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New optimisation methodology to uncover robust low energy designs that accounts for occupant behaviour or other unknowns

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ABSTRACT

The use of software to aid in the design of buildings or to show compliance is now commonplace. This has led several authors to investigate the potential for using such software to automatically optimise a design, or to generate a variety of near-optimal designs. One area where this approach has been found useful is in minimising annual energy demand. It is known that any estimate of demand will depend not only on the architecture and constructions used, but on the preferences and behaviours of the occupants. This suggests which design is truly optimal will also depend on occupant behaviour. In this paper optimisation is carried out for an array of different occupant behaviours based on real records. It is found that the resultant designs are more robust in terms of predicted heating energy use and overheating than when only a single behaviour is considered. It is recommended that in future all such optimisations are made using a realistic spectrum of behaviours, and that the approach is expanded to include other elements of design that might show variance during construction, for example, *U*-values and air tightness. This, it is hoped, will reduce some of the risks of designing and asking people to occupy very low energy buildings. Importantly, it is found that the near-optimal building designs found under variable occupancy present different characteristics than when only a single statement of occupancy is used. Being cognisant of this reduces the potential for inappropriate designs to be created that rely on a serendipitous arrangement of design and occupancy parameters that might not be met on site or by the occupants.

1. Introduction

Improvements in building standards and codes have contributed to the creation of new design philosophies that require, at least in theory, much reduced levels of heating and cooling to maintain a comfortable internal environment. However, as can be expected, the final, monitored, thermal environment and energy consumption will to a large extent depend upon the behaviour of the occupants. There has been little use of the limited data concerning actual energy habits and routines observed in the home; therefore, it is rare that modelling or optimisation is completed under a range of occupant behavioural scenarios.

Several of the most popular approaches to low-energy design, including *Passivhaus*, gain much of their space heating requirement from incidental gains, require very low levels of uncontrolled infiltration, and have low capacity heating/cooling systems [1,2]. This suggests that such designs might be more sensitive than buildings that need larger amounts of energy to stay comfortable, to the behaviour of the occupant, and leads to concern over their applicability to a wider audience, including their use in social housing.

It is known from the CEPHEUS study [3], among others, that the in-use energy demand of low-energy housing is indeed sensitive to occupant behaviour, with demand differing by more than a factor of three (see Fig. 1), yet even in these buildings it is unusual for designers to model with more than one set of occupant behaviours. At least within academia this mono-behavioural paradigm would appear to be changing, with some suggesting a move to a more human-centric view of modelling with a large number of simulations being run so as to explore the sensitivities of a design to the demands, desires and vagaries of occupants [4]. As Fig. 2 shows, such simulations have proved accurate at matching the distribution of energy use found in collections of real low-energy buildings.

This work attempts to meld human-centric modelling with optimisation to create designs that are not only low-energy and

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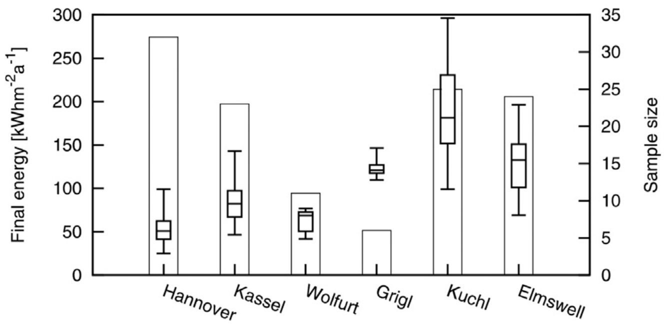

Fig. 1. Measured final energy consumption (candlesticks) of selected low-energy buildings (bars as sample size). The values contain all non-renewable energy supplies to the buildings, including household electricity and ancillary energy consumption. All data from the CEPHEUS data set [3] except the Elmswell data which is taken from Gill et al. [5].

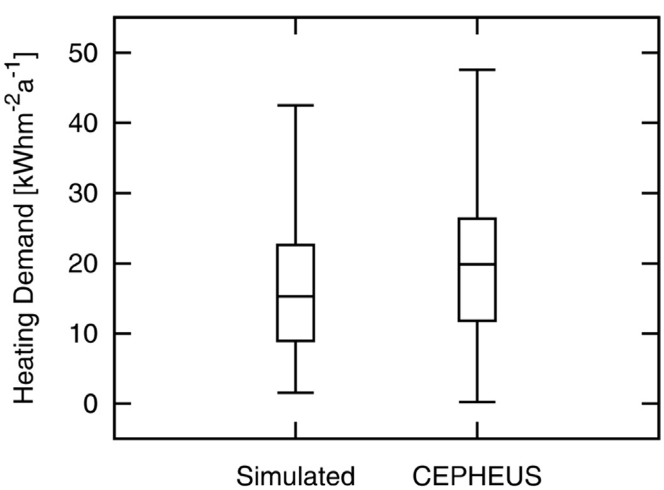

Fig. 2. Correlation between the data obtained by Blight and Coley [4] (left) and real data from the study CEPHEUS (right).

comfortable given a single representation of behaviour, but low-energy and comfortable when presented with a range of typical behaviours found within a society.

The predicted energy use and levels of comfort found from this multi-run, human-centric, modelling is used as the objective function within an optimisation algorithm to locate within the space of possible designs buildings that are simultaneously low-energy and comfortable for a wide range of occupant behaviours. This has required the creation of a new evolutionary algorithm capable of producing results in a reasonable time on a desk-top computer of a form that might be used by a practising engineer or architect.

This paper starts with a background section showing the bases of the work here presented. Following this, the methodology is described. The paper finishes with the presentation and discussion of results and conclusions. An appendix describing the evolutionary algorithm in detail is also included.

2. Background

2.1. Optimisation for building design

The potential for using optimisation within the modelling environment has a long history in building science; as early as 1956 Speyer investigated the optimal use and storage of solar energy [6]. Jurovics presented a method of optimising energy-efficient buildings in [7]. More specific works are found in the literature, concentrating on energy systems or constructions, such as the work of Bloomfield and Fisk on optimising the heating plant of a building [8], Michelson's multivariate optimisation of solar water heating using direct methods [9], and Marks' multi-objective optimisation of the building envelope [10]. A more holistic approach is found in more recent publications, such as the work of Coley and Schukart [11], Peippo et al. [12] or Magnier and Haghighat [13]; these take into account many parameters involved in building design including architectural characteristics and those related to energy systems.

2.2. Robust optimisation

Numeric optimisation is used to find the best combination of parameters that solve a given problem. Optimisation is often applied to find the minimum or maximum of a function termed the objective, or cost function. This function represents a model of the real system and will therefore be subject to uncertainties and inaccuracies. Robust optimisation implies finding the optimum of a given function subjected to such uncertainties.

The uncertainties present in an optimisation problem were classified by Beyer and Sendhoff [14] as:

(a) *Changing environmental and operating conditions*. the objective value is not dependent on the decision variables included in the model solely; it also depends on a set of parameters that are not decision variables and cannot be determined, but have a substantial influence on the results. For example, if the objective function is the heating demand of a building, and the geometry is to be optimised, environmental parameters and operating conditions are the weather and the behaviour of the occupants respectively.
(b) *Production tolerances and actuator imprecisions.* The decision variables chosen in the optimisation cannot always be achieved with enough accuracy in reality due to workmanship or other issues. In the previous example, these would correspond to for example fenestration ratios that cannot be achieved due to standardised sizes of windows.
(c) *Uncertainties in the system output.* The objective function can have mistaken outputs due to inaccuracy in the mathematical models or the measuring devices involved. In this case, the uncertainties for the example of this kind would be a mistaken result on the simulation that differ with the energy consumption of the design in the real world due to deficiencies of the code.
(d) *Feasibility uncertainties.* These uncertainties are applied to the constraints and not the objective function, resulting in an altered decision space. These uncertainties represent the variation of the boundaries that define the range of feasible solutions. In our example, feasibility uncertainties could be the upper and lower bound of a variable such as insulation thickness being unfeasible.

All four of these uncertainties are present in most real-world optimisations to some extent and many authors have considered them when applying optimisation (see Beyer's and Sendhoff's review). (see Fig. 3)

Many optimisation strategies are found in the literature; Evolutionary Algorithms (EA) have gained a substantial following and can be found in a large number of publications including those concerning the built environment [13,15–22]. EAs do not require knowledge of the global form of the objective function as they belong to the group of *direct methods:* meaning that they only require the value of the objective function at the points that are evaluated during the search.