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Ant colony algorithm for building energy optimisation problems and comparison with benchmark algorithms

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ABSTRACT

In the design of low-energy buildings, mathematical optimisation has proven to be a powerful tool for minimising energy consumption. Simulation-based optimisation methods are widely employed due to the nonlinear thermal behaviour of buildings. However, finding high-quality solutions with reasonable computational cost remains a significant challenge in the building industry.

In this paper, Ant Colony Optimisation for continuous domain (ACOR) is developed and applied to optimise a commercial building in Australia. The results for a typical commercial building showed that optimisation can achieve an additional energy savings of more than 11.4%, even after some common energy saving measures were implemented (e.g. double pane windows). The performance of ACOR was compared to three benchmark optimisation algorithms: Nelder-Mead (NM) algorithm, Particle Swarm Optimisation with Inertia Weight (PSOIW) and the hybrid Particle Swarm Optimisation and Hooke-Jeeves (PSO-HJ). This comparison showed that ACOR was able to consistently find better solutions in less time than the benchmark algorithms. The findings demonstrate that ACOR can further facilitate the design of low-energy buildings.

1. Introduction

Reducing energy consumption is one of the world's most challenging issues, particularly with increases in population and economic growth. According to the United Nations Environment Program in 2009, buildings consume approximately 40% of the world's energy and they are responsible for approximately one-third of greenhouse gas emissions in the world [1]. Clearly, improving energy efficiency of buildings is an important issue that not only decreases CO_2 emissions, but also reduces the need for non-renewable energy sources.

However, complex interactions between design and environmental variables complicate the design of energy efficient buildings. This is particularly true after "simple" energy saving measures are already employed (e.g. increasing insulation thickness) and it's not immediately obvious how to further reduce energy consumption. Mathematical optimisation is an important technique for systematically managing the numerous trade-offs in design. These Building Optimisation Problems (BOPs) typically seek to minimise the energy consumption of a building by employing simulation-based optimisation (coupling building simulation software with an optimisation algorithm). The extensive body of research in this area has clearly demonstrated that optimisation can dramatically reduce the energy consumption of buildings [2–12].

Nevertheless, solving BOPs remains challenging: Currently-available methods require hundreds to thousands of time-consuming building simulations to find the final solution, which may take several weeks [13,14]. In addition, the optimisation problem complexity increases strongly as the number of optimisation variables increases. More importantly, since building performance measures (e.g. energy consumption) generally have many local optima, the optimisation algorithm may fall into local optimum which may be far from the global optimal solution. These complexities in BOPs have driven research into new solution algorithms. However, reducing optimisation time and finding higher-quality solutions remains an important research area to increase utilisation of optimisation as a design tool [15].

Therefore, the principle aim of this research is to develop a new building optimisation approach that improves upon the benchmark algorithms in terms of the following key performance metrics: 1) solution quality (objective value), 2) consistency (reliably achieving solutions close to the optimal), and 3) computational cost (number

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of simulations). Using these metrics, a detailed statistical comparison of the new BOP algorithm is conducted. In addition, the detailed statistical analysis represents a significant contribution, since no detailed study on the convergence performance (speed and consistency) has been conducted to date.

In this paper, a new building optimisation approach based on Ant Colony Optimisation for continuous domain (ACOR) is proposed. ACOR is an optimisation method that has been developed in recent years, and has shown promise when compared with other popular optimisation algorithms [16]. First, a method for handling interval constraints (typically presented in BOPs) is added to the ACOR algorithm. Subsequently, this augmented ACOR algorithm is used to optimise a typical commercial building in selected cities in Australia for the first time. These optimisation experiments are used to both rigorously evaluate the effectiveness of the ACOR algorithm against the benchmark (using the aforementioned performance metrics), and to provide new design insight for designing low-energy commercial buildings in Australia.

The remainder of this paper is structured as follows. Section 2 discusses the existing literature for BOPs while Section 3 details the formulation of the BOP and the optimisation algorithms. In Section 4, the efficiency of ACOR is evaluated by comparing its results to baseline simulations and to the benchmark optimisation algorithms. Finally, Section 5 presents the conclusions and future work of the research.

2. Optimisation algorithms for BOPs

The dominant method for solving BOPs is simulation-based optimisation, where building simulation software is coupled with an optimisation algorithm. Frequently, the Derivative-free (DF) optimisation algorithms are employeddue to discontinuities and multi-modal behaviour of building optimisation problems (BOPs) [13,14,17]. In these methods, building simulation plays the role of the objective function (e.g. energy consumption, thermal comfort, etc.) and the decision variables are manipulated by optimisation algorithm to iteratively improve the objective function.

Many optimisation algorithms have been applied to solve BOPs such as Simulated Annealing [18] Genetic Algorithm (GA) [18–22], harmony search algorithm [23] Particle swarm optimisation algorithm (PSO) [24,25], Tabu Search [26] and artificial bee colony [27]. However, the selection of the best optimisation algorithm is still an open question, since it is highly dependent on the specifics of the problem [28,29]. Several studies investigated the performance evaluation of optimisation algorithms in solving BOPs in order to find which algorithm performs best for BOPs. Wetter and Wright [30] compared the performance of a Genetic Algorithm (GA) and a Hooke–Jeeves (HJ) algorithm in minimising energy consumption of a building. Their results showed that the GA has a better performance than the HJ algorithm and the latter may also fall into a local optimum. In another study, Wetter and Wright [31] compared the performance of nine different optimisation algorithms including a gradient based algorithm (Discrete Armijo gradient algorithm), direct search Algorithms (Coordinate search algorithm, HJ algorithm and Simplex algorithm of Nelder and Mead), Meta heuristic algorithms (Simple GA and two versions of PSO), and Hybrid PSO-HJ algorithm in solving simple and complex building models. It was found that the Hybrid Particle Swarm Optimisation/Hooke-Jeeves (PSO-HJ) achieved the largest energy reduction among all algorithms. Their results also showed that the GA was close to the optimal point with fewer simulations than PSO-HJ. In contrast, it was observed that Nelder and Mead and Discrete Armijo gradient algorithm failed to find high-quality solutions.

More recent comparative studies have also been carried out for BOPs. Tuhus-Dubrow and Krarti [4] compared the performance of GA and PSO, and found the GA obtained the solutions which were close to PSO with the fewer number of building simulations. Another study investigated the performance of GA, PSO and Sequential Search technique, and indicated that the computational efforts for the Sequential Search technique are higher than others [7]. Hamdy et al. [32] compared the performance of three multi-objective algorithms: Non-dominated Sorting Genetic Algorithm-II (NSGA-II), NSGA-II with active archive (aNSGA-II), and NSGA-II with a passive archive strategy (pNSGA-II). It was found aNSGA-II is more consistent in finding optimal solutions with a lower number of function evaluations than others. Hamdy et al. [33] compared the performance of seven multi-objective evolutionary algorithms with respect to different criteria. Their results indicated that two-phase optimisation using the genetic algorithm (PR_GA) can be considered the first choice for solving multi-objective BOPs. Bucking et al. [34] compared the performance of the modified Evolutionary Algorithm (EA) and Mutual Information Hybrid Evolutionary Algorithm (MIHEA) against GenOpt's particle swarm inertial weight (PSOIW) algorithm. Results indicated that MIHEA finds better solutions with less computational time. Kämpf et al. [35] examined the performance of two hybrid algorithms (Covariance Matrix Adaptation Evolution Strategy with the Hybrid Differential Evolution (CMA-ES/HDE) and PSO-HJ) in minimizing the five standard benchmark functions of Ackley, Rastrigin, Rosenbrock, Sphere functions and a highly-constrained function as well as real buildings. It was observed that both algorithms perform well but CMA-ES/HDE is preferable when the optimisation problem is highly multi-modal. Another study showed that CMA-ES with sequential assessment can find the same results as a GA in less time [36]. PSO showed a slightly better performance than GA in finding the optimal size of the solar system components for a single-family house [37]. Another study showed that a combination of GA with a modified simulated annealing algorithm can find more reliable results than the GA solely [38]. Futrell et al. [39] compared four optimisation algorithms in a building design for daylighting performance. They compared Simplex Algorithm of Nelder and Mead (NM), HJ, PSOIW, and PSO-HJ. They found that PSOIW found the best overall solution but PSO-HJ found solutions which are very close to the best solutions in less time.

As the literature review revealed, the application of optimisation in to buildings remains an active research area. In addition, comparative studies in literature indicate Particle Swarm Optimisation with Intertia Weight (PSOIW) and the hybrid PSO-HJ algorithms perform well on BOPs [34,35,37,39], outperforming many other popular optimisation algorithms (e.g. GA). Accordingly, they are selected as benchmark algorithms against the proposed algorithm in this paper. In addition to these benchmark algorithms, the NM algorithm is also selected as a benchmark direct search algorithm.

It should be noted that with regard to buildings' design using simulation-based optimisation in Australia, there are very few studies [40]. This highlights the importance of the results of current study which can be used practically to design high performance buildings in Australia.

3. Methodology

The building optimisation problem considered in this paper can be formally stated as

$$\begin{aligned} &\min f(\mathbf{x}) \\ &\text{subject to}: \mathbf{x} \in \mathbb{X} \subseteq \mathbb{R}^N \end{aligned} \tag{1}$$

where $f(\cdot): \mathbb{X} \to \mathbb{R}$ is the objective function, $\mathbb{X} \subset \mathbb{R}^N$ is the feasible space, $\mathbf{x} = [x_1, x_2, \ldots, x_N]$ is the vector of independent design variables. For the BOP considered in this paper, the feasible design space is simply stated in terms of upper and lower bounds on param-