Definition of a useful minimal-set of accurately-specified input data for Building Energy Performance Simulation

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ABSTRACT

Developing BEPS models which predict energy usage to a high degree of accuracy can be extremely time consuming. As a result, assumptions are often made regarding the input data required. Making these assumptions without introducing a significant amount of uncertainty to the model can be difficult, and requires experience. Even so, rules of thumb from one geographic region are not automatically transferrable to other regions. This paper develops a methodology which can be used to determine useful guidelines for defining the most influential input data for an accurate BEPS model. Differential sensitivity analysis is carried out on parametric data gathered from five archetype dwelling models. The sensitivity analysis results are used in order to form a guideline minimum set of accurately defined input data. Although the guidelines formed apply specifically to Irish residential dwellings, the methodology and processes used in defining the guidelines is highly repeatable. The guideline minimum data set was applied to practical examples in order to be validated. Existing buildings were modelled, and only the parameters within the minimum data set are accurately defined. All building models predict annual energy usage to within 10% of actual measured data, with seasonal energy profiles well-matching.

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1. Introduction

In the EU, buildings account for 40% of primary energy consumption and 33% of CO_2 emissions [1]. Thus, reducing energy consumption of the building sector is crucial to reducing overall primary energy consumption. Many look towards effective Building Energy Performance Simulation (BEPS) to help decrease building energy usage. However, studies have found that a significant "performance gap" often exists between building energy usage predicted by BEPS, and actual measured building energy usage [2–6].

Buildings are highly complex and stochastic systems by nature, and thus, the data which theoretically could be gathered and provided to a BEPS tool is almost inexhaustible [5]. Gathering this data is both costly and time consuming [7]. Providing this detailed data

to a BEPS tool and creating a detailed energy model of a building can also be extremely time consuming. Simplifications and assumptions regarding input data are often made. The assumptions and simplifications which must be made can lead to buildings being insufficiently represented by models [8]. Furthermore, each simplification and assumption introduces a degree of uncertainty into the energy model [9,10]. Uncertainty analysis has been identified as one method of addressing the "performance gap" [9,11–15]. However, uncertainty analysis can only be employed in order to quantify the expected accuracy levels of simulations, and is not intended to physically reduce the disparity between simulation and reality [15]. Understanding the implications and impacts of these introduced uncertainties on simulation accuracy is difficult and requires experience [16]. De Wit and Augenbroe [9] suggest that incomplete or inaccurate specification of the building and associated systems is one of the main sources of uncertainty which is introduced to building energy models.

Calibration is a popular method used in an attempt to reduce the performance gap between simulated and actual energy consumption. Typically, as part of this calibration process, inputs

Nomenclature

ACH	Overall dwelling air change rate (ach)
BEPS	Building Energy Performance Simulation
COP	Coefficient of performance
COP_sys	Heating system COP
DHW	Domestic hot water
DHW_use	Domestic hot water requirements (L $^{-2}$day^{-1})
DSA	Differential sensitivity analysis
E_aux	Heating system aux. energy (kWh m^{-2} year^{-1})
Equip_density	Equipment density (W m^{-2})
GSA	Global sensitivity analysis
HSBT	Heating set-back temperature (°C)
HSPT	Heating set-point temperature (°C)
IC	Influence coefficient
IP	Input parameter
IPbc	Base-case input parameter
L_dens	Lighting density (W m^{-2})
MCA	Monte-Carlo analysis
Occ_gains	Occupancy density (heat gains only) (m^2 person^{-1})
OP	Output parameter
OPbc	Base-case output parameter
Orientation	Building orientation (°)
p	Interval value between simulated points
r	Number of simulation points
Roof_abs	Roof surface solar absoptivity
Roof_emiss	Roof surface emissivity
SA	Sensitivity analysis
SHGC	Window solar heat gain coefficient
Thm_mass_floor	Ground floor thermal mass (kJ m^{-2} K^{-1})
Thm_mass_roof	Roof thermal mass (kJ m^{-2} K^{-1})
Thm_mass_wall	External wall thermal mass (kJ m^{-2} K^{-1})
U_door	External door U-value (W m^{-2} K^{-1})
U_floor	Ground floor U-value (W m^{-2} K^{-1})
U_frame	Window frame U-value (W m^{-2} K^{-1})
U_g	Glazing U-value (W m^{-2} K^{-1})
U_part	Internal partition U-value (W m^{-2} K^{-1})
U_roof	Roof U-value (W m^{-2} K^{-1})
U_wall	External wall U-value (W m^{-2} K^{-1})
Vt	Window visible light transmittance value
Wall_abs	External wall surface solar absorptivity
Wall_emiss	External wall surface emissivity
WWR	Window-to-Wall Ratio (%)
ΔX	Input parameter range

ing energy usage [20–26]. According to Hamby [27], Differential Sensitivity Analysis (DSA) is the backbone of all other sensitivity analysis techniques. To employ DSA to examine the relative influence of different input parameters, a base case simulation must first be executed. The values of all base case inputs (IP_{bc}) should be recorded, and also the resultant output energy consumption (OP_{bc}). Each input parameter should then be varied one at a time (ΔIP). The relative influence that each input parameter has on the output (ΔOP) is quantified by the non-dimensional Influence Coefficient (IC):

$$IC = \frac{\Delta OP/OP_{bc}}{\Delta IP/IP_{bc}} \tag{1}$$

It can be seen from examining previous studies that this method of SA is commonly used for BEPS applications [20,23,25]. This derivative based form of SA is known as local SA. MacDonald et al. [28] note that one underlying assumption of DSA is that varying the input affects the output linearly, over the range of input values. Global Sensitivity Analysis (GSA) techniques are viewed as providing more dependable results in cases where nonlinearity may be present. Parameters are generally varied simultaneously and randomly. Thus, GSAs (e.g. Monte Carlo Analysis (MCA)) are considered to be unaffected by nonlinearity, and interactions between input parameters are accounted for. However, GSA techniques can be quite computationally expensive [29,30]. Wainwright et al. [29] state that there is an argument that GSA methods (such as MCA) do not provide enough additional information over local SA methods (such as DSA) to justify the increased computational expense.

In one of the earliest case studies of SA in BEPS, Lomas and Eppel [20] employed the simple DSA method and the more advanced MCA to three detailed energy models. Interestingly, the results produced by both methods were in good agreement, in terms of the weighted ranking of parameters , despite DSA being quite a simplistic approach to SA. Rees and Dadioti [25] also conducted a study where two different methods of SA are compared; the DSA method and the Morris method. Again, the results were quite similar, with the exception of two parameters whose rank of importance was reversed. An analysis of the results obtained by Jin and Overend [26] using two different methods of SA also revealed that results for both methods were in good agreement.

This paper aims at using the computationally frugal yet effective DSA method in order to identify the most influential input parameters for a given set of building archetypes. The DSA method will be employed on data describing how the output (building energy consumption) changes as the inputs are varied, thus providing a weighted representation of the influence of each input parameter. The most influential input parameters will be used in order to form a guideline minimum set of accurately defined input data. The minimum data set can be used in order to add some objectivity to the decisions made regarding input data assumptions and simplifications, ultimately leading to increased modelling accuracy and/or decreased modelling time. Waltz [31] states that for a building simulation to be classified as accurate, predicted annual energy usage ought to be within 5% of the actual recorded consumption, with seasonal energy usage profiles matching reasonably well. For **time-restricted models**, Waltz [31] suggests that **10%** is an acceptable goal.

DesignBuilder, a user interface for the EnergyPlus simulation engine has been chosen to be used for all modelling and simulation purposes. In Section 2, the methodology which has been developed in order to form the minimum data sets will be outlined in detail. Section 3 examines the results of the applied methodology to a given set of building archetypes. A minimum data set will

are "adjusted" on a trial-and-error basis until the simulated results are within 5% of measured utility data [17,18]. Although the model may now closely represent measured utility data, on a subutility level the model may be an extremely poor representation of the building [8]. For this reason, Raftery et al. [8] have developed a method aimed at adding some objectivity to the calibration process. However, as Coakley et al. [19] state, due to the sheer number of inputs required for detailed building energy simulation and the limited number of measured outputs, calibration will always remain an indeterminate problem which yields a non-unique solution.

Sensitivity Analysis (SA) can be used in order to determine how influential a given input parameter of a system or process is on the resultant output of that system or process. For BEPS purposes, SA is generally employed in order to determine how influential various model and simulation input parameters are on build-

Fig. 1. Process diagram illustrating how to ascertain and apply a minimum measurement set for a defined subset of the building stock.

be applied to a practical example in Section 4. Section 5 finally summarises the main outcomes.

2. Methodology

This paper focuses on producing guidelines for typical Irish dwelling types. However, the processes and methodology used are highly repeatable, and applicable to almost any category of building situated in any given location.

As guidelines for typical Irish dwellings must be produced, archetype models which are representative of a significant portion of the Irish dwelling stock are required to be modelled. These models will be referred to as the base-case archetype models. It is imperative that the values used for all input parameters for each of the base-case models are representative of the "most probable" values for Irish dwellings.

A process diagram outlining the overall methodology used in this study is shown in Fig. 1. The first step is defining the base case input parameter values, and generating the base case energy models, representative of Irish archetype dwellings. The base case energy model simulations can then be executed, and the resultant base case output (annual energy usage) values recorded. Subsequently, the parametric modelling phase can be initiated. In this stage of the process, a range of values and intervals are defined for each input parameter. The process of defining these ranges and intervals will be outlined in Section 2.3. Parametric simulations can then be executed in order to obtain the parametric data required for SA. By performing SA (the SA process will be described in detail in Sections 2.4 and 2.5 on the parametric data recorded for each archetype and input parameter, a useful minimal-set of accurately-

specified input data can be defined, based on the results of the SA. The minimum data set can then be applied to a practical example in order to be confirmed. Note the feedback process link, between the application of the minimum data set and the definition of the minimum data set, shown in Fig. 1. If the applied minimum data set produces unsatisfactory results, the minimum data set can be re-defined (this feedback process will be described in detail in Section 2.5).

This process diagram can be referred to, when repeating the processes outlined in this paper, in order to form guideline minimum data sets for other building archetypes. All processes illustrated in the process diagram are described in detail in this section.

2.1. Archetype dwelling models

2.1.1. Base-case archetype model inputs

Comprehensive Irish dwelling archetypes have been developed by Nue and Sherlock [32,33]. The five archetype dwellings are based on a DECLG report [34], and are deemed to be representative of over 80% of the Irish building stock. However, for each archetype, three separate constructions are considered (new insulated cavity wall, existing uninsulated cavity wall, and existing uninsulated hollow block wall [35]), resulting in a total of 15 models (the dimensional characteristics for each archetype remained the same, but the physical characteristics of the constructions were changed). Given the number of input parameters which must be examined as part of this project, a thorough parametric analysis using 15 models is considered an unfeasible and time-consuming approach.

Table 1
Summary of archetype geometries.

Dwelling	Area of external N/W/S/E façade (m²)	Window-to-Wall ratio for N/W/S/E façade	Volume (m³)	Total floor area (m²)
Detached	41/51/41/51	0.5/0/0.5/0	408	160
Bungalow	31/19/31/19	0.4/0/0.4/0	250	104
Semi-detached	36/46/36/0	0.4/0/0.4/1	321	126
Mid-floor apartment	0/0/22/14	0/0/0.5/0	130	54
Top-floor apartment	0/0/22/15	0/0/0.5/0	130	54

(a) Detached   (b) Semi-detached

(c) Bungalow   (d) Apartment
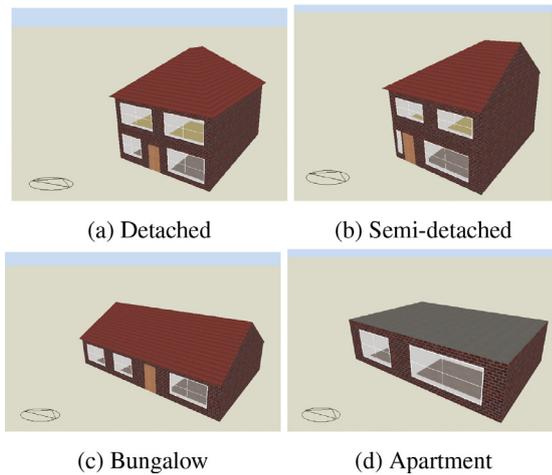
Fig. 2. 3-D visualisations of the model archetype dwellings illustrating a representative variation in archetype geometries.

Famuyibo et al. [36] previously conducted a statistical analysis of two housing databases (Energy Performance Survey of Irish Housing (EPSIH) and the Irish National Survey of Housing Quality (INSHQ)), and used the results of this statistical analysis order to develop the average, or "most probable" characteristics of different Irish dwelling archetypes. The combined use of the physical characteristics of typical Irish dwellings defined by Famuyibo et al. [36], and the dimensional archetype models developed by Neu and Sherlock [32,33], allowed five archetype models (as opposed to 15) to be developed which represent a significant portion of the Irish residential stock. The five archetypes which are developed and used as the basis of this study are as follows:

1. A two-storey detached dwelling (hereafter referred to as "detached").
2. A two-storey semi-detached dwelling (hereafter referred to as "semi-detached").
3. A single-storey detached dwelling (hereafter referred to as "bungalow").
4. A mid-floor apartment.
5. A top-floor apartment.

As Ireland is located within one single climatic zone [37], it is decided that the models should be simulated in an area where the majority of Irish dwellings are located (although Ireland lies within one climatic zone, differing EnergyPlus weather data files are available, depending on location). According to data from [38], over 28% of Irish dwellings were located in county Dublin in 2011, a far greater proportion than any other region. Dublin is therefore selected as a suitable location for the model simulations.

3-D archetype model visualisations are shown in Fig. 2, and the archetype geometries are summarised in Table 1. Note that a value of zero for the external wall area means that a particular wall has been modelled adiabatically. It also is worth noting at this point that, as suggested by Sherlock [33], the heating system for the base

case archetype models follows a common hot water radiator template (powered by a standard boiler). However, the overall seasonal COP/efficiency of the heating system is taken from the archetypes defined by Famuyibo et al. [36]. The modelling process of the base-case archetype dwellings is described in detail in [39].

2.1.2. Base-case archetype model outputs

Once the modelling process was complete for all archetypes, the next step was to execute the base-case simulations and record the annual energy consumption values for each (the base-case outputs). These outputs, broken down by energy usage subcategory (heating, DHW requirements, electrical equipment, lighting and system pumps) are shown in Fig. 3(a). The annual energy densities for each archetype (kWh per m² of floor area) are shown in Fig. 3(b).

It can be seen that as a consequence of relatively greater external surface areas the energy consumption of the more voluminous dwellings is heavily dominated by space heating requirements. Almost 70% of the detached archetype energy requirements are consumed by space heating. This is not the case for the less voluminous archetypes. For example, only 38.6% of the mid-floor apartment energy requirements are devoted to space heating. Other factors such as DHW requirements, electrical equipment and lighting make up a greater proportion of total annual energy requirements for the less voluminous dwellings (the apartment archetypes).

2.2. Parametric analysis

In order to obtain a sufficient resolution of how the output Y varies as a function of each input parameter X_i, each input parameter should be simulated at r_i points within the specified parameter range. Taking n to be the number of input parameters, the total required number of simulations (Z) can be described by the equation:

$$\sum_{i=1}^{n} r_i \tag{2}$$

Controlling the number of intervals and points (r_i) in each input parameter range (ΔX_i) is the only feasible way of controlling the total required number of simulations (Z), whilst ensuring that a sufficient resolution of data describing how the output varies in response to varying the input. Therefore, $r = 4$ or $r = 5$ are selected as a suitable number of simulated points in each input parameter range. It is assumed that this will provide a sufficient resolution of how annual building energy consumption varies as a function of each input parameter examined. Let p be the value of the interval between simulation points (r) in each defined parameter range. p for the ith input parameter can be described by:

$$p_i = \frac{\Delta X_i}{r_i} \tag{3}$$

2.3. Input parameter range of values

In order to examine the relative influence of each input parameter on annual building energy consumption, data describing how
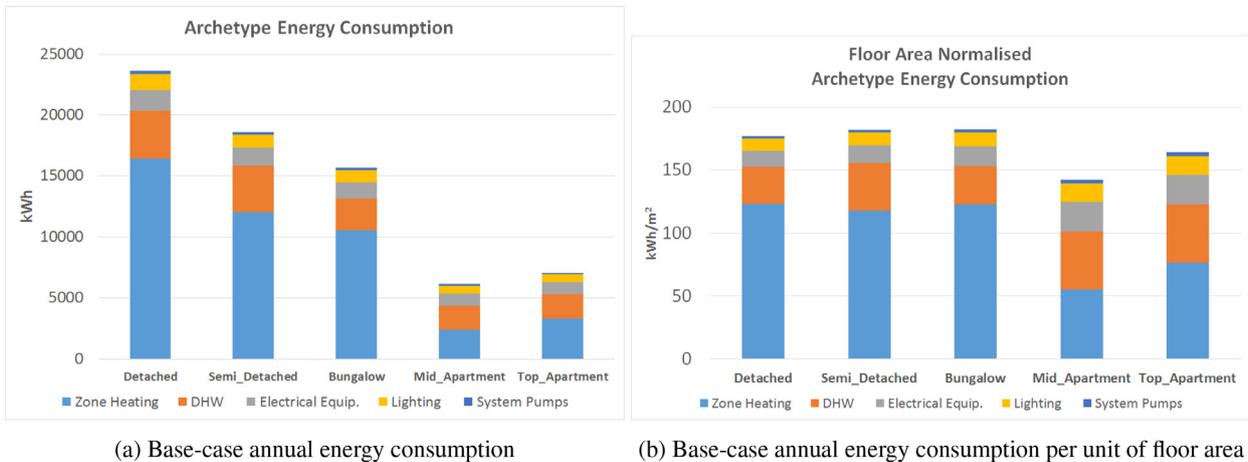
(a) Base-case annual energy consumption   (b) Base-case annual energy consumption per unit of floor area

Fig. 3. Annual (a) and normalised (b) energy consumption illustrating large differences in energy use but minor differences in energy density.

Table 2
Input parameter range of values and associated increment.

Parameter	Unit	Acronym	Minimum	Maximum	Increment
External wall U-value	W m^{-2} K^{-1}	U_wall	0.1 [40]	1.1	0.25
Roof U-value	W m^{-2} K^{-1}	U_roof	0.1 [40]	0.9	0.2
Ground floor U-value	W m^{-2} K^{-1}	U_floor	0.1 [40]	1.1	0.25
Internal partition U-value	W m^{-2} K^{-1}	U_part	1	3	0.5
External door U-value	W m^{-2} K^{-1}	U_door	0.5	3	0.5
External wall internal thermal mass	kJ m^{-2} K^{-1}	Thm_mass_wall	75	175	25
Roof internal thermal mass	kJ m^{-2} K^{-1}	Thm_mass_roof	125	225	25
Ground floor internal thermal mass	kJ m^{-2} K^{-1}	Thm_mass_floor	100	200	25
External wall emissivity		Wall_emiss	0.15	0.95	0.2
External wall solar absorptance		Wall_abs	0.15	0.95	0.2
Roof emissivity		Roof_emiss	0.15	0.95	0.2
Roof solar absorptance		Roof_abs	0.15	0.95	0.2
Window-to-Wall Ratio	%	WWR	10 [41]	70 [41]	20
Glazed portion U-value	W m^{-2} K^{-1}	U_g	0.6 [40]	4.6	1
Frame U-value	W m^{-2} K^{-1}	U_frame	0.5	4.5	1
Solar heat gain coefficient		SHGC	0.1 [42]	0.9 [42]	0.2
Light transmittance value		V_t	0.19 [42]	0.99 [42]	0.2
Heating system seasonal COP/efficiency		COP_sys	0.5	2.5 [43]	0.5
Auxiliary energy consumption	kWh m^{-2} year^{-1}	E_aux	1	5	1
Heating set-point temperature	°C	HSPT	18 [44]	23 [44]	1
Heating set-back temperature	°C	HSBT	10 [44]	14 [44]	1
DHW usage	L m^{-2} day^{-1}	DHW_use	0.5	3.5	1
Occupancy density	m^2 person^{-1}	Occ_gains	0	0.1	0.025
Lighting density	W m^{-2}	L_dens	1	9	2
Equipment density	W m^{-2}	Equip_dens	1	21	5
Air changes per hour	ach	ACH	0.5 [40]	1.5 [33]	0.2
Orientation	°	Orientation	0	180	45

the output (annual energy usage) varies as a function of the input must be acquired. As aforementioned, in order to obtain this data, each input parameter which is to be examined should be varied over a range of values at specified intervals (see Eq. (3)). The chosen range of values should reflect the range of possible values of each input parameter for Irish dwellings. The threshold minimum and maximum values for the input parameters to be examined are listed in Table 2. Many of the sources of these threshold values are also listed in Table 2. However, in some cases, engineering judgement was required in the selection of the minimum or maximum values. For example, many of the predefined constructions within the predefined DesignBuilder libraries were examined in order to define the range of thermal masses to be examined for the walls, floor and roof. The reasoning behind the selection of the threshold values is described in detail in [39]. The logic behind the selected simulated intervals within the range has been described in Section 2.2). Once the range and incremental values were defined, the parametric simulations were executed. This provided the

parametric data required in order to perform DSA on each input parameter.

Once the range and incremental values were defined, the parametric simulations were executed. This provided the parametric data required in order to perform DSA on each input parameter.

2.4. Sensitivity analysis

As per Section 1, Eq. (1), Differential Sensitivity Analysis (DSA) has been selected as a suitable method of SA to be used in this study. As noted by Macdonald et al. [28], an underlying assumption of DSA is that varying the input affects the output linearly. In order to reduce the effects of non-linearity, an IC value between each simulated point, spaced at intervals of p is calculated. An average IC value over the input parameter range can then be determined. Consider an input parameter range of ΔIP, with r simulated points at intervals of p over the range of input parameter values. Taking
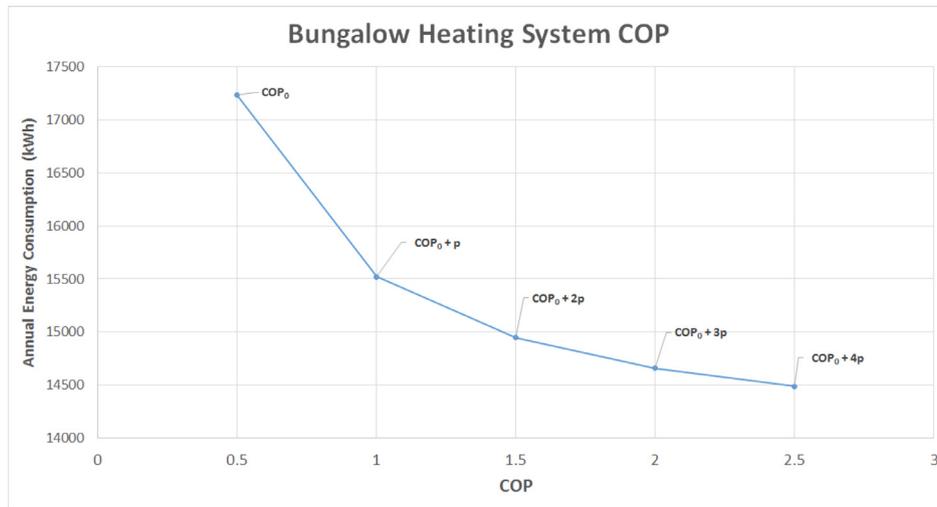
Fig. 4. Variation in annual energy usage for the bungalow archetype as heating system COP/efficiency is varied.

the first simulated point as IP_0, the average IC value over the range of input parameter values can be described by Eq. (4):

$$IC = \frac{1}{r-1}\left(\left|\frac{\frac{OP_{IP_0+p} - OP_{IP_0}}{OP_{bc}}}{\frac{p}{IP_{bc}}}\right| + \left|\frac{\frac{OP_{IP_0+2p} - OP_{IP_0+p}}{OP_{bc}}}{\frac{p}{IP_{bc}}}\right|\right.$$

$$\left. + \ldots + \left|\frac{\frac{OP_{IP_0+(r-1)p} - OP_{IP_0+(r-2)p}}{OP_{bc}}}{\frac{p}{IP_{bc}}}\right|\right) \qquad (4)$$

Using this method for calculating the IC value for each input parameter is considered to significantly reduce the influence of the DSA linearity assumption on the results of the sensitivity analysis. This method can be seen to be somewhat similar to applying a segmented or "piecewise linear" regression fit to the data for each input parameter.

2.5. Applying the DSA method to the parametric data

The DSA method now must be applied to the parametric data gathered from the process described in Section 2.2. In order to fully describe the application of the DSA method to the parametric data, an example is used. The variation in total annual energy usage as the seasonal COP/efficiency of the heating system is varied incrementally is shown in Fig. 4. This specific case is chosen as it exemplifies a situation where varying the input does not affect the output linearly. Note that the COP/efficiency is varied between a range of 0.5 and 2.5, at intervals of 0.5 ($COP_0 = 0.5$, $p = 0.5$). Taking E_{COP} as the energy usage at each of the five simulated points ($r = 5$), the IC of heating system COP for the bungalow archetype can be described by the following Eq. (5):

$$IC = \frac{1}{4}\left(\left|\frac{\frac{E_{COP_0+p} - E_{COP_0}}{E_{bc}}}{\frac{p}{COP_{bc}}}\right| + \left|\frac{\frac{E_{COP_0+2p} - E_{COP_0+p}}{E_{bc}}}{\frac{p}{COP_{bc}}}\right|\right.$$

$$\left. + \left|\frac{\frac{E_{COP_0+3p} - E_{COP_0+2p}}{E_{bc}}}{\frac{p}{COP_{bc}}}\right| + \left|\frac{\frac{E_{COP_0+4p} - E_{COP_0+3p}}{E_{bc}}}{\frac{p}{COP_{bc}}}\right|\right) \qquad (5)$$

For this study, the IC value for each input parameter is determined in order to quantify how sensitive annual building energy

usage is to each parameter. Whether varying the input parameter affects the output (annual energy consumption) positively or negatively is not of interest. For this reason, the absolute values of the ICs over input parameter range are calculated, and an average of these values taken (see Eq. (5)). Thus, the IC value for each input parameter will be consistently positive and easily compared against others in order to view the most influential parameters. The process described in this section for the calculation of the IC for the bungalow heating system COP/efficiency, from the parametric data recorded, is repeated for each input parameter to be examined. The IC values for the examined input parameters can then be plotted, compared and ranked for each archetype dwelling.

A threshold IC value can then be determined from examining the ranked data globally, above which parameters will be considered influential, and thus be included in the minimum dataset. The minimum dataset will then be applied to a practical example. If the applied minimum dataset does not provide sufficiently accurate results, the threshold IC value can be increased, and a new minimum dataset formed. The new minimum dataset can then be reapplied to a practical example and the accuracy of the results checked again (this feedback loop is shown in Fig. 1). The results of the SA will be discussed in detail in Section 3.

3. Results of the sensitivity analysis

In this section, the parameter sensitivities computed using DSA will be examined in detail. Note that from henceforth, all input parameters shown in figures and tables will be abbreviated using representative parameter symbols as defined in Table 2. It should also be noted that all discussions of the results in Section 3 will be based on the results displayed in Fig. 5.

3.1. Overview of parameter sensitivities

As expected, the U-value of the archetype external walls proves to have a significant influence on building energy use. In most cases, the U-value of the roof proves to be slightly less influential (with the exception of the top-floor apartment). Interestingly, the results show that the floor U-value has a lower impact on the energy usage of the archetype models. According to data taken from [45], mean annual ground temperatures (at 10 cm depth) are 1 °C higher than average ambient air temperatures for the Dublin region in 2014. Furthermore, the external surface of the floor is not
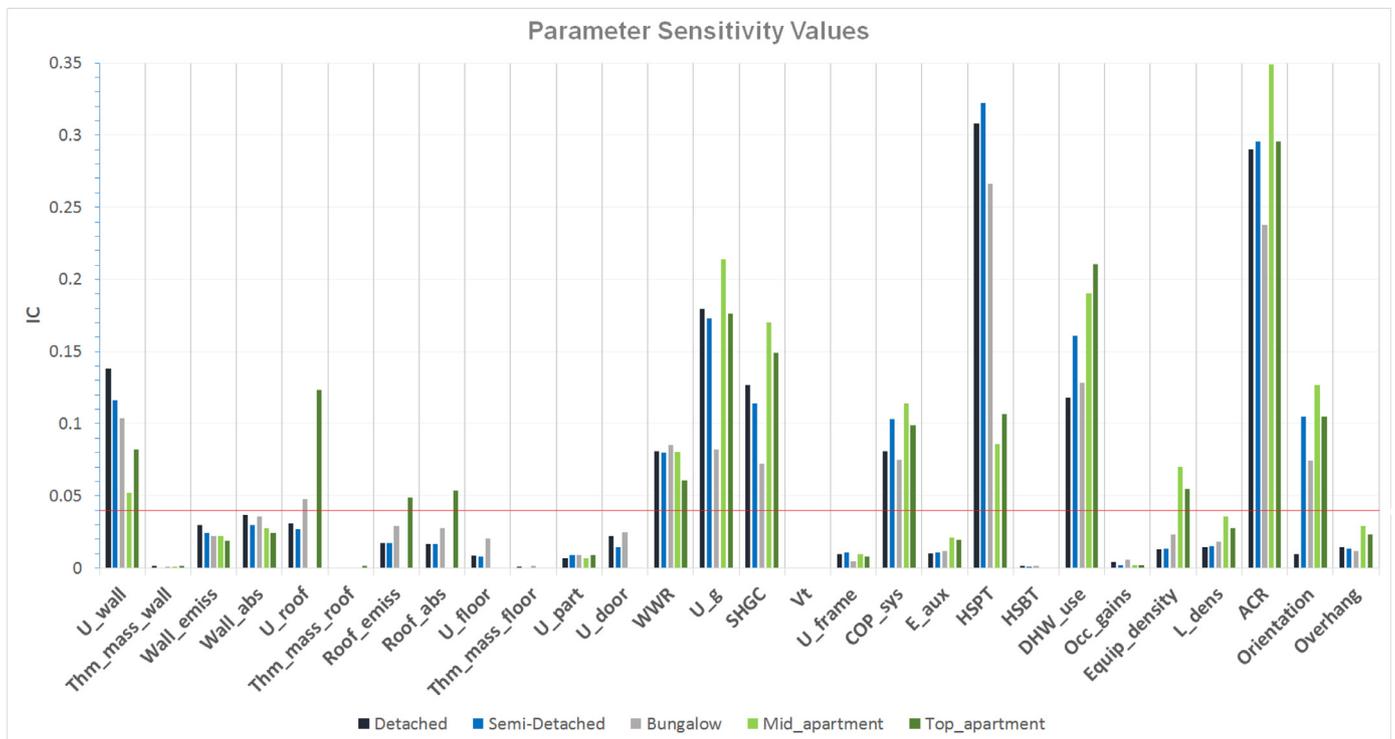
Fig. 5. Sensitivity values for all input parameters examined with ten parameters above IC cut-off of 0.04.

subject to convective cooling, unlike the external surfaces of the walls and roof. The higher average ground temperatures and lack of convective cooling may be the cause of the floor U-value being less influential than that of the walls and roof. The influence of the internal partition and external door U-values are significantly lower than wall and roof U-values. Overall, the thermal masses of the constructions have a negligible effect on the output. Wall and roof surface properties (emissivity and absorptivity) have a somewhat considerable impact on building energy consumption for all archetypes, in most cases having a greater *IC* value than that of the floor U-value.

In all cases, the glazing U-value proved to be more influential than any of the U-values of the opaque building elements. Window SHGC value is also a hugely influential parameter. As expected, WWR also has a significant impact on energy consumption. The visible transmittance (V_t) value of the windows had no impact on energy use. This can be attributed to the fact that the artificial lighting template used in the models is operated on an on/off schedule and is not governed by outdoor luminance levels. Although this is not ideal, and V_t values of the windows should have an effect on lighting energy, it is uncommon in Irish dwellings to control indoor lighting levels based on available daylight.

Devising a method to test the effect of window V_t values on zones in which lighting levels are not controlled by the level of daylight being received is outside the scope of this paper. Regarding window frame U-values, the impact on annual building energy requirements is small-scale when compared to glazing U-values and SHGC values.

It can be seen that HSPT has an extremely forceful influence on dwelling energy consumption, particularly for the more voluminous archetypes, with greater external surface areas. Heating setback temperatures (HSBT) appear to have a much more small-scale impact. As expected, daily DHW consumption levels also strongly influence energy requirements. The heating system COP/efficiency also has a weighty impact on the output. Heating system auxiliary energy requirements effects cannot be described as negligible,

however they appear to be much less influential than the overall heating system COP/efficiency.

Overall, gains due to the density of occupants in each dwelling has a relatively small impact on energy requirements. Equipment and lighting densities have a greater influence on dwelling energy consumption for the less voluminous archetypes, with smaller external surface areas (apartments). This is attributed to the fact that the relative densities of equipment and lighting is greater for the smaller archetypes. Zones with high lighting and equipment densities (e.g. kitchens) account for a greater proportion of the total floor area. Also, as discussed in Section 2.1.2, the energy requirements of the archetypes with greater levels of exposed surface area, is much more heavily dominated by heating requirements. Thus, the equipment and lighting energy requirements will naturally have less of an impact on these larger dwellings. On average, ACH proved to be the most influential parameter of all those considered. Building orientation proved to be quite influential also (the detached archetype being an exception).

3.2. Formation of the minimum data sets

A thorough analysis of the ranked *IC* values (which are shown graphically in [39]) considered each input parameter and archetype. This paper then postulates that an *IC* value of =0.04 should serve as the cutoff point for parameters which should be included in the guideline minimum set of accurately-defined input data. This postulation will be tested in Section 4. The guideline minimum sets of accurately-defined input data are shown in Table 3.

4. Application of the minimum data set

4.1. Overview & background

The minimum data sets, listed in Table 3, are now applied to and validated against a practical example of each archetype.

Table 3
Minimum set of well-defined input data shown for each archetype ($IC = 0.04$ used as cut-off value).

Rank	Detached	Semi-detached	Bungalow	Mid-floor apartment	Top-floor apartment
1	HSPT	HSPT	HSPT	ACH	ACH
2	ACH	ACH	ACH	U_g	DHW_use
3	U_g	U_g	DHW_use	DHW_use	U_g
4	U_wall	DHW_use	U_wall	SHGC	SHGC
5	SHGC	U_wall	WWR	Orientation	U_roof
6	DHW_use	SHGC	U_g	COP_sys	HSPT
7	COP_sys	Orientation	COP_sys	HSPT	Orientation
8	WWR	COP_sys	Orientation	WWR	COP_sys
9	–	WWR	SHGC	Equip_density	U_wall
10	–	–	U_roof	U_wall	WWR
11	–	–	–	–	Equip_density
12	–	–	–	–	Roof_abs
13	–	–	–	–	Roof_emiss
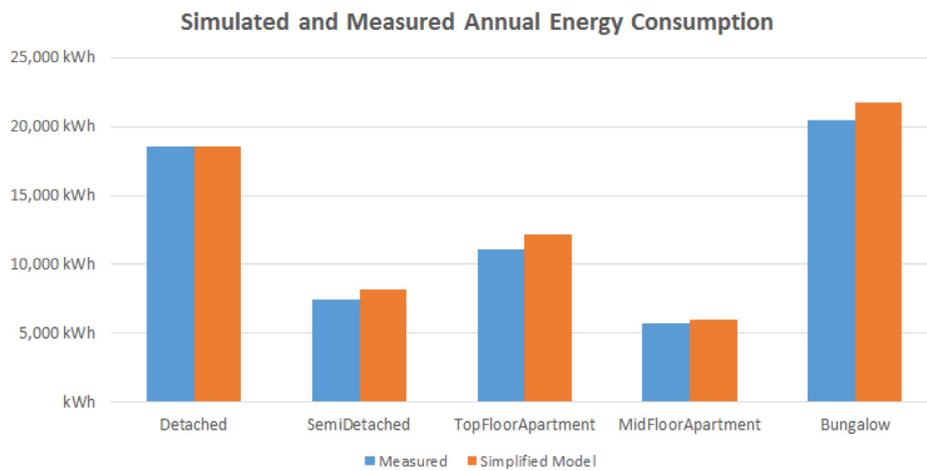
Fig. 6. Annual simulated and measured results of each exiting archetype used to validate the results of this study.

Fig. 7. 3-D model and photograph of test house [46].

Physical archetype buildings themselves do not exist as all previous dwellings used in order to form the minimum data sets are representative archetype models only. Thus, pragmatic verification uses a simplified energy model of an existing building for each archetype.

This section applies, in detail, the minimum data set to the bungalow archetype and uses both measured energy data and a calibrated energy model outputs. For the other archetypes (detached, semi-detached, mid-floor apartment and top-floor apartment), a similar approach was used in validating their respective minimum datasets. The simulated annual energy use for all dwellings is shown alongside measured data in Fig. 6. For photographs and more detailed information on the monthly energy profiles of the detached, semi-detached, mid-floor apartment and top-floor apartment archetypes, refer to Appendix B.
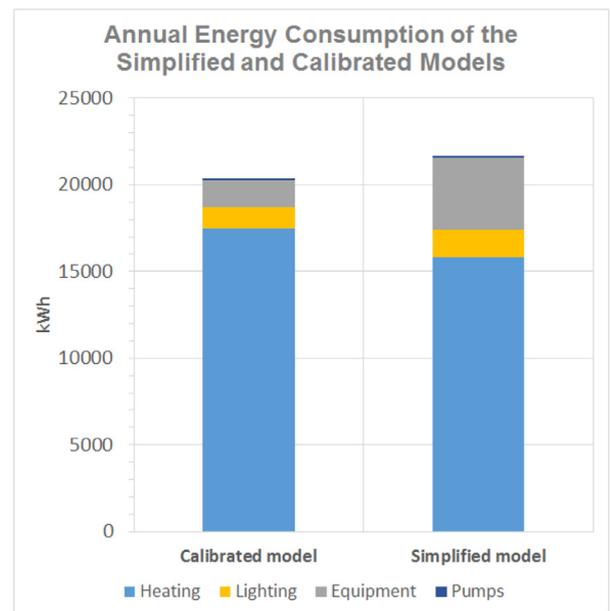
Fig. 8. Annual energy use for the simplified model is within 6% of the calibrated energy model.

This study uses a calibrated building energy model which was previously developed by Pallonetto et al. [46] to examine the impact of retrofitting an existing dwelling from conventional mixed fuel based heating to a smart-grid enabled all-electric heating. It
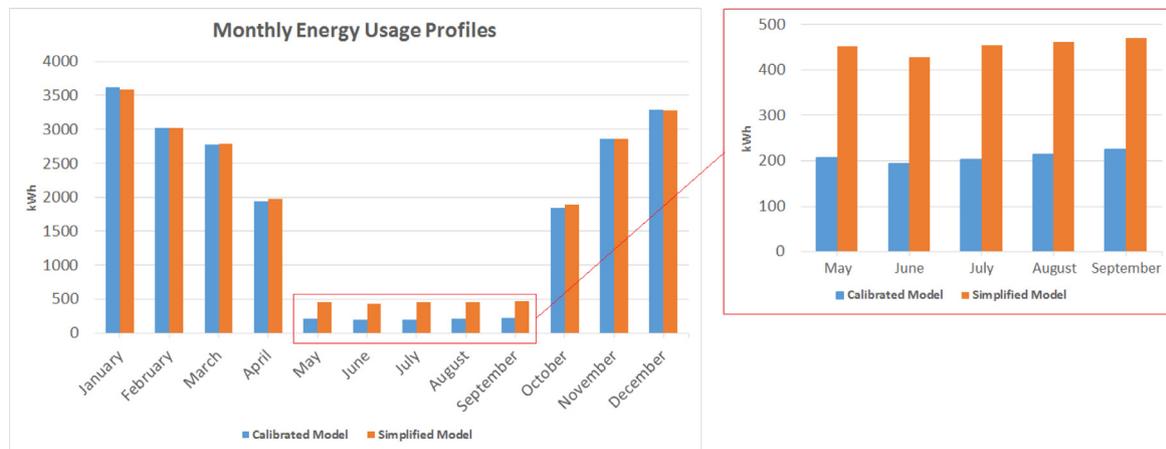
Fig. 9. Monthly energy profile shown for the simplified and calibrated energy models illustrates a close fit during winter spring and summer but a significant discrepancy during summer months.

should be noted that the version of the model used in this project is the version prior to the all-electric retrofit. The dwelling is a single-storey detached (bungalow) construction, located in county Wicklow, Ireland (Fig. 7). As this model has been extensively calibrated against measured data, it is considered to sufficiently represent actual performance of the bungalow.

This bungalow was constructed in 1973, with a high level of insulation in its opaque elements for that time (almost satisfying 2011 Irish Building Regulations [35]. Since then, the original single-glazed windows have been removed and upgraded to double-glazed. A solar thermal collector has also been installed to contribute towards the dwelling's DHW requirements. Space heating requirements are provided by a conventional kerosene-fired boiler.

4.2. Modelling approach

For the simplified model, the influential parameters that comprise the minimum data set are defined accurately and use the values present in the original calibrated model. Parameters which are not listed in the guideline minimum data set for the bungalow archetype dwelling in Table 3 are given "typical", standard or non-accurately defined values.

Typical constructions for the external walls, roof and ground floor listed in Appendix A of the Technical Guidance Document Part L [35] are used for the simplified model as the constructions of this bungalow are relatively close to current building regulation standards. Internal partitions are modelled as a single leaf masonry wall finished with lightweight plaster (for simplicity the same block and plaster type used for the external walls is used). Where required, the U-value of the constructions is adjusted by altering the thermal conductivity of the insulation (or air gap in some cases).

Based on the minimum data set for the bungalow, typical values for each given zone type were employed in order to model the occupancy, equipment and lighting densities for the simplified model. As used previously during archetype model development, typical operating schedules for occupancy, equipment and lighting levels in each zone type were also used in this simplified model. A similar approach was used for parameters of the heating system, zone temperatures, infiltration rates and all others. Parameters which are listed in the minimum data set are defined using the values present in the original calibrated model, others are given "typical" values which were used for the base-case models.

4.3. Comparison of the simplified and advanced model outputs

The study compared outputs from annual simulations of both the advanced-calibrated model and the simplified model. The total annual energy consumption differs by just over 6% (Fig. 8). Monthly energy usage profiles also match quite well, with the exception of the summer period (Fig. 9).

When examining energy consumption by subcategory (heating, lighting, equipment and pumps), slightly greater deviations can be seen between the simplified and calibrated models, particularly for the energy consumption due to electrical equipment. As such, the Electrical equipment energy requirements are over 2.5 times greater for the simplified model than measured data represented by the calibrated model. This suggests that the "typical" values and schedules used for equipments densities in each zone type are too high for this particular dwelling. The overestimated equipment energy requirements are the cause of the discrepancies in the energy usage for the summer months (Fig. 9). Zone heating requirements are slightly under-estimated in the simplified model (by just over 9%). The additional heat gains due to the surplus levels of electrical equipment offer an explanation for the under-estimation of zone heating requirements. Thus, the under-estimation of heating requirements and overestimation of equipment energy requirements cancel each other out somewhat during the period between October and April. However, in the summer months when there are no space heating requirements, the over-estimation of equipment energy requirements leads to a visible divergence from the actual monthly energy usage profile.

Although some discrepancies exist between the outputs of the simplified model and reality, the results are quite promising, considering the level of simplification applied to the model. As aforementioned, Waltz [31] states that for a building simulation to be classified as accurate, predicted annual energy usage ought to be within 5% of the actual recorded consumption, with seasonal energy usage profiles matching reasonably well. However, it is also suggested that for simulations where modelling time is restricted, 10% is an acceptable goal. The simplified model used in this study falls into the time-restricted category, and thus annual energy usage ought to be within 10% of actual measured data in order for this model to be classified as accurate. The output of the simplified model considered in this project differed from actual annual consumption by only 6%, with seasonal energy profiles matching reasonably well.

5. Conclusion

A guideline minimum data set outlining the input data which is required to be accurately-defined, for the performance simulation of Irish dwellings, has been developed. Five base-case archetype models, which are considered to be representative of a significant portion of Irish dwellings were defined and modelled. Performing sensitivity analysis on parametric data which was gathered for each dwelling successfully outlined the most influential input parameters. The influential input parameters outlined were then used to for the guideline minimum set of accurately-defined input data for Irish dwellings.

The minimum data set formed has been tested and validated. Simplified models of existing dwellings were constructed based on the guideline minimum data set. Only the parameters listed in the minimum data set were accurately defined. All other parameters were given "typical" or standard values. The simplified models predicted annual energy consumption to within 10% of actual measured consumption, with seasonal energy profiles matching quite well.

The guideline minimum data sets which can be defined, if the processes outlined in this project are repeated, are considered to be valuable during numerous stages of BEPS over a building's life-cycle. The time spent gathering and defining input parameter data, as well as the time spent modelling this data, can be significantly reduced by defining and modelling only the influential parameters with a high degree of accuracy. By carefully defining the parameters defined within the minimum data set, accurate models of existing buildings to be used in the testing of different retrofit solutions can be developed quite quickly. Furthermore, in the late design and/or commissioning stages of a building's life-cycle, when a high degree of modelling accuracy is required, the minimum data set can be referenced in order to ensure that the most influential input parameters are very accurately defined indeed. Finally, the minimum data sets may also be referred to for various policy-making procedures.

One key issue that is worthy of future work is the selection of the correct influence coefficient for a given modelling scenario. In the case presented in this paper, the authors chose an influence coefficient that clearly separated highly influential and less influential parameters based on a relative weighing of parameters against each other. Applications of the methodology in different regions may not have the luxury of such a clear discrepancy and should leverage a more rigorous process for the selection of such coefficients. The key issue with which is the definition of what is "good enough" for an influence coefficient in a given context. For example, standard engineering tolerances are 3% [47]. Standard engineering safety factors can vary significantly from 1.2 upwards, while 20% oversizing is a common structural and mechanical design safety factor. This challenge is worthy of further research.

Although the minimum data set produced in this study is applicable to Irish dwellings only, the methodology and processes used in order to define this data set are highly repeatable, and can be recast to almost any building archetype in any given geographical location. Future studies should aim to define guideline minimum datasets for a variety of building archetypes in a range of different climatic zones. Incorporating the effects of shading into the parametric analysis and sensitivity analysis should be investigated (the base case archetypes used in this study contain no impacting shading parameters, making testing the effects of shading difficult in this case). Future studies should also aim to make the methodology outlined in this paper as streamlined and automated as possible, particularly the parametric simulations which required a significant amount of user-input in this study.

Appendix A. Existing archetype dwellings
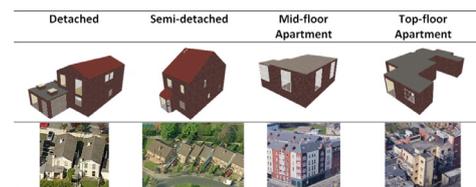
Fig. 10. Existing detached, semi-detached, mid-floor and top-floor apartment archetypes. A rendered version of the model is shown above an aerial photograph of each dwelling.
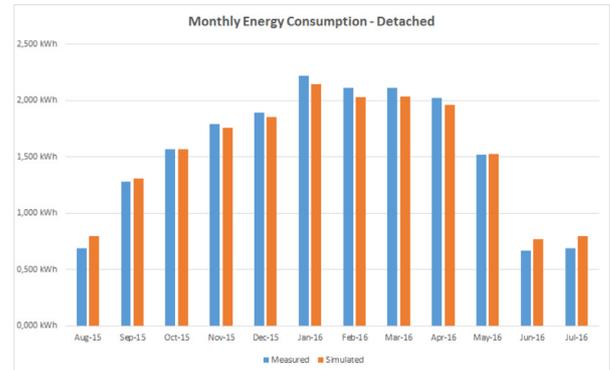
Fig. 11. Monthly energy profile shown for the simplified model and the measured data for the detached archetype.
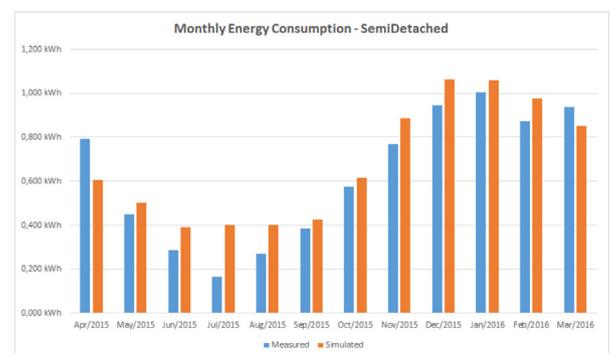
Fig. 12. Monthly energy profile shown for the simplified model and the measured data for the semi-detached archetype.

Appendix B. Results of simplified models shown against measured data
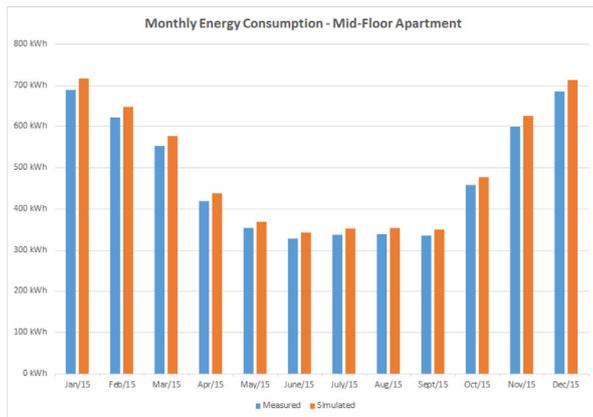
Fig. 13. Monthly energy profile shown for the simplified model and the measured data for the mid-floor apartment archetype.
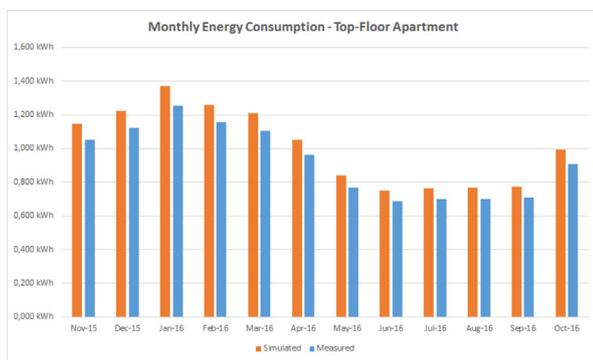
Fig. 14. Monthly energy profile shown for the simplified model and the measured data for the top-floor apartment archetype.

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