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Exploring the impact of different parameterisations of occupant-related internal loads in building energy simulation

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ABSTRACT

A building energy simulation relies on accurate parameterisation of occupant-related internal loads to simulate a realistic energy balance within a building. The internal loads are inextricably linked to occupant behaviour, both directly through the contribution of occupant heat output to thermal energy balance and indirectly via the interactions between occupants, appliances and building services. While occupancy itself is difficult to measure directly, most buildings possess a wealth of data in the form of monitored electricity consumption in varying degrees of resolution. These data, particularly plug loads, may be used to inform the model of occupant-related internal loads. Different approaches to parameterisation of plug loads have been investigated, with the purpose of exploring the conditions that might lead to preference of one approach over another. The models have been tested through a case study and simulation results have been compared against a range of response variables. Conclusions have been drawn as to the most important features of plug load parameterisation for a model to be used for forecasting future demand.

1. Introduction

In the UK the buildings sector accounts for 37% of the total annual greenhouse gas emissions, with non-domestic buildings being responsible for 36% of the sector emissions [1]. Progress has been slow in improving this performance and building energy simulation has a role to play in assessing the impact of potential changes to building fabric and operation on building energy consumption for all types of non-domestic building [2–4].

A building energy simulation relies on accurate input of internal loads to facilitate a realistic simulation of the energy balance within a building. It is well known that building energy consumption simulated at the design stage rarely agrees with observed data post-design, and with increasing deployment of energy monitoring systems this so-called ‘performance gap’ is becoming increasingly visible [5]. One would expect that forecast consumption for an already existing building would be in closer agreement with reality, yet it is still notoriously difficult to match the simulation to the observed data [6].

One fundamental cause of the gap is the inadequacy of current approaches to definition of occupancy-related loads, even in fully operational buildings [7]. The internal loads in a building are inextricably linked to occupant behaviour, both directly through the contribution of occupant heat output to thermal energy balance and indirectly via the interactions between occupants, appliances and building energy services. Occupant-related services are a principal component of building electricity consumption and must be understood if accurate estimations are to be made. However, occupancy and occupant-related internal loads are difficult to specify as occupant behaviour is inherently stochastic; hence these loads represent a significant source of uncertainty in the simulation results [8]. A comprehensive review of the state of the art in occupant behaviour modelling has been performed [9], and many issues are being addressed under the auspices of the International Energy Agency Energy in Buildings and Communities Program (IEA EBC) Annex 66: Definition and Simulation of Occupant Behaviour in Buildings.

Not only is occupant behaviour inherently stochastic, occupant presence is also difficult to measure directly. An alternative approach to simulating occupancy is to infer building occupancy from a measurable quantity; the feasibility of such an ‘implicit occupancy’ approach has been demonstrated using monitored computer status to infer occupancy using existing IT infrastructure [10]. One must bear in mind though that occupant presence

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may not be the best or a complete indicator of energy demand as many devices, e.g. lights, air-conditioning, are controlled centrally — especially in the case of non-domestic buildings. Indeed, recent studies have indicated a greater correlation in device state between one hour and the next, rather than between occupancy and device state in any hour [11]. Nonetheless for an operational building a wealth of data exists in the form of monitored electricity consumption and many non-domestic buildings are now routinely sub-metered by end-use e.g. plug loads, lights and air conditioning. Accessing these data is relatively straightforward and gives an immediate insight into actual electricity consumption, and hence building operation, that can be further augmented by an understanding of the building control settings.

This paper examines the different ways by which sub-metered electricity consumption data may be used to define the occupancy-related internal loads, specifically small power electricity consumption or 'plug loads', in a non-domestic building. Focus has been placed on plug loads alone as the demand is measurable and more closely related to occupancy than lighting, which may be centrally controlled. Small power equipment is diverse and highly dependent on the building function, but for a typical office building comprises primarily computers and peripheral equipment, together with catering equipment. Plug loads were found to account for 23% of total electricity consumption in California's commercial office buildings [12] but [13] suggest that this could increase to as high as 50% for a high-efficiency office. In the UK, the Energy Consumption Guide 19 [14] provides data for the energy consumption of typical and 'good practice' offices which suggest that plug loads account for between 28 and 58% of the total electricity consumption of an office building, and give a range of values varying between 1.9 and 19.1 W/m^2.

Different approaches have been identified for quantifying plug loads comprising both the accepted methodology used in the UK and possible alternatives; top down data-driven, bottom-up deterministic and bottom-up stochastic models. Each approach has its advantages, and the aims of this paper are threefold:

1) To explore the conditions which might lead to preference of one model over another for the quantification of plug loads.
2) To explore the extent to which the different sources of uncertainty identified in the models are adequately represented, and
3) To identify the most important features of plug load quantification for forecasting of future demand.

Recognizing that the 'adequate' level of complexity may be governed by the nature of the design problem, or 'context', the different models have been applied to an existing building. Model outputs have been compared against a range of standard Key Performance Indicators (KPIs), such as the mean weekday and weekend demand profiles, peak hourly, daily total and the timing of the peak hourly electricity consumption. A particular KPI may be more relevant than another depending on the design problem. For example, peak demand may be more important from the point of view of electricity tariffs, and mean weekday profiles become more relevant for quantifying associated heat gains to size cooling systems.

The models have been applied both with and without making use of monitored plug-load data to tune model inputs for the building in question. An implicit question posed through this exercise is whether the availability of sub-metered data from the same building is necessary for a sufficiently accurate quantification of plug loads. The top-down models of course require some kind of relevant and applicable data set, and we use plug-loads monitored in another very similar building to train the top-down models. At the same time, bottom-up models also greatly benefit from using sub-metered data to tune model inputs.

A brief review of the current methods for characterisation of occupancy-related internal loads in building energy simulation is presented in the next section of this paper, together with an outline of the desirable qualities for such a model. This is followed by a description of the models selected for use in the comparative study and the results of the case study are presented and discussed in Sections 4 and 5. The paper concludes with a consideration of the models' performance against the desirable criteria based on the case study results.

2. Parameterisation of occupant related internal loads

In a typical computational building energy simulation plug loads are characterised by the user-defined peak power demand associated with devices. These are multiplied by (user-defined) schedules of diversity factors that simulate the typical daily change in use. For an existing building a detailed energy audit may be undertaken to understand how the building operates, but it can be prohibitively time consuming to observe schedules and peak power demand for every end-use and building zone. To reduce the effort required by audit-based studies, a number of alternative approaches have been proposed in the literature.

The approaches identified for use here range from simple aggregation of demand to fully stochastic simulation. Within the simplest models it is assumed that there is different weekday/weekend power demand that fluctuates between peak and off-peak values (estimated from benchmarks, literature, or measured) according to the weekday or weekend time schedule [15]. More complexity may be added by assigning different schedules of use and power demand to different device types and hence building up an aggregate power demand; this is the 'bottom-up' deterministic approach [16]. Aggregating the demand like this may misrepresent an essentially stochastic load, however [7]; whether this is significant may depend on the purpose of the simulation and the key parameters of interest. The DELORES model [17] accounts for the stochastic nature of the power demand by generating a fully stochastic 365 day/24 h demand profile based on the probability of each individual device changing state in each hour. An alternative way to generate a stochastic demand is by using a top-down approach; synthetic time histories may be generated via a statistical analysis of monitored data [6] or a time series analysis [11]. Both of these approaches use the mean monitored daily profile, but differ in the way in which the variability about that mean is simulated.

The 'best' model may be different according to the context and the key parameters of interest [18]. If the purpose of the simulation is to extract aggregate consumption, as might be the case for an analysis of the impact of potential retrofit scenarios on the annual electricity consumption of a building, then an aggregate model may well be adequate. However if the key parameters of interest include such quantities as peak daily power demand and the timing of that peak, e.g. for demand scheduling purposes, then it is necessary to use a model which encompasses the inherent stochasticity of the power demand. Further desirable qualities include being able to assimilate large quantities of data as data acquisition becomes more prolific, and to be able to use those data to improve forecast accuracy. It is also important that a model is flexible in its ability to simulate building operation; if aspects of that operation change, for example if the building layout or occupancy are re-organised, or if building use changes, a model should be able to simulate the corresponding change in power demand.

The models are assessed against these desirable qualities in the comparative study of the different types of model currently available detailed in the following sections.