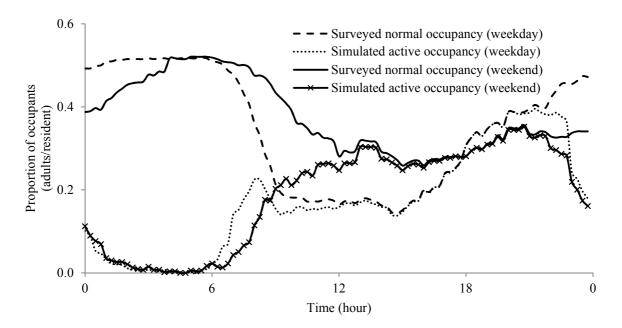| Residents per household	No. dwellings	Surveyed average annual total consumption (kWh)	Objective average annual appliance consumption (kWh)	Synthetic average annual appliance consumption (kWh)
1	697	2,660	N/A	1,607
2	44	3,734	N/A	1,926
3	1,148	4,004	N/A	2,093
≥4	1,592	5,650	N/A	2,119
Total	3,481	4,484	2,018	2,005

Figure 3: Simulated active occupancy and surveyed normal occupancy for a household with ≥4 residents
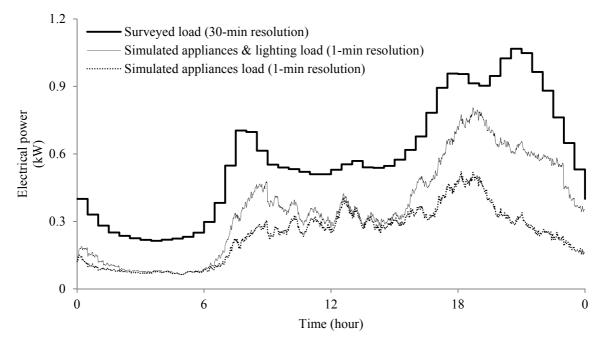

Figure 4: Simulated average daily power consumption and surveyed average daily power consumption for a household with ≥4 residents, during a weekday