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Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings

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ABSTRACT

There has been a history of low-energy design failing to translate into low measured energy consumption in domestic buildings. In part this failure can be attributed to occupant behaviour and household variation. It is therefore important to provide a method whereby such variation can be accounted for so that deviations from design values can be identified as natural variation rather than design failure. This paper addresses the likely range of occupant behaviour and the resultant impact on heating energy consumption for domestic Passivhaus buildings. Realistic, quasi-empirical, profiles for different occupancies, lighting, and appliance-use were applied to a set of 100 terraced Passivhaus units, and modelled in a dynamic building simulation programme. Strong correlations between the results and measured data from a large set of similar properties are shown. Multiple regression techniques were used to identify the relationship between space heating load and behavioural variables. This led to the development of a regression equation which can be used to estimate the likely space-heating requirements of a household given particular behavioural variables, and to the test the impact of certain behaviours on annual heating energy demand. It is found that in general passive houses are less sensitive to behaviour than anticipated.

1. Introduction

It is known that building characteristics have a significant effect on energy consumption; and governments worldwide have introduced regulations and policies in a bid to improve the energy performance of fabric and systems within the built environment [1,2]. The development of non-mandatory energy efficiency schemes has been improving on these mandatory performance requirements by considerable amounts; in terms of reducing space heat demand, none have been so successful as Passivhaus Certification [3]. To meet the low space heating and cooling limits of no more than 15 kWh/m^{2}a that such a philosophy demands, the building fabric has to be constructed to maximise insulation, and to minimise thermal bridging and uncontrolled air exchange. This can be challenging within the design phase, and even more so during construction.

One issue with estimating energy consumption based on a specific design philosophy is if the final in-use performance deviates from the expected performance the design can be seen as failed. In reality this may just be an example of a particular user's consumption being above average. In addition, when energy systems are sized for an individual dwelling, or for clusters of dwellings powered over a district-wide scheme, there is a probability that the system will not be able to meet demand if the cluster has above average demand. This is likely to cause the greatest issues when renewable energy systems have been sized to match the expected demand and the number of dwellings is small (the smaller the number of dwellings, the greater the likelihood of a significant deviation from the mean).

Although on-going improvements to system efficiency, materials, and construction methods have significantly reduced the amount of energy used for space heating [4,5], studies have indicated that as buildings become more energy efficient, the behaviour of occupants play an increasingly important role in consumption [6–9]. Homes are a particularly indeterminate energy sink, as a number of factors make accounting for consumption difficult; firstly there is the wide-ranging variety of structure, sizes, and materials found in the UK housing stock; additionally privacy issues limit the collection of data, and detailed sub-metering of houses has a prohibitive cost on a large scale; also, it is known that much of the discrepancy in energy consumption amongst buildings with

Abbreviations: UK TUS, United Kingdom Time Use Survey; PHPP, Passive House Institute's 'Passive House Planning Package'; CO_2, carbon dioxide; IES VE, Integrated Environmental Solutions' 'Virtual Environment' software; CEPHEUS, 'Cost Efficient Passive Houses as a European Standard' project; UQ & LQ, upper quartile & lower quartile; RSD, relative standard deviation; BU, bottom-up; CDA, conditional demand analysis; NN, neural network.

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similar constructions can be attributed to differences in occupancy patterns and occupant behaviour [10–12]. In research by Gill et al., in which a post-occupancy evaluation was carried out on a UK Eco-Homes site, the contribution of energy behaviours accounted for 51% of the variance in heating energy use. Other studies have indicated higher levels of behavioural effect of energy consumption, as much as 100% for a given dwelling [13].

Karlsson et al. stresses the importance of building occupant behaviour when designing energy simulations, and also highlights the difficulty of doing so [14]. Wood and Newborough propose that behavioural change is a major untapped area for energy savings, however they argue that the diversity of understanding, attitude, and abilities are a salient barrier to change [15].

Several studies have since investigated the effect that the type of thermostatic control has on energy use [16–18]. Shipworth found that in households with thermostats the mean temperature was generally lower than in dwellings without a thermostat in a study of over 400 dwellings [18]. Furthermore, they found that households with a programmable thermostat kept the heating system on for longer than households with non-programmable thermostats, though the difference was not statistically significant at the $p = 0.05$ level.

The paper is organised as follows: Firstly the varieties of bottom-up models are introduced, the methodology then describes our modelling approach, beginning with a look at the stochastic behavioural representation methods and is followed by a justification of the thermal modelling tools used. To conclude the methodology, a discussion of the data interrogation techniques used, namely linear multiple regression models. The results are then presented and validated against expected results gathered from various sources, and a regression model is employed to analyse the results from the modelling. Finally, we discuss the salient points of our study and suggest future work in the area.

2. Bottom-up modelling techniques

Swan and Ugursal conducted a thorough review of various household energy-consumption modelling techniques, highlighting the benefits and drawbacks of 'top-down' modelling approaches and 'bottom-up' (BU) type models [19]. Where models are built up from individual appliance and occupancy details to form representations of a large number of homes, this is a BU approach. Swan and Urgusal define two distinct categories of BU models: Statistical Methods (SM), which use historical data and regression techniques to quantify the relationships between end-uses and energy-consumption; and Engineering Methods (EM), which make use of power-ratings and cycle lengths of equipment found in a dwelling to model the overall-picture of energy use for a set of similar buildings.

2.1. Statistical methods

Regression techniques can determine whether input parameters are coefficients of some dependent variable. For example, in the case of a domestic setting, aggregated data such as the total space heating use or CO_2 use can be regressed onto parameters that may have an effect on the dependent variable. These could be coefficients such as the level of occupancy, level of ventilation, degree of space heating and external physical variables. Regression models have been successful in giving good estimates of apparently complex relationships in the built environment [9,20–25].

Swan terms a regression dependent upon the presence of end-use appliances conditional demand analysis (CDA) [19]. This process uses hundreds or thousands of houses' worth of electricity data and a survey of appliance ownership to regress the electricity use onto individual appliance variables. Studies have shown that the CDA method may represent aggregate energy use well on an hourly scale, but that individual load profiles are poorly represented without adequate specification of appliance use periodicity [26].

Another method of modelling the energy use of the housing stock is by neural networks (NN), which uses a simplified mathematical model inspired by the interconnected parallel structure of biological neural networks. Each end use is represented by a series of parallel 'neurons'. A number of studies have demonstrated this technique as a viable method for representing aggregate energy use given the correct 'training' of the network [27–30], and NNs are even used to model continually updated data, allowing for coefficients to become updated as new information becomes available, known as an 'adaptive' NN, demonstrated with success by Yang et al. [31].

2.2. Engineering methods

Using information about power consumption characteristics of equipment and appliances can be aggregated to inform a limitless number of models of interest, from a simple PV array on a roof, using solar irradiation data, to a complex thermal model of a building, using weather data and heat gain characteristics from all energy uses occurring inside the building.

With enough data about the power cycles of appliances and the usage and ownership of appliances, it is feasible to construct a model of power demand which represents a regional or national level of energy demand. This technique has been demonstrated on a number of occasions in a variety of locations around the world, from Sweden to Malaysia, and in general give good representative outputs [32–35]. Such models are informed by distributions, and thus named so by Swan et al.

Archetyping is a process of generalisation, taking a broad sample of dwellings and grouping those with similar characteristics. The Archetype method forms a set of houses which broadly represent the whole stock, based on key differences in geometries, thermal characteristics, and operating parameters. The regional distributions of each building type will inform the end model, which has been shown to give useful results, including building stock information [36].

3. Methodology

In this paper, occupancy, appliance-use, and door-opening profiles are generated by a third-party tool [35] based on a survey of 20,000 weekly UK household journals, which detail time use at a 10-min resolution by 11,600 individuals [37]. These profiles are used in the thermal model of a Passivhaus to represent unique households, which, by nature of the method used to derive the profiles, represent statistically likely behaviour. The results of this thermal modelling are validated using comparisons to measured data from Passivhaus projects around central Europe [3]. Across the heating season (October to April) we examine the sensitivity of the required heating energy of the homes to variation in particular behaviours.

3.1. Representing behavioural variation

The appliance-use and the occupancy profiles were generated using software written by Richardson et al. at the University of Loughborough. Their model uses data from the United Kingdom Time Use Survey (TUS), and generates stochastic profiles based on a Markov-Chain Monte Carlo method.

The Markov-Chain technique is an established stochastic method for generating data for a system with a discrete number of possible states [38]. A first-order Markov-chain means that the