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

James Egan [a], Donal Finn [a], Pedro Henrique Deogene Soares [b], Victor Andreas Rocha Baumann [c], Reihaneh Aghamolaei [a], Paul Beagon [a], Olivier Neu [a], Fabiano Pallonetto [a], James O'Donnell [a,*]

[a] School of Mechanical and Materials Engineering, UCD Energy Institute, University College Dublin, Belfield, Dublin 4, Ireland
[b] Pontifical Catholic University of Minas Gerais, Belo Horizonte, Minas Gerais, Brazil
[c] Federal Institute of Santa Catarina, Santa Catarina, Brazil

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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.

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

* Corresponding author.
E-mail addresses: james.egan.4@ucdconnect.ie (J. Egan), donal.finn@ucd.ie (D. Finn), reihaneh.aghamolaei@ucdconnect.ie (R. Aghamolaei), paul.beagon@ucd.ie (P. Beagon), olivier.neu@ucd.ie (O. Neu), fabiano.pallonetto@ucd.ie (F. Pallonetto), james.odonnell@ucd.ie (J. O'Donnell).

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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 (%)
$\mathbf{\Delta X}$	Input parameter range

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):

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

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