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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.

Keywords:

Building simulation, Sensitivity analysis, Influence coefficient, Simulation accuracy, Input data

1. Introduction

In the EU, buildings account for 40% of primary energy consumption and 33% of CO₂ 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 simu-

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lation 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 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 sub-utility 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 building 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):

$$IC = \frac{\Delta OP / OP_{bc}}{\Delta IP / IP_{bc}} \quad (1)$$

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. Param-

eters 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

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

133 2. Methodology

134 This paper focuses on producing guidelines for typ-
135 ical Irish dwelling types. However, the processes and
136 methodology used are highly repeatable, and applicable
137 to almost any category of building situated in any given
138 location.

139 As guidelines for typical Irish dwellings must be pro-
140 duced, archetype models which are representative of a
141 significant portion of the Irish dwelling stock are re-
142 quired to be modelled. These models will be referred
143 to as the base-case archetype models. It is imperative
144 that the values used for all input parameters for each
145 of the base-case models are representative of the “most
146 probable” values for Irish dwellings.

147 A process diagram outlining the overall methodology
148 used in this study is shown in Figure 1. The first step is
149 defining the base case input parameter values, and gen-
150 erating the base case energy models, representative of
151 Irish archetype dwellings. The base case energy model
152 simulations can then be executed, and the resultant base
153 case output (annual energy usage) values recorded. Sub-
154 sequently, the parametric modelling phase can be initi-
155 ated. In this stage of the process, a range of values and
156 intervals are defined for each input parameter. The pro-
157 cess of defining these ranges and intervals will be out-
158 lined in Section 2.3. Parametric simulations can then be
159 executed in order to obtain the parametric data required
160 for SA. By performing SA (the SA process will be de-
161 scribed in detail in Sections 2.4 & 2.5 on the parametric
162 data recorded for each archetype and input parameter,
163 a useful minimal-set of accurately-specified input data
164 can be defined, based on the results of the SA. The min-
165 imum data set can then be applied to a practical exam-
166 ple in order to be confirmed. Note the feedback pro-
167 cess link, between the application of the minimum data
168 set and the definition of the minimum data set, shown
169 in Figure 1. If the applied minimum data set produces
170 unsatisfactory results, the minimum data set can be re-
171 defined (this feedback process will be described in detail
172 in Section 2.5).

173 This process diagram can be referred to, when re-
174 peating the processes outlined in this paper, in order
175 to form guideline minimum data sets for other build-
176 ing archetypes. All processes illustrated in the process
177 diagram are described in detail in this section.

178 2.1. Archetype Dwelling Models

179 2.1.1. Base-case Archetype Model Inputs

180 Comprehensive Irish dwelling archetypes have been
181 developed by Nue and Sherlock [32, 33]. The five
182 archetype dwellings are based on a DECLG report [34],
183 and are deemed to be representative of over 80% of
184 the Irish building stock. However, for each archetype,
185 three separate constructions are considered (new insu-
186 lated cavity wall, existing uninsulated cavity wall, and
187 existing uninsulated hollow block wall [35]), result-
188 ing in a total of 15 models (the dimensional characteris-
189 tics for each archetype remained the same, but the physi-
190 cal characteristics of the constructions were changed).
191 Given the number of input parameters which must be
192 examined as part of this project, a thorough paramet-
193 ric analysis using 15 models is considered an unfeasible
194 and time-consuming approach.

195 Famuyibo et al. [36] previously conducted a statisti-
196 cal analysis of two housing databases (Energy Per-
197 formance Survey of Irish Housing (EPSIH) and the
198 Irish National Survey of Housing Quality (INSHQ)),
199 and used the results of this statistical analysis order to
200 develop the average, or “most probable” characteris-
201 tics of different Irish dwelling archetypes. The com-
202 bined use of the physical characteristics of typical Irish
203 dwellings defined by Famuyibo et al. [36], and the
204 dimensional archetype models developed by Neu and
205 Sherlock [32, 33], allowed five archetype models (as
206 opposed to 15) to be developed which represent a sig-
207 nificant portion of the Irish residential stock. The five
208 archetypes which are developed and used as the basis of
209 this study are as follows:

- 210 1. A two-storey detached dwelling (hereafter referred
211 to as “detached”).
- 212 2. A two-storey semi-detached dwelling (hereafter re-
213 ferred to as “semi-detached”).
- 214 3. A single-storey detached dwelling (hereafter re-
215 ferred to as “bungalow”).
- 216 4. A mid-floor apartment.
- 217 5. A top-floor apartment.

218 As Ireland is located within one single climatic zone
219 [37], it is decided that the models should be simulated
220 in an area where the majority of Irish dwellings are located
221 (although Ireland lies within one climatic zone, differing
222 EnergyPlus weather data files are available, depending
223 on location). According to data from [38], over 28% of
224 Irish dwellings were located in county Dublin in 2011,
225 a far greater proportion than any other region. Dublin
226 is therefore selected as a suitable location for the model
227 simulations.

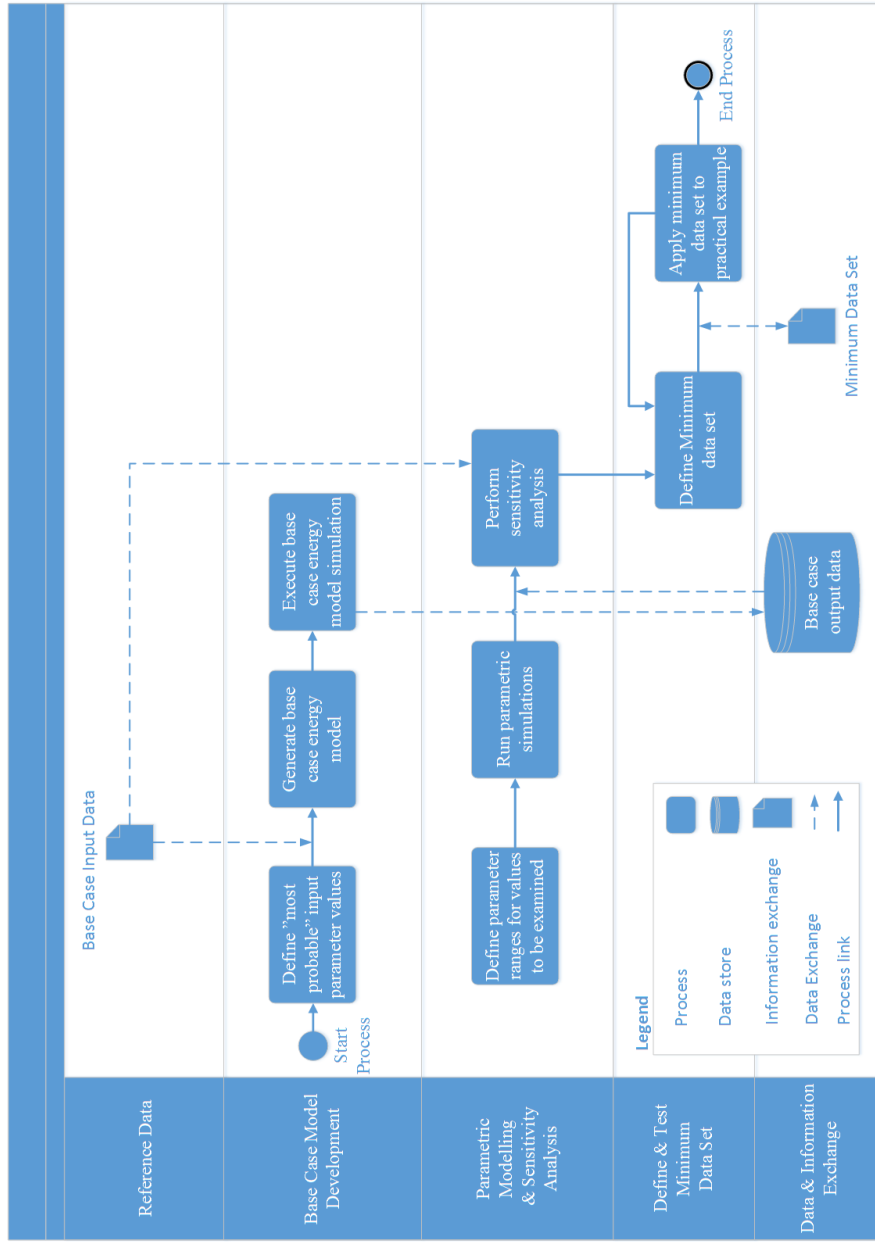


Figure 1: Process diagram illustrating how to ascertain and apply a minimum measurement set for a defined subset of the building stock.

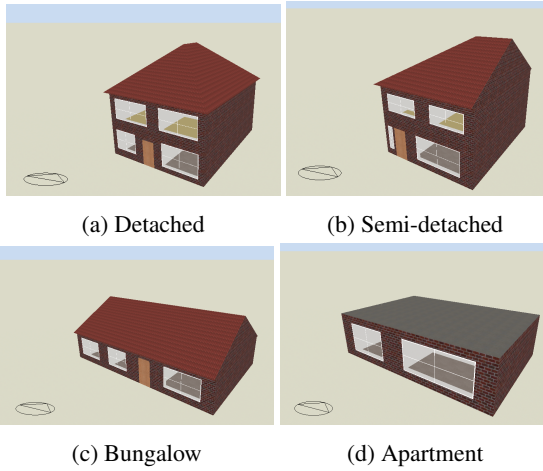


Figure 2: 3-D visualisations of the model archetype dwellings illustrating a representative variation in archetype geometries

228 3-D archetype model visualisations are shown in Fig-
 229 ure 2, and the archetype geometries are summarised
 230 in Table 1. Note that a value of zero for the external
 231 wall area means that a particular wall has been mod-
 232 elled adiabatically. It also is worth noting at this point
 233 that, as suggested by Sherlock [33], the heating sys-
 234 tem for the base case archetype models follows a com-
 235 mon hot water radiator template (powered by a standard
 236 boiler). However, the overall seasonal COP/efficiency
 237 of the heating system is taken from the archetypes de-
 238 fined by Famuyibo et al. [36]. The modelling process of
 239 the base-case archetype dwellings is described in detail
 240 in [39].

241 2.1.2. Base-case Archetype Model Outputs

242 Once the modelling process was complete for all
 243 archetypes, the next step was to execute the base-case
 244 simulations and record the annual energy consumption
 245 values for each (the base-case outputs). These out-
 246 puts, broken down by energy usage subcategory (heat-
 247 ing, DHW requirements, electrical equipment, lighting
 248 and system pumps) are shown in Figure 3a. The annual
 249 energy densities for each archetype (kWh per m^2 of floor
 250 area) are shown in Figure 3b.

251 It can be seen that as a consequence of relatively
 252 greater external surface areas the energy consumption
 253 of the more voluminous dwellings is heavily domi-
 254 nated by space heating requirements. Almost 70% of
 255 the detached archetype energy requirements are con-
 256 sumed by space heating. This is not the case for the
 257 less voluminous archetypes. For example, only 38.6%
 258 of the mid-floor apartment energy requirements are de-
 259 voted to space heating. Other factors such as DHW

260 requirements, electrical equipment and lighting make
 261 up a greater proportion of total annual energy require-
 262 ments for the less voluminous dwellings (the apartment
 263 archetypes).

264 2.2. Parametric Analysis

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

$$\sum_{i=1}^n r_i \quad (2)$$

271 Controlling the number of intervals and points (r_i) in
 272 each input parameter range (ΔX_i) is the only feasible
 273 way of controlling the total required number of simu-
 274 lations (Z), whilst ensuring that a sufficient resolution
 275 of data describing how the output varies in response to
 276 varying the input. Therefore, $r = 4$ or $r = 5$ are selected
 277 as a suitable number of simulated points in each input
 278 parameter range. It is assumed that this will provide a
 279 sufficient resolution of how annual building energy con-
 280 sumption varies as a function of each input parameter
 281 examined. Let p be the value of the interval between
 282 simulation points (r) in each defined parameter range. p
 283 for the i^{th} input parameter can be described by:

$$p_i = \frac{\Delta X_i}{r_i} \quad (3)$$

284 2.3. Input Parameter Range of Values

285 In order to examine the relative influence of each in-
 286 put parameter on annual building energy consumption,
 287 data describing how the output (annual energy usage)
 288 varies as a function of the input must be acquired. As
 289 aforementioned, in order to obtain this data, each in-
 290 put parameter which is to be examined should be varied
 291 over a range of values at specified intervals (see Equa-
 292 tion 3). The chosen range of values should reflect the
 293 range of possible values of each input parameter for
 294 Irish dwellings. The threshold minimum and maximum
 295 values for the input parameters to be examined are listed
 296 in Table 2. Many of the sources of these threshold val-
 297 ues are also listed in Table 2. However, in some cases,
 298 engineering judgement was required in the selection of
 299 the minimum or maximum values. For example, many
 300 of the predefined constructions within the predefined
 301 DesignBuilder libraries were examined in order to de-
 302 fine the range of thermal masses to be examined for the

Table 1: Summary of archetype geometries

Dwelling	Area of external N/W/S/E façade (m ²)	Window-to-Wall ratio for N/W/S/E façade	Volume (m ³)	Total floor area (m ²)
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

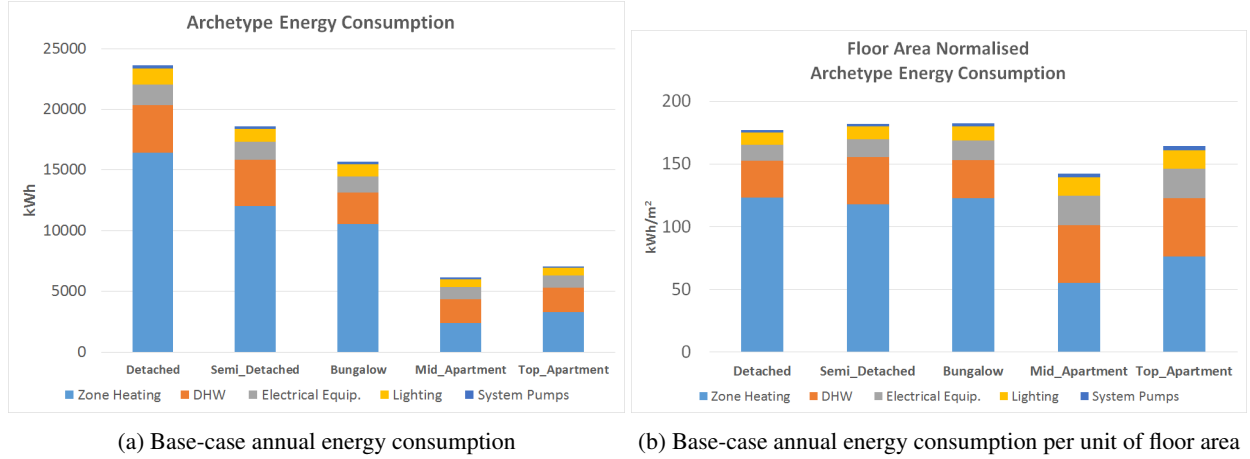


Figure 3: Annual (a) and normalised (b) energy consumption illustrating large differences in energy use but minor differences in energy density

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, Equation 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 affects 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 the first simulated point as IP_0 , the average IC value over the range of input parameter values can be described by Equation 4:

$$IC = \frac{1}{r-1} \left(\left| \frac{OP_{IP_0+p} - OP_{IP_0}}{\frac{p}{IP_{bc}}} \right| + \left| \frac{OP_{IP_0+2p} - OP_{IP_0+p}}{\frac{p}{IP_{bc}}} \right| + \dots + \left| \frac{OP_{IP_0+(r-1)p} - OP_{IP_0+(r-2)p}}{\frac{p}{IP_{bc}}} \right| \right) \quad (4)$$

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.

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	$^{\circ}C$	HSPT	18 ^[44]	23 ^[44]	1
Heating set-back temperature	$^{\circ}C$	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	<i>ach</i>	ACH	0.5 ^[40]	1.5 ^[33]	0.2
Orientation	$^{\circ}$	Orientation	0	180	45

337 2.5. Applying the DSA Method to the Parametric Data 351 archetype can be described by the following Equation 5:

338 The DSA method now must be applied to the para-
339 metric data gathered from the process described in Sec-
340 tion 2.2. In order to fully describe the application of
341 the DSA method to the parametric data, an example is
342 used. The variation in total annual energy usage as the
343 seasonal COP/efficiency of the heating system is varied
344 incrementally is shown in Figure 4. This specific case
345 is chosen as it exemplifies a situation where varying the
346 input does not affect the output linearly. Note that the
347 COP/efficiency is varied between a range of 0.5 and 2.5,
348 at intervals of 0.5 ($COP_0 = 0.5$, $p = 0.5$). Taking E_{COP}
349 as the energy usage at each of the five simulated points
350 ($r = 5$), the IC of heating system COP for the bungalow

$$IC = \frac{1}{4} \left(\left| \frac{E_{COP_0+p} - E_{COP_0}}{\frac{E_{bc}}{p}} \right| + \left| \frac{E_{COP_0+2p} - E_{COP_0+p}}{\frac{E_{bc}}{p}} \right| + \left| \frac{E_{COP_0+3p} - E_{COP_0+2p}}{\frac{E_{bc}}{p}} \right| + \left| \frac{E_{COP_0+4p} - E_{COP_0+3p}}{\frac{E_{bc}}{p}} \right| \right) \quad (5)$$

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

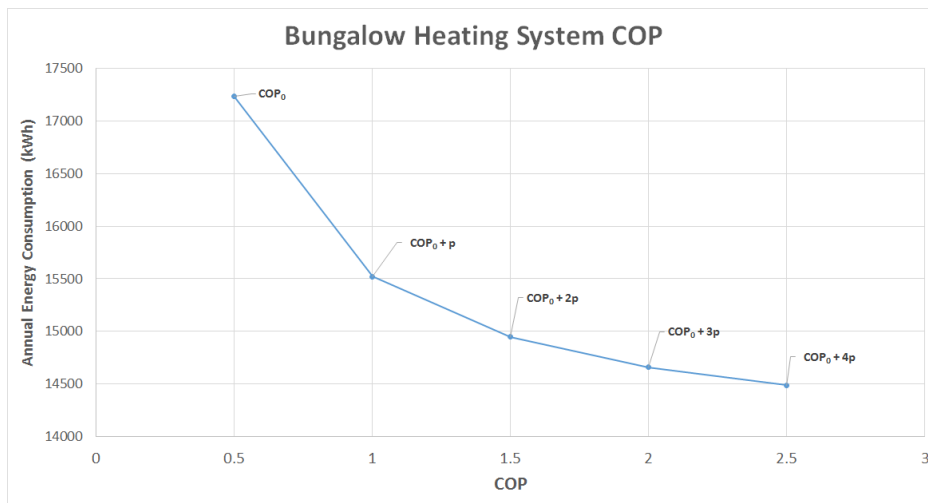


Figure 4: Variation in annual energy usage for the bungalow archetype as heating system COP/efficiency is varied

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

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

381 3. Results of the Sensitivity Analysis

382 In this section, the parameter sensitivities computed
 383 using DSA will be examined in detail. Note that from

384 henceforth, all input parameters shown in figures and
 385 tables will be abbreviated using representative parameter
 386 symbols as defined in Table 2. It should also be noted
 387 that all discussions of the results in Section 3 will be
 388 based on the results displayed in Figure 5.

389 3.1. Overview of Parameter Sensitivities

390 As expected, the U-value of the archetype external
 391 walls proves to have a significant influence on building
 392 energy use. In most cases, the U-value of the roof
 393 proves to be slightly less influential (with the exception
 394 of the top-floor apartment). Interestingly, the results
 395 show that the floor U-value has a lower impact on
 396 the energy usage of the archetype models. According to
 397 data taken from [45], mean annual ground temperatures
 398 (at 10 cm depth) are 1°C higher than average ambient
 399 air temperatures for the Dublin region in 2014. Furthermore,
 400 the external surface of the floor is not subject to
 401 convective cooling, unlike the external surfaces of the
 402 walls and roof. The higher average ground temperatures
 403 and lack of convective cooling may be the cause of the
 404 floor U-value being less influential than that of the
 405 walls and roof. The influence of the internal partition
 406 and external door U-values are significantly lower than
 407 wall and roof U-values. Overall, the thermal masses of
 408 the constructions have a negligible effect on the output.
 409 Wall and roof surface properties (emissivity and absorptivity)
 410 have a somewhat considerable impact on building energy
 411 consumption for all archetypes, in most cases having
 412 a greater IC value than that of the floor U-value.

413 In all cases, the glazing U-value proved to be more
 414 influential than any of the U-values of the opaque building
 415 elements. Window SHGC value is also a hugely

416 influential parameter. As expected, WWR also has a 467
417 significant impact on energy consumption. The visible 468
418 transmittance (V_t) value of the windows had no impact 469
419 on energy use. This can be attributed to the fact that the 470
420 artificial lighting template used in the models is operated 471
421 on an on/off schedule and is not governed by outdoor 472
422 luminance levels. Although this is not ideal, and 473
423 V_t values of the windows should have an effect on light-
424 ing energy, it is uncommon in Irish dwellings to control
425 indoor lighting levels based on available daylight.

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

433 It can be seen that HSPT has an extremely force-
434 ful influence on dwelling energy consumption, partic-
435 ularly for the more voluminous archetypes, with greater
436 external surface areas. Heating set-back temperatures
437 (HSBT) appear to have a much more small-scale im-
438 pact. As expected, daily DHW consumption levels also
439 strongly influence energy requirements. The heating
440 system COP/efficiency also has a weighty impact on the
441 output. Heating system auxiliary energy requirements
442 effects cannot be described as negligible, however they
443 appear to be much less influential than the overall heat-
444 ing system COP/efficiency.

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

464 3.2. Formation of the Minimum Data Sets

465 A thorough analysis of the ranked IC values (which
466 are shown graphically in [39]) considered each input pa-

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 pos-
tulation will be tested in Section 4. The guideline mini-
mum sets of accurately-defined input data are shown in
Table 3.

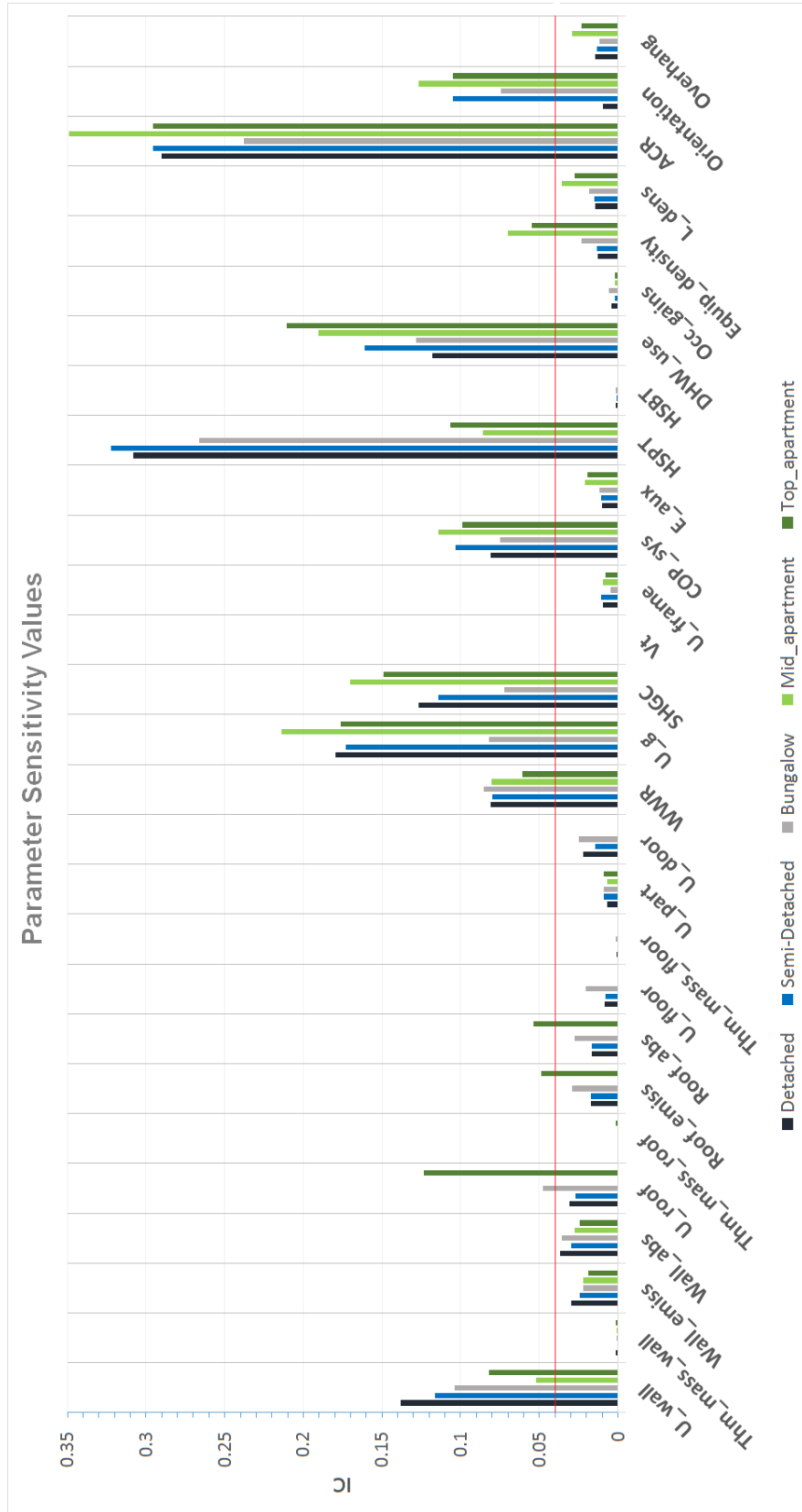


Figure 5: Sensitivity values for all input parameters examined with ten parameters above IC cut-off of 0.04

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. 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 Figure 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 6.

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 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 (Figure 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% (Figure 8). Monthly energy usage profiles also match quite well, with the exception of the summer period (Figure 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 over-estimated equipment energy requirements are the cause of the discrepancies in the energy usage for the summer months (Figure 9). Zone heating requirements are slightly underestimated in the simplified model (by just over 9%). The additional heat gains due to the surplus levels of

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

573 electrical equipment offer an explanation for the under-
574 estimation of zone heating requirements. Thus, the
575 under-estimation of heating requirements and overesti-
576 mation of equipment energy requirements cancel each
577 other out somewhat during the period between October
578 and April. However, in the summer months when there
579 are no space heating requirements, the over-estimation
580 of equipment energy requirements leads to a visible di-
581 vergence from the actual monthly energy usage profile.

582 Although some discrepancies exist between the out-
583 puts of the simplified model and reality, the results are
584 quite promising, considering the level of simplification
585 applied to the model. As aforementioned, Waltz [31]
586 states that for a building simulation to be classified as
587 accurate, predicted annual energy usage ought to be
588 within 5% of the actual recorded consumption, with sea-
589 sonal energy usage profiles matching reasonably well.
590 However, it is also suggested that for simulations where
591 modelling time is restricted, 10% is an acceptable goal.
592 The simplified model used in this study falls into the
593 time-restricted category, and thus annual energy usage
594 ought to be within 10% of actual measured data in order
595 for this model to be classified as accurate. The output
596 of the simplified model considered in this project dif-
597 fered from actual annual consumption by only 6%, with
598 seasonal energy profiles matching reasonably well.

599 5. Conclusion

600 A guideline minimum data set outlining the input data
601 which is required to be accurately-defined, for the per-

602 formance simulation of Irish dwellings, has been devel-
603 oped. Five base-case archetype models, which are con-
604 sidered to be representative of a significant portion of
605 Irish dwellings were defined and modelled. Performing
606 sensitivity analysis on parametric data which was gath-
607 ered for each dwelling successfully outlined the most
608 influential input parameters. The influential input pa-
609 rameters outlined were then used to for the guideline
610 minimum set of accurately-defined input data for Irish
611 dwellings.

612 The minimum data set formed has been tested and
613 validated. Simplified models of existing dwellings were
614 constructed based on the guideline minimum data set.
615 Only the parameters listed in the minimum data set were
616 accurately defined. All other parameters were given
617 “typical” or standard values. The simplified models pre-
618 dicted annual energy consumption to within 10% of ac-
619 tual measured consumption, with seasonal energy pro-
620 files matching quite well.

621 The guideline minimum data sets which can be de-
622 fined, if the processes outlined in this project are re-
623 peated, are considered to be valuable during numerous
624 stages of BEPS over a building’s life-cycle. The time
625 spent gathering and defining input parameter data, as
626 well as the time spent modelling this data, can be sig-
627 nificantly reduced by defining and modelling only the
628 influential parameters with a high degree of accuracy.
629 By carefully defining the parameters defined within the
630 minimum data set, accurate models of existing build-
631 ings to be used in the testing of different retrofit solu-
632 tions can be developed quite quickly. Furthermore, in

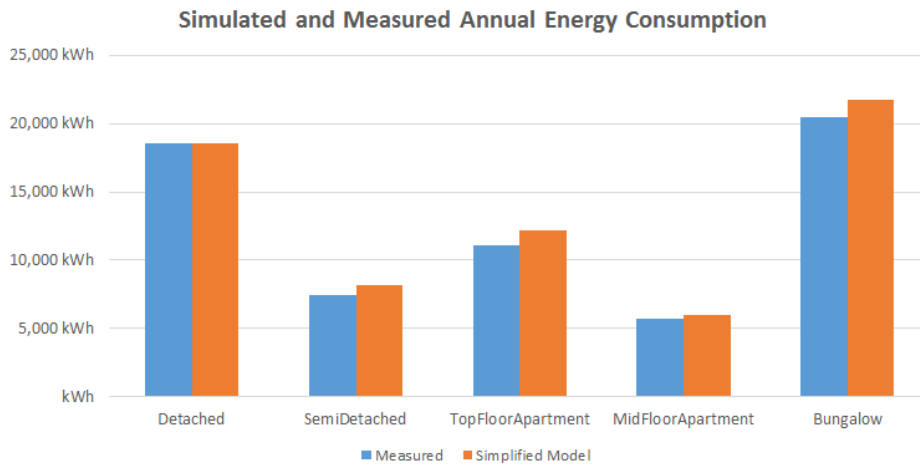


Figure 6: Annual simulated and measured results of each existing archetype used to validate the results of this study.



Figure 7: 3-D model and photograph of test house [46]

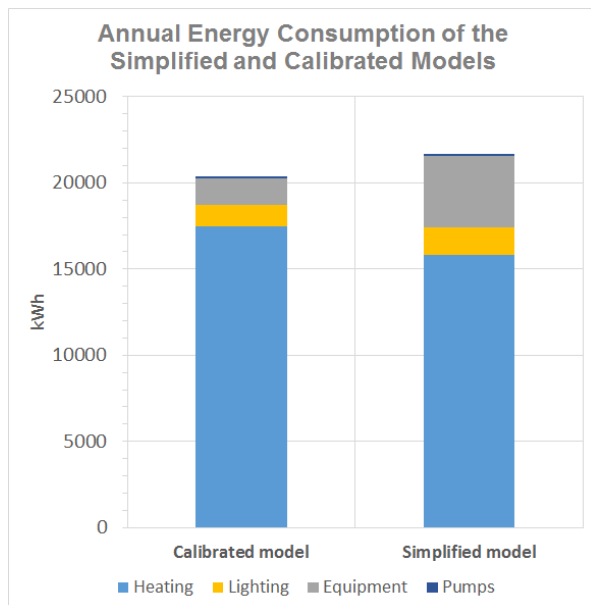


Figure 8: Annual energy use for the simplified model is within 6% of the calibrated energy model

633 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.

640 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.

657 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 sen-

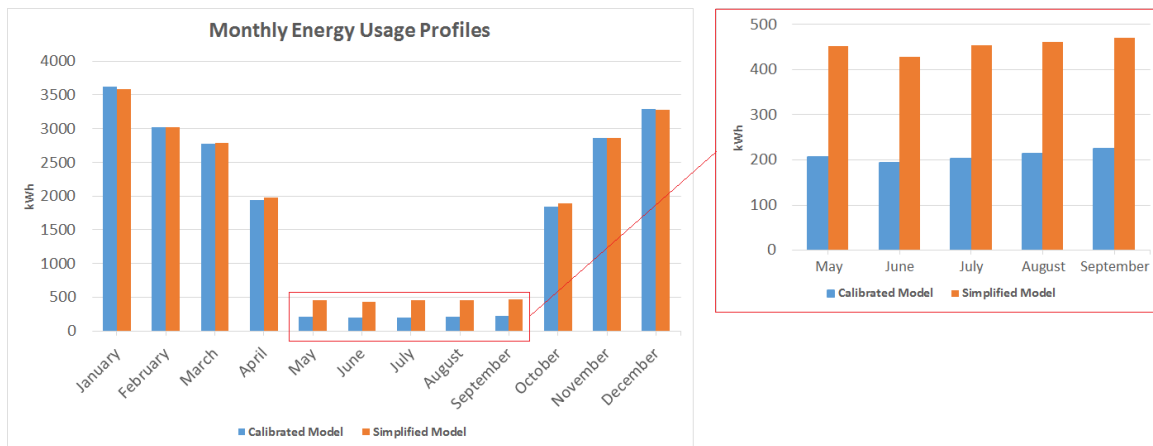


Figure 9: Monthly energy profile shown for the simplified and calibrated energy models illustrates a close fit during winter spring and summer but a significant discrepancy during summer months.

666 sitivity analysis should be investigated (the base case
 667 archetypes used in this study contain no impacting shading
 668 parameters, making testing the effects of shading
 669 difficult in this case). Future studies should also aim to
 670 make the methodology outlined in this paper as stream-
 671 lined and automated as possible, particularly the para-
 672 metric simulations which required a significant amount of
 673 user-input in this study.

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687 Nomenclature

688 Appendix A: Existing Archetype Dwellings

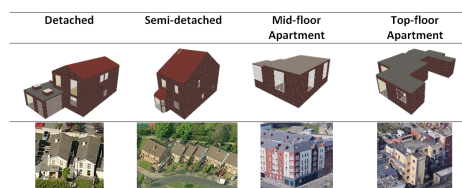


Figure 10: Existing detached, semi-detached, mid-floor and top-floor apartment archetypes. A rendered version of the model is shown above an aerial photograph of each dwelling.

689 Appendix B: Results of Simplified Models Shown 690 Against Measured Data

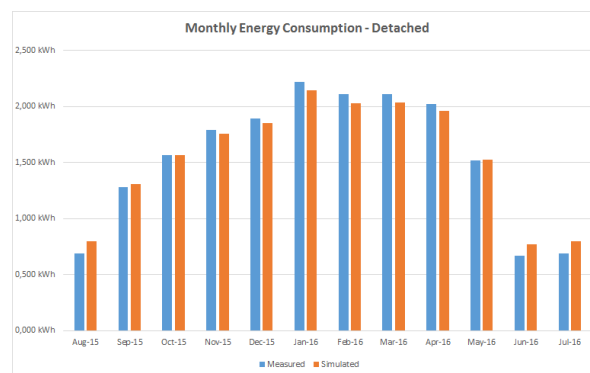


Figure 11: Monthly energy profile shown for the simplified model and the measured data for the detached archetype.

ACH	Overall dwelling air change rate (<i>ach</i>)
BEPS	Building Energy Performance Simulation
COP	Coefficient Of Performance
COP_sys	Heating system COP
DHW	Domestic Hot Water
DHW_use	Domestic hot water requirements ($L.m^{-2}day^{-1}$)
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 ($^{\circ}C$)
HSPT	Heating set-point temperature ($^{\circ}C$)
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 ($^{\circ}$)
p	Interval value between simulated points
r	Number of simulation points
Roof_abs	Roof surface solar absorptivity
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

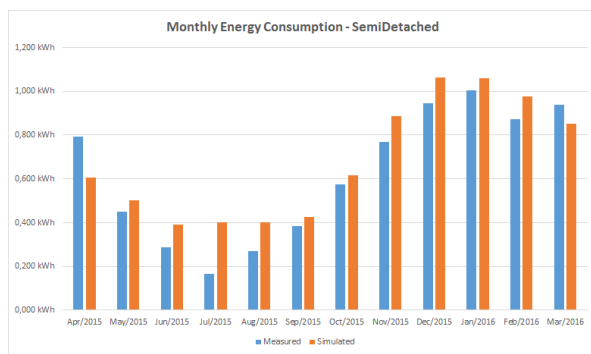


Figure 12: Monthly energy profile shown for the simplified model and the measured data for the semi-detached archetype.

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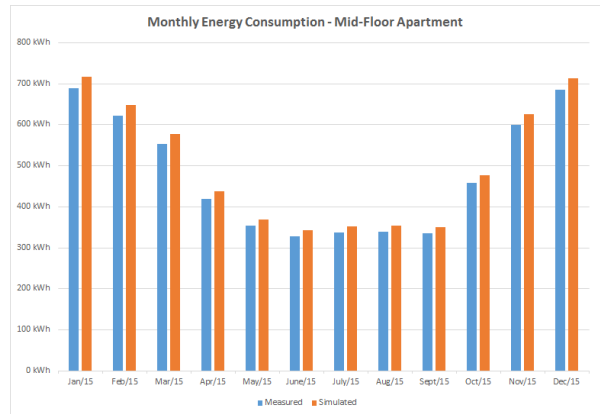


Figure 13: Monthly energy profile shown for the simplified model and the measured data for the mid-floor apartment archetype.

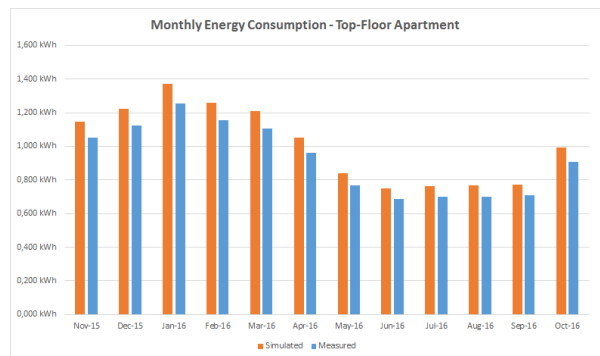


Figure 14: Monthly energy profile shown for the simplified model and the measured data for the top-floor apartment archetype.

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