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Building energy optimisation under uncertainty using ACOMV algorithm

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ABSTRACT

In building optimisation many parameters are uncertain due to their dependence on the building operation and environment (e.g. internal loads). This uncertainty implies that the "optimised" building is likely sub-optimal for the actual parameters.

This study develops a new scenario-based optimisation methodology to address building parameter uncertainty. A multi-objective optimisation problem based on three objective functions ("low", "base", and "high" simulation scenarios) is developed and scalarised using the weighted sum method to find the optimised compromise between energy use for different scenarios. Necessitated by the increased computational demand of multi-objective problems, a modified version of the Ant Colony Optimisation algorithm for Mixed Variables (ACOMV-M) is developed. A comparison between ACOMV-M and a benchmark algorithm showed that ACOMV-M converged to solutions of similar quality with approximately 50% fewer simulations. The results on an Australian office building showed that the energy-optimised building parameters can vary significantly for different assumptions. Furthermore, inaccurate assumptions on internal loads and infiltration rate can reduce energy savings achieved by optimisation up to 4.8 percentage points. The proposed methodology is used to identify parameters that are sensitive to different scenarios and demonstrated that more robust solutions can be achieved through modest sacrifices in optimality to any one scenario.

1. Introduction

Buildings consume over 40% of end-use energy worldwide and are responsible for approximately one-third of greenhouse gas (GHG) emissions [1]. Clearly, designing high energy performance buildings and/or identifying effective energy retrofit measures not only decrease CO_2 emissions, but also reduce the need for non-renewable energy sources. A powerful tool to design energy-efficient buildings is simulation-based optimisation (coupling building simulation software with an optimisation algorithm), which can systematically manage the numerous trade-offs in design. However, a simulation-based optimisation method is typically a very complex task due to multi-modal and nonlinear behaviour of building thermal performance, discontinuities in the optimisation variables (e.g. window type) [2,3], and discontinuities in the output of building simulation software (e.g. EnergyPlus) [4,5]. Importantly, time and computational burdens also increase the complexity of solving building optimisation problems (BOPs) [6].

The optimisation results are also dependent on a priori specification of quantities that are poorly known (e.g. equipment and lighting loads). Due in part to this uncertainty, the simulated building and actual energy consumption may be quite different (i.e. the "performance gap" noted in many studies [7,8]). A recent study using high and low range simulation assumptions showed more than 50% discrepancy in predicted energy consumption compared to the original case in typical office buildings in Australia [9]. In BOPs, this sensitivity to uncertain quantities implies that the "optimised" building may be far from the actual optimum.

In this paper, a new scenario-based optimisation methodology is developed to address uncertainty in building parameters. A multi-objective optimisation problem is developed to find the optimised compromise between energy use for different building parameter scenarios. To solve the optimisation problem, the multi-objective problem is first transformed to single objective problem using Weighted Sum Method (WSM). Necessitated by the high computational cost of multi-objective problems, a new modification of the Ant Colony Optimisation algorithm for Mixed Vari-

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ables (ACOMV-M) was developed with the specific aim of localising the search in the later stages of optimisation. This algorithm is then benchmarked against hybrid Particle Swarm Optimisation and Hooke Jeeves (PSOHJ) algorithm, which has been successfully applied to many BOPs [4,10].

ACOMV-M is deployed in an Australian case study to investigate the sensitivity of the configuration of energy-optimised building to different simulation assumptions. Motivated by the sensitivity of the optimal configuration to the simulation assumptions, a multi-objective optimisation methodology is then applied to allow designers to transparently manage the risks associated with simulation assumption uncertainty.

The remainder of this paper is organised as follows. The next section discusses the existing literature for BOPs and optimisation under uncertainty. The Methodology section details the formulation of the BOP, the optimisation algorithms, details of the case study, and optimisation variables. In the Results section, firstly the performance of the ACOMV algorithms is compared against the PSOHJ algorithm, and then the sensitivity of optimisation results in both single-objective and multi-objective optimisation problems to internal loads is examined. The last section presents the discussion and conclusion of the research.

2. Literature review

This section reviews the prior work in uncertainty in building simulation assumptions and its effect on the energy consumption prediction and optimisation. Subsequently, the research in building optimisation algorithms is reviewed with the aim of identifying computationally efficient benchmark algorithms.

2.1. Uncertainty in building simulation and optimisation

In the vast majority of simulation/optimisation problems, building designers assume that building input parameters are deterministic (or perfectly known). However, in real building problems, especially at the early stages of building design, parameters are often highly uncertain. These uncertainties may arise from different sources, including uncertainties in the thermophysical properties of construction materials and in weather data, lack of designers' knowledge of building occupancy, occupant behaviour and appliance loads, and uncontrolled infiltration rates [11,12]. These uncertainties cause a significant discrepancy between the predicted and actual building energy performance [8,9,13]. In Building Performance Simulation (BPS), the impact of uncertainty in building simulation assumptions has been broadly investigated by a number of studies [7,11,14–20]. For example, Silva [18] analysed the uncertainties on user behaviour and physical parameters for a residential building simulation and found up to a 43.5% deviation in energy consumption.

In contrast to BPS problems, studies considering uncertainty in BOPs are quite limited. Hoes, et al. [21] proposed a building performance indicator based on uncertainty in the users' behaviour to rank Pareto solutions to select the most robust solution. They used Monte Carlo Simulation and NSGA-II to calculate and minimise the mean value of building performance indicators. Bucking [22] applied Monte Carlo Simulation and an evolutionary algorithm to optimised energy consumption and life-cycle cost under economic uncertainty. To address the well-known issue of high computational cost for Monte Carlo Simulation, Ramallo-González et al. [23] developed a Changing Environment Evolutionary Strategy (CEES) to optimise energy under uncertainty in occupant behaviour. In this strategy, the algorithm's populations are evaluated with a different environmental parameter at each generation. In another study, Hopfe et al. [12] developed a Kriging meta-model of building performance and used Monte Carlo Simulation to do optimisation under uncertainty. However, construction of a sufficiently accurate meta-model is a key factor in the performance of the surrogate-based optimisation problems (which was not discussed in [12]). This construction depends strongly on the samples that are used in training the meta-model and the selection of free parameters, which have no generally-accepted guidelines for their selection and require significant expertise and/or time to properly tune [24].

In addition to the issue of high computational cost, probability models (e.g. for Monte Carlo simulation) require probabilistic distributions of parameters that may not be available, particularly in light of the fact that uncertainties may change during the building life time [12]. In such cases, *scenario analysis* (i.e. analysing the behaviour of the building under a number of different specific building assumptions) may provide a complementary tool to enable uncertainty analysis when detailed distributional information is lacking [25].

2.2. Building optimisation algorithms

Simulation-based optimisation is a common method for solving BOPs, in which building simulation software is coupled with an optimisation algorithm. In this method, building simulation plays the role of the objective function such as energy consumption and/or life cycle cost, and the decision variables are manipulated by optimisation algorithm to iteratively improve the objective function.

For building optimisation problems, many optimisation algorithms have been developed and applied to design energy-efficient buildings in recent years [6]. For example, Fesanghary et al. [26] developed a multi-objective optimisation model based on a harmony search algorithm to minimise life cycle cost and carbon dioxide emissions. Shirazi et al. [27] used a genetic algorithm to optimise solar heating and cooling absorption chillers for hotel and office buildings under Sydney's climate. Bamdad et al. [28] applied an ACOMV algorithm to find an optimised retrofit for an office building in Australia.

The performance of the simulation-based optimisation depends heavily on the optimisation algorithm. The performance of optimisation algorithms can be measured through different metrics such as convergence speed, best solution found and arithmetic mean of the objective over different optimisation runs. However, the selection of an appropriate measure of performance depends on the optimisation problem [29]. In BOPs, apart from the quality of optimised solutions, algorithm convergence speed is another key performance measure due to the high computational cost of solving BOPs [4,5]. Therefore, finding an approximated optimised design in reasonable time is preferable. A comparison between a Genetic Algorithm (GA) and a Hooke–Jeeves (HJ) algorithm in minimising energy consumption of an office building in three climate conditions showed that the GA had a better performance than the HJ algorithm in two climate conditions [30]. Another study investigated the performance of nine optimisation algorithms in solving simple and complex building models [4]. It was found that the Hybrid Particle Swarm Optimisation and Hooke-Jeeves (PSOHJ) achieved the largest energy reduction among all algorithms. It was also observed that the GA was close to the optimal point with fewer building simulations than PSOHJ. In contrast, neither Nelder–Mead nor Discrete Armijo gradient algorithms were competitive.

More recent comparative studies have also been conducted on BOPs. A comparison between GA and PSO indicated that PSO was slightly better in finding the optimum solution, while GA could find the solutions that were very close to PSO with a fewer number of simulations [31]. Another study investigated the performance of Sequential Search technique; GA and PSO showed that the computational efforts for the Sequential Search technique are higher than other algorithms [32]. A comparison of three multi-objective