

# Natural ventilation in residential building archetypes: a stochastic approach based on occupant behaviour and thermal comfort

Olivier Neu<sup>1</sup>, Valentin Evon<sup>2</sup>, Simeon Oxizidis<sup>3</sup>, Damian Flynn<sup>1</sup> and Donal Finn<sup>4</sup>

<sup>1</sup>Electricity Research Centre, University College Dublin, Dublin, Ireland

<sup>2</sup>Polytech Nantes, Graduate School of Engineering of the University of Nantes, France

<sup>3</sup>School of Environment and Technology, University of Brighton, Brighton, UK

<sup>4</sup>School of Mechanical & Materials Engineering, University College Dublin, Dublin, Ireland

## Abstract

As houses become more energy efficient due to highly thermal resistant fabrics, the impact of natural ventilation on indoor comfort and on transient heating and cooling loads increases. These two constraints must be integrated within building performance simulation models when assessing the potential for electrical load shifting strategies in residential buildings placed in a smart grid environment.

A natural ventilation model is developed and implemented for five residential building archetypes. A bottom-up methodology based on occupant behaviour, through the use of time-of-use data, is implemented at room level within EnergyPlus. A stochastic approach determines whether to open or close windows, depending on the occupancy state, the activity type and level, and the thermal comfort experienced.

The algorithms proposed consider the main drivers governing window operation within a residential context. Focus is placed on the modelling challenges, and the impacts of the model are assessed using energy performance and thermal comfort.

## 1 Introduction

### *EU policy and targets*

The poor energy performance of the European building sector makes it one of the largest energy using and CO<sub>2</sub> emitting sectors at present. Residential buildings alone account for just over two-thirds of this energy consumption. The so-called “20-20-20” targets set by the EU challenge the building sector in terms of energy efficiency, greenhouse gas emissions and integration of renewable energy sources (RES). Furthermore, a series of EU directives have mandated each member state to improve the energy and environmental performance of dwellings. Through the Energy Performance of Buildings Directive (EPBD) (European Commission, 2010) a series of reference buildings, representative of the national building stock, should be defined and a standard methodology developed for the calculation of their energy and environmental performances. Through Directive 2009/28/EC (European Commission, 2009) on the promotion of energy use from RES, 20% of total energy consumption from RES is targeted by 2020. The residential sector has a key role to play in order to meet these objectives.

### *Response of the residential sector*

The direct response of each EU member state to the EPBD requirements is the development of national standard energy assessment procedures, while also enabling the publication of building energy rating certificates. These standard methodologies are key tools for policy

makers in order to verify the implementation of current building regulations and to elaborate stricter ones in terms of fuel and energy conservation within dwellings.

As acknowledged by the U.S. DoE (2011), the integration of RES requires more flexibility from the power system. This is due to the variable and uncertain nature of RES, particularly wind and solar generation. Utilisation of the flexibility offered by demand side management (DSM) strategies is one possible strategy. However, for residential buildings in particular, it is challenging to quantify this potential due to the wide range of electricity usage patterns, variability of electrical loads and uncertainty regarding human behaviour. Stricter energy efficiency regulations, the integration of new load types and the increasing electrification of space and water heating loads anticipated by the IEA (2011) further challenge the assessment of the associated flexible load resource capacity.

### ***Modelling of residential sector and natural ventilation***

Dineen and Ó'Gallachóir (2011) classified building energy and electricity demand models made into two categories: top-down and bottom-up approaches. Richardson et al. (2008) recognised that analysis of DSM in the domestic sector requires detailed and accurate knowledge of household consumer loads. By aggregating individual end-use loads, or groups of end-use loads, bottom-up approaches are capable of generating sufficient detail and are very useful for identifying the individual end-use contribution to the overall energy or electricity consumption of a national residential building stock (Swan & Ugursal, 2009). In the past decade, several bottom-up building energy or electricity demand models have been developed to study domestic loads with high time resolution (Richardson, et al., 2010; Widén & Wäckelgård, 2010) and with high spatial resolution (Chiou, et al., 2011). These models are usually based on time-of-use survey (TUS) data in order to extract the behavioural patterns of building residents, in terms of occupancy and use of electrical appliances. However, all of the above ignore an assessment of the thermal comfort of residents and each building model is representative of a single dwelling only, complicating the task of scaling outcomes to a national level. Consequently, Neu et al. (2013) proposed an approach to develop operational data, based on TUS data, as input in archetype building performance simulation (BPS) models, with each model being representative of a group of dwellings and dwelling loads. By integrating activity specific profiles for occupancy, electrical appliance use and lighting at high space and time resolution, EPBD reference dwellings can be converted into BPS archetypes, as recognized by Corngati et al. (2013). Indeed, it has been recognised that standard assessment procedures developed to meet the EPBD requirements have limitations, including an inability to account for occupancy variations and usage of appliances (Gupta, et al., 2011). As emphasized by Ma et al. (2013), this archetype approach is in line with the power system perspective on the aggregated flexibility potential offered by smaller loads, such as residential ones, through the implementation of any DSM strategy.

As houses become more energy efficient and air tight due to highly thermal resistant fabrics and stricter building regulations, the impact of natural ventilation on indoor thermal comfort, air quality and on transient heating and cooling loads increases. In order to assess the DSM potential in residential buildings, as a mechanism for electrical load shifting, these constraints, namely indoor comfort and transient heating loads, must be considered within BPS archetypes capable of simulating the energy and electricity demand of residential buildings. Dutton et al. (2012) recognised that stochastic probability-based models are more suitable for describing natural ventilation because human behaviour is not deterministic. The main drivers agreed for operating windows are listed below:

- Environmental conditions, especially outdoor temperature during the heating season and indoor temperature during the off-heating season.

- Indoor thermal comfort and air quality, such that window operation is driven by a temporary discomfort in order to re-establish acceptable conditions.
- Temporal events, such that window operation is related to a particular event (e.g. entering a room, cooking, cleaning or waking-up).

From those drivers, Andersen et al. (2013) identified the outdoor temperature and indoor air quality as the most important variables governing the operation of windows within dwellings. Generally, building occupants tend not to interact that often with windows. While this might be true for a commercial or office building, it is expected that residential building occupants would operate windows more dynamically in order to reach or to restore optimal comfort conditions (Peeters, et al., 2009). Indeed, the domestic environment is characterised by high variations, at a sub-hourly timescale, of internal heat gains associated with occupancy level, activity level and types, and electrical equipment use. As opposed to commercial or office buildings, such an environment also offers many ways for occupants to adapt, including the adjustment of natural ventilation rates by operating windows. This justifies the choice of an adaptive thermal comfort model to estimate an acceptable indoor temperature range, rather than a model based on Fanger's approach, which is more appropriate for commercial and office buildings (Peeters, et al., 2009).

### ***Our contribution and approach***

A set of EPBD reference dwellings is considered and modelled in detail through EnergyPlus and converted into a set of archetypes by integrating the high space and time resolution operational data developed by Neu et al. (2013), thus taking into account occupant behaviour. Combining such a TUS activity specific approach with the outcomes from Dutton et al. (2012) and Peeters et al. (2009), a domestic natural ventilation and adaptive thermal comfort model is developed and implemented at room level using the EnergyPlus Energy Management System (EMS) module. A stochastic approach decides whether to open or close windows, depending on the room occupancy state, the type of activity performed and the thermal comfort experienced. The algorithms proposed consider the main drivers governing window operation, and adapt them to the residential sector context. Focus is placed on the modelling challenges and an assessment of the impacts of the model, using energy performance and thermal comfort. The calibration of the natural ventilation model is performed in order to match a benchmark ventilation air change rate at a building level.

## **2 Methodology**

The set of EPBD Irish reference dwellings (DECLG & SEAI, 2013) is considered and modelled in detail through EnergyPlus. The operational data, required to convert this reference building into a BPS archetype, is integrated within each model, and a stochastic natural ventilation model appropriate for residential applications is developed.

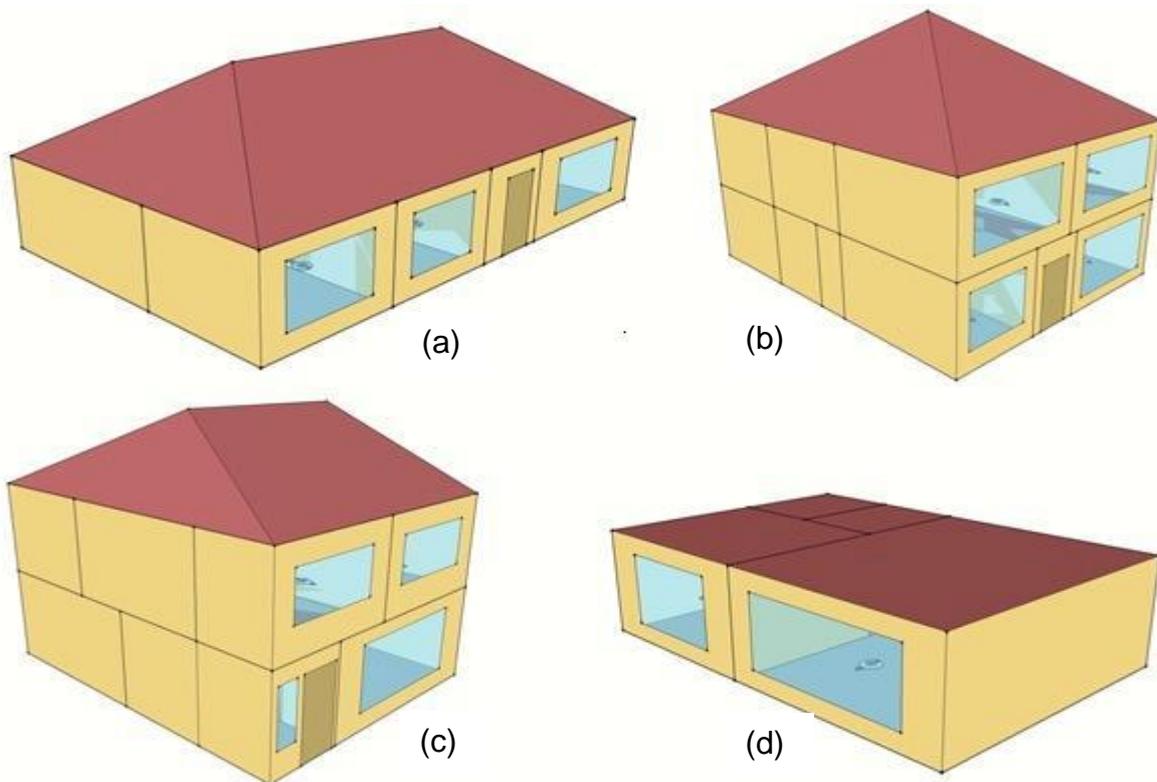
### ***Set of archetypes***

Table 1 introduces the two building categories considered, further divided into five dwelling types, as well as their conditioned total floor area (TFA) and the share of the Irish residential building stock represented, according to the results from Irish 2011 Census (CSO, 2012). The set of reference dwellings is representative of more than 80% of the Irish national dwelling stock and each dwelling type is considered over different construction periods, namely new and existing dwellings. The main geometrical characteristics, construction types and materials, infiltration levels and the heating system types and control are in line with DECLG and SEAI (2013), and adapted from the Irish building regulations (DECLG, 2011) for both new and existing constructions. The number of rooms, layouts and floor plans are adapted

from representative dwellings defined by Brophy et al. (1999). Figure 1 shows the SketchUp drawings of each reference dwelling. The new version of the most representative reference dwelling of the Irish national stock, namely the detached house (i.e. dwelling (b) in Figure 1), is considered in the current paper as a case study. According to its layout and the number of rooms, it is believed to be the most challenging archetype to model.

**Table 1 – Set of EPBD Irish reference dwellings**

Building category	Dwelling type	TFA (m <sup>2</sup> )	Number of rooms	Share of national stock (%)
Single family	Bungalow	104	8	43.2
	Detached	160	13	
	Semi-detached	126	10	28.2
Multi-family	Mid-floor flat	54	3	10.9
	Top-floor flat	54	3	



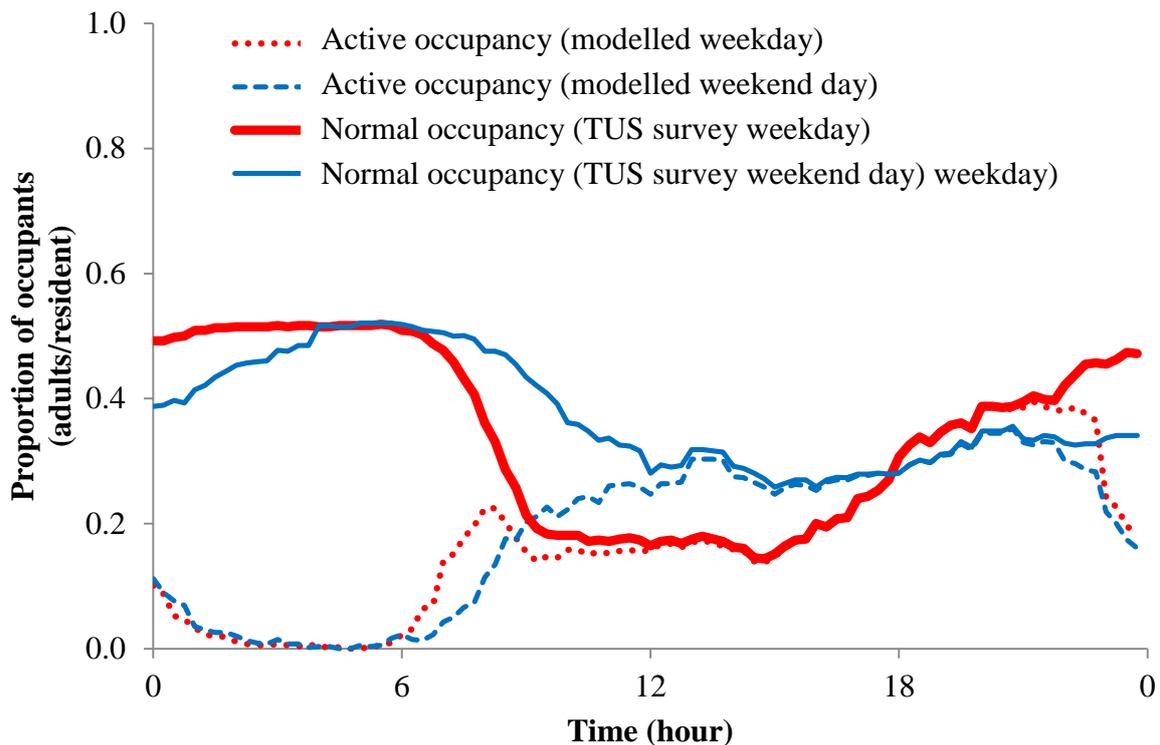
**Figure 1 - SketchUp drawings of reference dwellings: (a) bungalow, (b) detached, (c) semi-detached, and (d) flats**

### *Operational data*

From the four data subsets required by Corgnati et al. (2013) to develop BPS archetypes, the operational data subset is built following the bottom-up approach proposed by Neu et al. (2013), which applies Markov chain Monte Carlo techniques to TUS activity data to develop activity specific profiles for occupancy, disaggregated appliance and lighting electricity use for multi-zone residential BPS archetypes. As a result, the archetypes capture, at room level, the variations of electricity on a minute basis, and the variations of internal heat gains on a

fifteen-minute basis. Such space and time resolution is vital for investigation of issues related to thermal comfort and electrical load shifting at an aggregated level (Neu, et al., 2013).

The two types of occupancy profiles, namely normal and active profiles, are shown in Figure 2. An active occupant is defined as a normal occupant who is not sleeping, and is thus willing to use any domestic equipment (electrical appliances, lighting) or to perform any action to restore indoor comfortable conditions (operation of natural ventilation, change of clothing, etc.), depending on the active occupancy level and the performed activity type. The two main variables are the household size (1, 2, 3 and “4 or more” residents) and the day type (weekend or weekday). Since only adult residents were surveyed in the TUS data used, there is a risk of underestimating the internal heat gains associated with occupancy, the use of equipment (electrical appliances, lighting), or even the probability to operate natural ventilation.

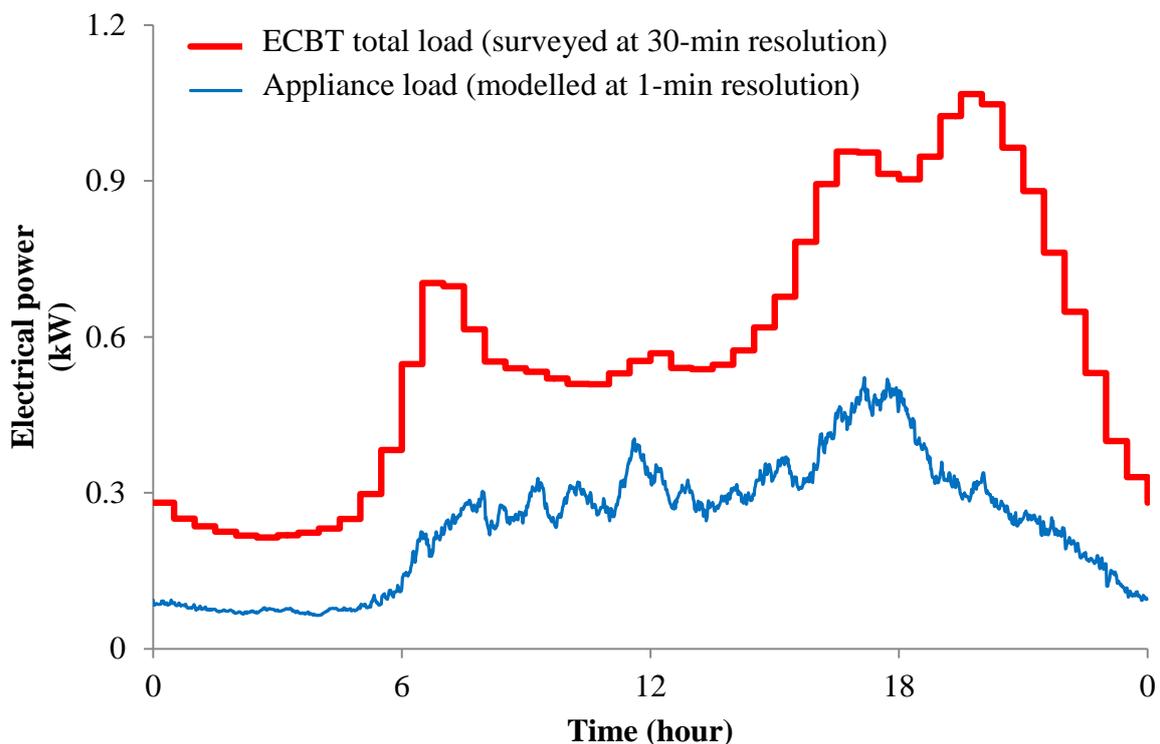


**Figure 2: Average daily modelled active occupancy and surveyed average daily normal occupancy for the detached house archetype with “4 or more” residents**

The average daily power consumption profiles for domestic electrical appliances integrated within the detached house archetype were developed and validated against metered data by Neu et al. (2013). In brief, the active occupancy profiles are combined with specific TUS activity profiles (probability of at least one occupant performing a particular activity) within a stochastic model to develop average appliance load profiles depending on the household size and day type, and taking into account the penetration of each appliance modelled within the national dwelling stock. In Figure 3, a noticeable underestimation of power consumption can be seen from electrical appliances, especially during the night time, mainly due to the TUS data used, which did not consider children. The lighting electricity demand is also activity specific, varying with the occupancy level, activity level and type, illuminance requirement, light bulb efficacy of the lighting technology installed, and the daylight level. For new dwellings, compact fluorescent technology was assumed, with a light source efficacy of 50 lm/W. For existing dwellings, a composite light bulb efficacy of 18 lm/W was assumed, based

on IESNA standards (2000) and the breakdown of lighting technologies surveyed in UK residential building stock (Energy Saving Trust, DECC & DEFRA, 2013).

The activity specific profiles for occupancy, domestic appliances and lighting electricity use have a direct impact on the internal heat gains. As proposed by Neu et al. (2013), occupants and their internal heat gains are mapped at room level by assigning a unique, or several, thermal zones to each activity. Similarly, by assigning a unique, or several, thermal zones to each electrical appliance and by considering the fraction of electrical power consumed which is converted into latent, radiant, convected heat or lost to the outdoor environment, appliances and their internal heat gains are spatially mapped at room level. Finally lighting internal heat gains are spatially mapped at room level, by attributing an illuminance requirement level to each activity detailed in the TUS dataset and by considering the fraction of electrical power consumed by lights which is converted into visible radiation, radiant and convected heat.



**Figure 3: Comparison of average daily electrical appliances load demand with surveyed average daily total load demand for the detached house archetype during a weekday**

#### *Natural ventilation and adaptive thermal comfort algorithms*

The core of the stochastic window use approach developed by Dutton et al. (2012), using the EnergyPlus EMS module, is combined with the adaptive thermal comfort model algorithms developed by Peeters et al. (2009) for residential building applications, as shown in Table 2. Both models were selected because they had been developed for BPS applications and validated against measured data. However, some significant differences are introduced by that algorithm combination. First, the developed algorithms could be defined as a natural ventilation model rather than a window use model. Indeed, the controlled variable is the activation or deactivation of natural ventilation at a fixed air change rate for each room, rather than opening each single window of the building by a certain fraction. Another significant difference lies in the field of application, namely an archetype model, representative of a group of dwellings: when the natural ventilation is activated, it does not mean that one or several windows of a single dwelling are opened or closed, but that a majority of dwellings

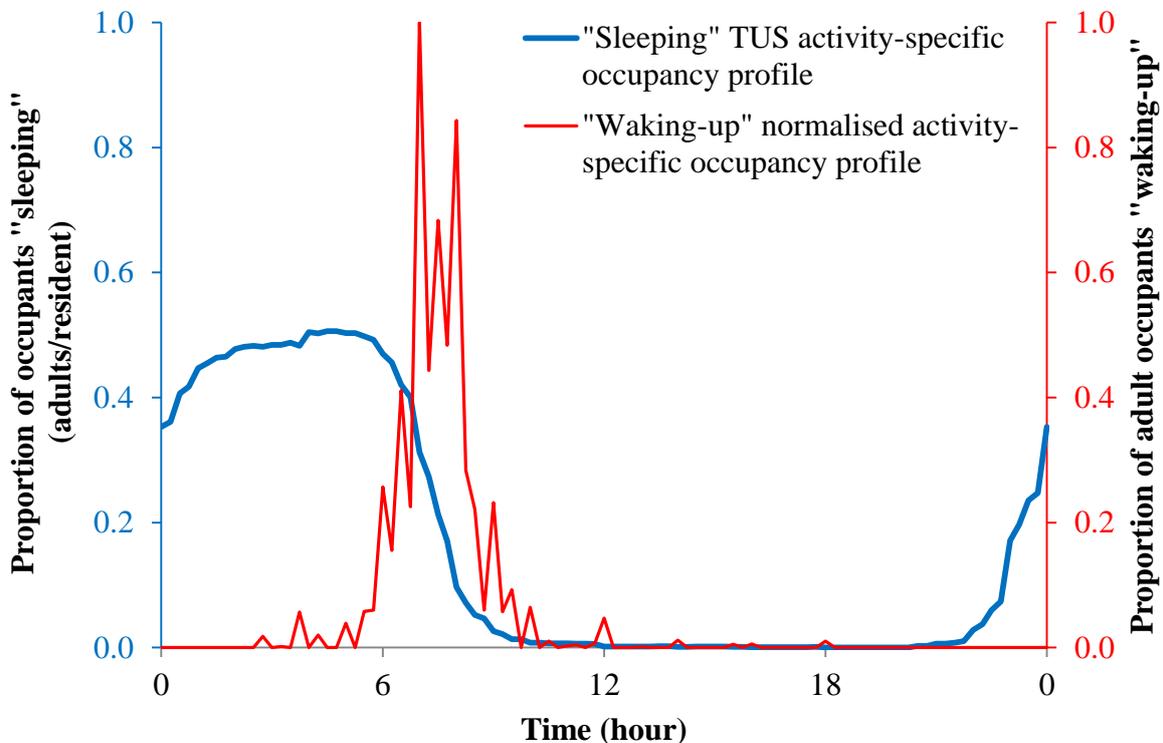
represented by a particular archetype are activating or deactivating natural ventilation through the operation of windows. Finally, the algorithms developed in this work are strongly dependent upon the variations of occupancy level, activity level and activity type, by connecting them to the activity specific occupancy profiles introduced earlier. These variables, which embed the occupant behaviour, were not considered in existing models.

**Table 2: Algorithms for the natural ventilation and the adaptive thermal comfort model**

Model variables	Room type		
	Bedroom	Bathroom	Other room
Running mean temperature constant $c$	0.6		
Running mean temperature $T_{RM}^n$ ( $^{\circ}\text{C}$ )	$c \times T_{RM}^{n-1} + (1-c) \times T_{DM}^{n-1}$ (1)		
Comfort band width $\omega$ ( $^{\circ}\text{C}$ )	5 (for 10% of people dissatisfied, PPD) or 7 (for 20% PPD)		
Comfort band constant $\alpha$	0.7		
Comfort band upper limit $T_{upper}$ ( $^{\circ}\text{C}$ )	$\min[26, T_n + \omega \times \alpha]$	$T_n + \omega \times \alpha$ (2)	
Comfort band lower limit $T_{lower}$ ( $^{\circ}\text{C}$ )	$\max[16, T_n - (1-\omega) \times \alpha]$	$\max[18, T_n - \omega \times (1-\alpha)]$ (3)	
Comfort band neutral temperature $T_n$ ( $^{\circ}\text{C}$ )	<p>If <math>T_{RM}^n &lt; 0</math>; 16</p> <p>If <math>0 \leq T_{RM}^n &lt; 12.6</math>; <math>0.23 \times T_{RM}^n + 16</math></p> <p>If <math>12.6 \leq T_{RM}^n &lt; 21.8</math>; <math>0.77 \times T_{RM}^n + 9.18</math></p> <p>If <math>T_{RM}^n \geq 21.8</math>; 26</p>	<p>If <math>T_{RM}^n &lt; 11</math>; <math>0.112 \times T_{RM}^n + 22.65</math></p> <p>If <math>T_{RM}^n \geq 11</math>; <math>0.306 \times T_{RM}^n + 20.32</math></p>	<p>If <math>T_{RM}^n &lt; 12.5</math>; <math>0.06 \times T_{RM}^n + 20.4</math></p> <p>If <math>T_{RM}^n \geq 12.5</math>; <math>0.36 \times T_{RM}^n + 16.63</math></p>
Probability of natural ventilation operation $p_{nv}$	$expo = \text{logit}(p_{nv}) = 0.171 \times T_{op} + 0.166 \times T_{out} - 6.4$ $p_{nv} = e^{expo} / (1 + e^{expo})$ (5)		

The general layout of the resulting model implemented within the EnergyPlus EMS module for each archetype is as follows:

- The running mean temperature  $T_{RM}^n$  is calculated, Equation (1), at the beginning of each day, giving a weight of 40% to the average outdoor dry bulb temperature for the previous day  $T_{DM}^{n-1}$  and a greater weight of 60% to the running mean temperature  $T_{RM}^n$  for the previous day. By doing so, adaptation to the outdoor climate is incorporated.
- For each room, depending on the activities performed, the activity sets are clustered into four categories: “main activities” which require the activation of natural ventilation independently from the thermal comfort level (e.g. cooking, cleaning); “waking-up activity”, which is derived from the negative slope of the activity specific occupancy pattern for the “sleeping” TUS activity data, Figure 4, and requires the activation of natural ventilation independently from the thermal comfort level; “other activities” which do not require the activation of natural ventilation independently from the thermal comfort assessment (e.g. studying, watching TV); “all activities” which regroups the “main activities” and “other activities”.



**Figure 4: Activity specific occupancy profiles for the “sleeping” and “waking-up” normalised activity, detached house archetype with “4 or more” residents, weekday**

- Independent from the indoor thermal comfort assessment, a random threshold is compared to the “main activities” and the “waking-up activity” probability distributions, normalised with respect to the minimum slope of the “sleeping” activity-specific occupancy profile, as shown in Figure 4. Such operation of natural ventilation depending on the occupancy level, activity level and activity type, relates window operation with temporal events, but adapted to the residential context.
- The running mean temperature  $T_{RM}^n$  feeds into calculation of the comfort band neutral temperature  $T_n$ , depending on the room type, Equation (4).

- The comfort band neutral temperature  $T_n$  feeds into calculation of both the lower and upper limits of the comfortable temperature range,  $T_{lower}$  and  $T_{upper}$ , depending on the room type, Equations (2) and (3). The width of the comfort temperature ranges is also dependent upon the requested percentage of people dissatisfied (PPD) through the value of  $\omega$ , as per Table 2.
- The indoor operative temperature  $T_{op}$  is compared to the respective limits of the comfort temperature range. However, if  $T_{op}$  is outside the limits, meaning that the indoor conditions are either too cold or too hot, the natural ventilation operation state is either left closed or the probability of operating the natural ventilation  $p_{nv}$  is calculated, Equation (5). In order to take into account the active occupancy level and the activity type,  $p_{nv}$  is scaled by “all activities” probability distribution, before being compared to a random threshold.

### 3 Results and discussion

The behaviour of the natural ventilation model and the capabilities that such algorithms confer to the archetypes, in terms of DSM investigation and related thermal comfort issues, are addressed. Focus is placed on the modelling challenges associated with its implementation within residential BPS archetypes.

#### *Challenges associated with the modelling process*

A threshold limit needs to be set on the minimum level of activity specific occupancy level below which the natural ventilation cannot be operated. It prevents natural ventilation operation from cycling, especially for bedrooms in the early morning when the operation of natural ventilation is highly dependent on the “waking-up activity” probability distribution. Such cycling is unacceptable, even at an aggregated level in a residential context. It is mainly due to the continuous nature of activity specific occupancy profiles, being representative of a group of dwellings and thus never equal to “0”. A threshold value of 0.1 was found to be effective in eliminating the cycling issue without compromising the general behaviour of the model.

The initial state of the natural ventilation operation must be reset for each simulation timestep, assuming that operable windows “closed” is the normal state of operation for a majority of dwellings represented by a particular residential archetype. It prevents natural ventilation operation from being continuous over long periods of time (several hours), even when unacceptable thermal comfort conditions are met. It is mainly due to the priority given to some particular activities (waking-up, cooking and cleaning) for operating windows independently from the thermal comfort assessment, and to the continuous nature of activity specific occupancy profiles. This re-initialisation of the state of operation of natural ventilation at each simulation timestep is believed to be necessary for archetype models but not for individual building models for which activity specific occupancy profiles are discrete or stepped.

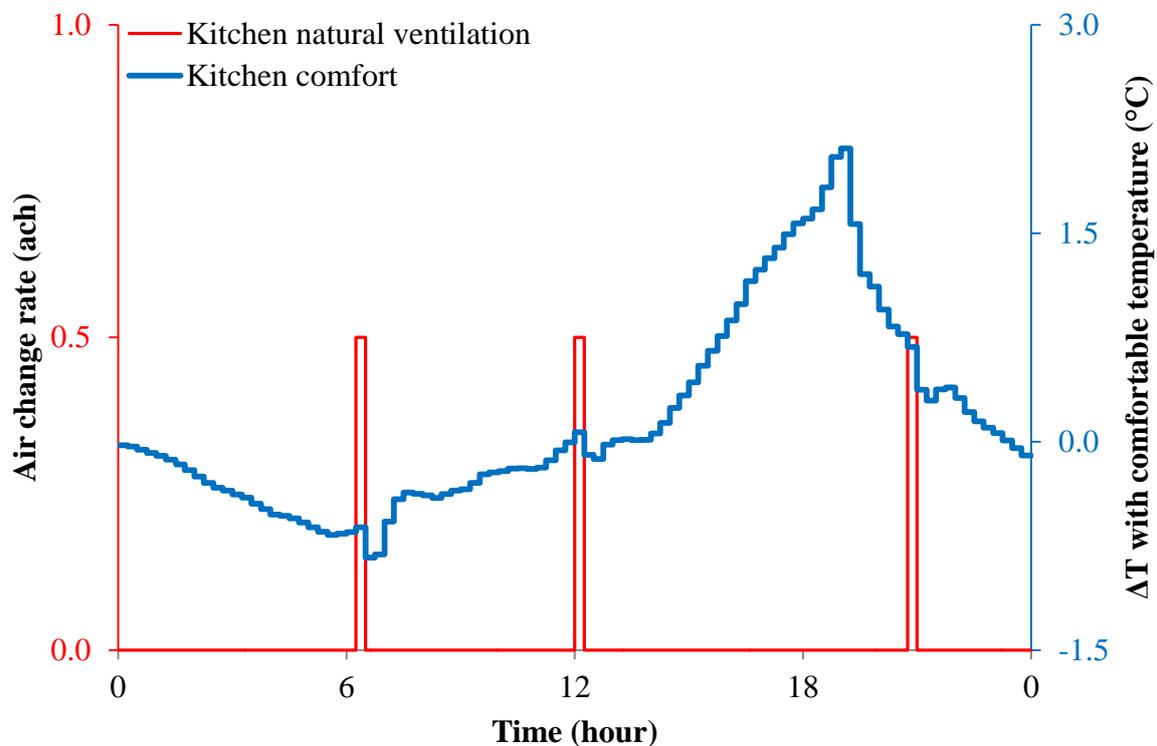
The natural ventilation algorithms must be “called” only once the warm-up simulations are completed by the BPS platform to auto-size some input components, such as the size of a circulation pump. It prevents results obtained for heating and cooling loads during the warm-up periods from diverging, as observed by Dutton et al. (2012), even if this “non-convergence” issue does not impede the simulation to complete. It is directly related to the stochastic behaviour of the natural ventilation model which is integrated within a

deterministic BPS platform: results differ from one simulation to another when all other inputs are constant.

It is vital to adjust the comfortable temperature ranges as well as the occupancy and activity patterns derived from TUS data in order to reflect the specific behaviour of occupants at a particular location. As emphasised by Peeters et al. (2009), in domestic buildings in particular, there is a very strong relationship between thermal comfort and outdoor conditions, especially outdoor temperature. Also, occupancy and activity patterns of occupants vary greatly with the climatic zone and the social habits. However, the general layout of the algorithms and the modelling challenges associated with their integration within BPS archetype models might not differ from one location to another.

Depending on the quality of the TUS data used, it might be necessary to normalise the probability distribution of each activity set (“main activities” and “other activities”), with respect to either the “all activities” probability distribution or the average household size (4.94 in this case study for a household with “4 or more” residents), when comparing their value to the random threshold. The assumption behind such a normalisation process is whether the operation of natural ventilation is mostly performed by adults or by any occupant, adult or not. Indeed, as observed in Figure 2, only adult residents were surveyed in the TUS used in this case study, with a risk of underestimating the probability to perform any action to restore indoor comfortable conditions, such as the operation of natural ventilation. Without real measurement data to support that assumption, the TUS active occupancy data used in this case study is not extrapolated and the normalisation process is not performed. As a consequence, higher probabilities of operation of natural ventilation would be met in smaller households.

#### *Natural ventilation model behaviour*



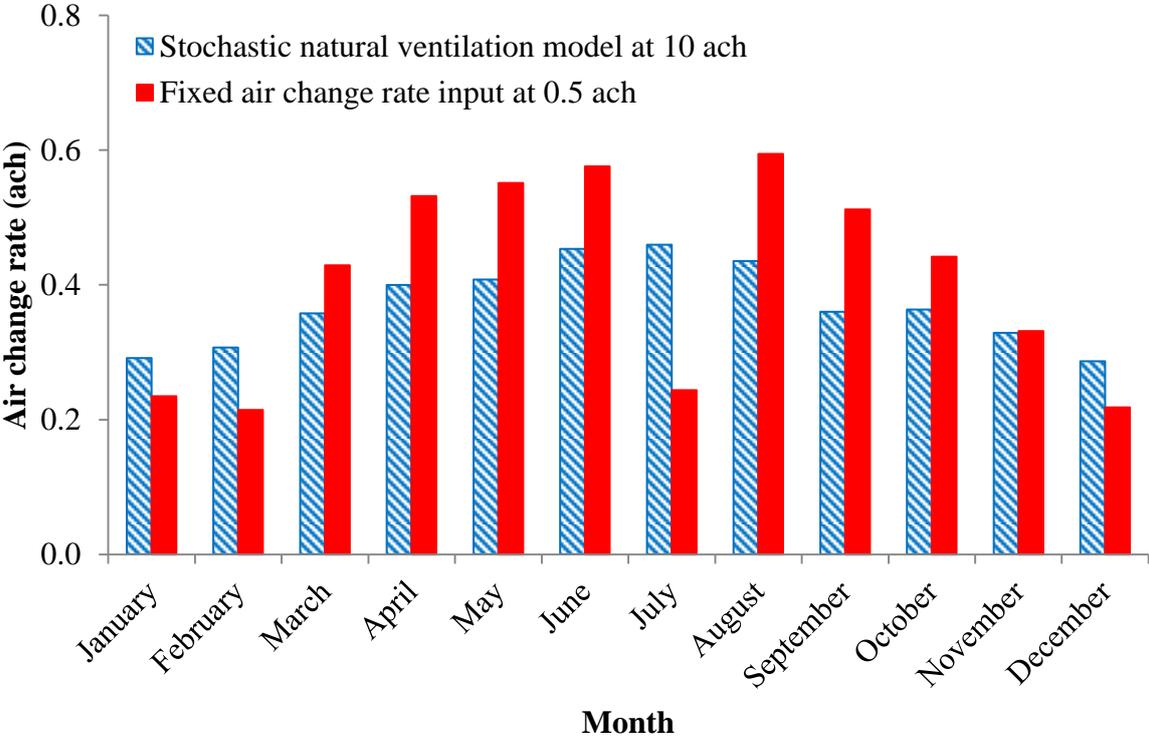
**Figure 5 - Kitchen natural ventilation and thermal comfort, weekday, 15-min resolution**

Figure 5 shows an example operation of natural ventilation only, at a fixed air change rate of 0.5 ach, during a September weekday for the kitchen of the detached house archetype. The

indoor operative temperature is within the comfortable range all day, thus not requiring the natural ventilation operation due to thermal comfort issues. Natural ventilation is activated early in the morning, at noon and in the evening, due to the cooking activity taking place at those times. An extra fixed air change rate input of 0.25 ach is set, due to infiltration through the building envelope, in line with DECLG and SEAI (2013) for new detached houses. The effective infiltration level is computed at each simulation timestep based on the fixed air change rate input, the indoor and outdoor conditions (temperature, wind speed and direction).

**Table 3 – Annual average natural ventilation air change rates per room**

Room	Annual average natural ventilation output (ach)							
	Fixed air change rate input at 0.5 ach	Stochastic natural ventilation model at different air change rate inputs						
		0.5 ach	1 ach	2 ach	4 ach	8 ach	10 ach	12 ach
Bath	0.39	0.01	0.02	0.04	0.07	0.14	0.17	0.19
Bed 1	0.37	0.01	0.02	0.04	0.07	0.13	0.16	0.19
Bed 2	0.36	0.01	0.02	0.03	0.06	0.12	0.15	0.17
Bed 3	0.42	0.06	0.12	0.22	0.42	0.80	0.98	1.17
Bed 4	0.41	0.05	0.11	0.21	0.40	0.78	0.96	1.14
Dining	0.41	0.01	0.02	0.04	0.08	0.15	0.18	0.22
Kitchen	0.45	0.03	0.04	0.08	0.15	0.28	0.34	0.40
Living	0.48	0.02	0.04	0.07	0.12	0.19	0.23	0.26
Study	0.46	0.01	0.02	0.03	0.06	0.12	0.15	0.18
<b>Building</b>	<b>0.42</b>	<b>0.13</b>	<b>0.15</b>	<b>0.18</b>	<b>0.24</b>	<b>0.36</b>	<b>0.42</b>	<b>0.47</b>



**Figure 6: Monthly average natural ventilation air change rates for the whole building**

Table 3 introduces the calibration process of the average annual ventilation air change rates simulated with the stochastic natural ventilation algorithm compared to benchmark results with a fixed air change rate input of 0.5 ach set for each room with operable windows. With the stochastic natural ventilation algorithm, an air change rate input of 10 ach is found to produce the same results as the benchmark, at a building level. As observed by Andersen et al. (2013), bedrooms exhibit the greatest natural ventilation levels, whereas very low levels are observed in all other rooms. The low natural ventilation levels observed in bedrooms 1 and 2 are due to the low active occupancy levels met in those rooms, because of the TUS data quality, as discussed in the section above.

Figure 6 compares the monthly variations of air change rates, due to natural ventilation only, between the benchmark fixed air change rate input of 0.5 ach and the stochastic natural ventilation algorithm with an air change rate input of 10 ach. In both cases, a seasonal variation is characterised, with higher air change rates during summer than during winter, Figure 6. In the benchmark case, the seasonal and weather variations are reflected by EnergyPlus calculations which modify the fixed air change rate input of 0.5 ach at each simulation timestep, based on both the indoor and outdoor conditions (temperature, wind speed and direction). With the stochastic natural ventilation algorithm, the seasonal variations are reflected by an increase of the frequency of window operation in summer time due to the uncomfortable indoor temperatures met and the adaptive behaviour of occupants. However, the algorithm used to calculate the probability of natural ventilation operation does not consider the CO<sub>2</sub> indoor concentration, one of the most significant drivers for governing the operation of windows, together with the outdoor temperature, as observed by Andersen et al. (2013).

#### **4 Conclusions and further work**

Natural ventilation and adaptive thermal comfort algorithms, developed for applications within BPS models, have been successfully integrated within EPBD archetypes. The model behaviour is in line with recommendations drawn from similar modelling studies performed and validated against real data. The algorithms proposed consider the main drivers governing the operation of natural ventilation, and adapt them to a domestic context. The concept of active occupancy, which was initially related to the use of domestic electrical appliances and lighting, has been extended to the operation of natural ventilation. By controlling a single variable, namely the air change rate, it is possible to calibrate the model in order to match the required overall annual air change rate. Furthermore, by integrating high resolution models for occupancy and equipment use, and by increasing the time resolution of the EPBD archetypes from a yearly level to a sub-hourly level, the proposed approach expands previous investigations to include electrical load shifting, thermal comfort and indoor air quality issues. Due to the stochastic nature of the natural ventilation model, it is non-trivial to implement it within a deterministic BPS platform, and some technical challenges must be overcome so that the algorithms can reflect the main drivers governing the operation of natural ventilation. While some solutions are proposed for each challenge associated with the modelling process, an innovative approach is proposed, characterised by a strong relationship between the probability of operating windows and the activity specific occupancy patterns of residents, thus further embedding occupant behaviour within BPS archetype models.

Further features of the natural ventilation model include a modification of the main control variable in order to further account for the seasonal and weather variations: as initially performed by EnergyPlus, the air change flow rate can be calculated at each simulation timestep based on both the air change rate input, the indoor and outdoor conditions (temperature, wind speed and direction). Also, the algorithm used to calculate the probability of natural ventilation operation could be modified in order to consider the CO<sub>2</sub> indoor

concentration as one of the most significant drivers for governing the operation of windows, together with the outdoor temperature. Further features of the archetype models may include the electrification of space and water heating systems and the development of a methodology for the assessment of the demand response potential embedded within residential BPS archetypes through the implementation of load shifting and operating reserve provision strategies constrained by thermal comfort. Also, the archetypes modelled are key to scaling up the potential flexibility resource from individual representative buildings to a national scale.

## 5 Acknowledgements

This work was conducted in the Electricity Research Centre, University College Dublin, Ireland, which is supported by the Commission for Energy Regulation, Bord Gáis Energy, Bord na Móna Energy, Cylon Controls, EirGrid, Electric Ireland, Energia, EPRI, ESB International, ESB Networks, Gaelectric, Intel, SSE Renewables, and UTRC.

This publication has emanated from research conducted with the financial support of Science Foundation Ireland under Grant Number SFI/09/SRC/E1780.

## 6 References

- Andersen, R. et al., 2013. Window opening behaviour modelled from measurements in Danish dwellings. *Building and Environment*, Volume 69, pp. 101-113.
- Chiou, Y.-S., Carley, K. M., Davidson, C. I. & Johnson, M. P., 2011. A high spatial resolution residential energy model based on American Time Use Survey data and the bootstrap sampling method. *Energy and Buildings*, Volume 43, pp. 3528-3538.
- Corgnati, S. P., Fabrizio, E., Filippi, M. & Monetti, V., 2013. Reference buildings for cost optimal analysis: Method of definition and application. *Applied Energy*, Volume 102, pp. 983-993.
- CSO, 2012. *Central Statistics Office Ireland Census 2011: The Roof over our Heads - Housing in Ireland*. [Online] Available at: <http://www.cso.ie/en/media/csoie/census/documents/census2011profile4/Profile,4,The,Roof,over,our,Heads,Full,doc,sig,amended.pdf> [Accessed 11 November 2013].
- DECLG & SEAI, 2013. *Report on the Development of Cost Optimal Calculations and Gap Analysis for Buildings in Ireland Under Directive 2010/31/EU on the Energy Performance of Buildings (Recast) – Section 1: Residential Buildings*, Dublin: AECOM for the Department of the Environment, Community and Local Government of Ireland and the Sustainable Energy Authority of Ireland.
- DECLG, 2011. *Building Regulations 2011 - Technical Guidance Document L*, Dublin: Department of the Environment, Community and Local Government of Ireland.
- Dineen, D. & Ó Gallachóir, B., 2011. Modelling the impacts of building regulations and a property bubble on residential space and water heating. *Energy and Buildings*, 43(1), pp. 166-178.
- Dutton, S. et al., 2012. *Application of a Stochastic Window Use Model in EnergyPlus*. Madison, Wisconsin, SimBuild 2012.
- Energy Research Group & Environmental Institute, University College Dublin, 1999. *Homes for the 21st Century: The Costs & Benefits of Comfortable Housing for Ireland*, Dublin: Energy Research Group & Environmental Institute, University College Dublin for Energy Action Limited.

- Energy Saving Trust, DECC & DEFRA, 2013. *Powering the Nation – Household electricity-using habits revealed*, London: Energy Saving Trust, Department of Energy & Climate Change, Department for Environment Food and Rural Affairs.
- European Commission, 2009. *Directive 2009/28/EC of the European Parliament and of the Council on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC*, Brussels: European Commission.
- European Commission, 2010. *Directive 2010/31/EU of the European Parliament and the Council on the Energy Performance of Buildings (recast)*, Brussels: European Commission.
- Gupta, A., Hopfe, C. J. & Rezgui, Y., 2011. *A low-energy retrofit study of an off-gas welsh village using renewable energy simulation combined with the UK standard assessment procedure*. Sydney, Building Simulation 2011: 12th Conference of International Building Performance Simulation Association.
- IESNA, 2000. *The IESNA Lighting Handbook, 9th Edition - Reference & Application*. Ninth ed. New York(NY): The Illuminating Engineering Society of North America.
- International Energy Agency, 2011. *Technology Roadmap\_Energy-efficient Buildings: Heating and Cooling Equipment*, Paris: The Organisation for Economic Co-operation and Development (OECD) / International Energy Agency (IEA).
- Ma, O. et al., 2013. Demand response for ancillary services. *IEEE TRANSACTIONS ON SMART GRID*, December, 4(4), pp. 1988-1995.
- Neu, O. et al., 2013. *High Resolution Space - Time Data: Methodology for Residential Building Simulation Modelling*. Chambéry, Building Simulation 2013: 13th Conference of International Building Performance Simulation Association.
- Peeters, L., Dear, R. D., Hensen, J. & D'haeseleer, W., 2009. Thermal comfort in residential buildings: Comfort values and scales. *Applied Energy*, Volume 86, pp. 772-780.
- Richardson, I., Thomson, M. & Infield, D., 2008. A high-resolution domestic building occupancy model for energy demand simulations. *Energy and Buildings*, 40(8), pp. 1560-1566.
- Richardson, I., Thomson, M., Infield, D. & Clifford, C., 2010. Domestic electricity use: A high-resolution energy demand model. *Energy and Buildings*, 42(10), pp. 1878-1887.
- Swan, L. G. & Ugursal, V. I., 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy Reviews*, Volume 13, pp. 1819-1835.
- U.S. DoE, 2011. *Load Participation in Ancillary Services - Workshop Report*, Washington: U.S. Department of Energy.
- Widén, J. & Wäckelgård, E., 2010. A high-resolution stochastic model of domestic activity patterns and electricity demand. *Applied Energy*, 87(6), pp. 1880-1892.