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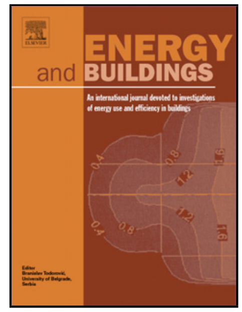

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Ant Colony Algorithm for Building Energy Optimisation Problems and Comparison with Benchmark Algorithms

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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.

Keywords: Optimisation Algorithm Benchmarking; Building Optimisation; Ant Colony Optimisation; Particle Swarm Optimisation; Australian Commercial Building

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 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 employed due 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

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

where $f(\cdot): \mathbb{X} \rightarrow \mathbb{R}$ is the objective function, $\mathbb{X} \subset \mathbb{R}^N$ is the feasible space, $\mathbf{x} = [x_1, x_2, \dots, x_N]$ 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 parameters: $-\infty < l_i \leq x_i \leq u_i < +\infty,\ i = 1,2, \dots, N$ where l_i and u_i are the lower bound and the upper bound of the variable i. Since the decision variable input ranges can be normalized, we may assume (without loss of generality) that $l = 0$ and $u = 1$. The objective function, $f(\cdot)$, is the building annual end use energy consumption $(\mathrm{MJ/m^2\ Year})$, which is calculated by EnergyPlus [41], which can be written as follows:

$$f(\mathbf{x}) = E_c(\mathbf{x}) + E_f(\mathbf{x}) + E_l(\mathbf{x}) + E_p(\mathbf{x}) + E_h(\mathbf{x}) + E_m(\mathbf{x}) \tag{2}$$

where E_c is the energy consumption for space cooling $(\mathrm{MJ/m^2\ Year})$, E_f is the energy consumption of the supply and return fans of HVAC system $(\mathrm{MJ/m^2\ Year})$, E_l is the energy consumption of lighting $(\mathrm{MJ/m^2\ Year})$, E_p is the energy consumption of pumps $(\mathrm{MJ/m^2\ Year})$, E_h is the energy consumption for space heating $(\mathrm{MJ/m^2\ Year})$ and E_m is the energy consumption of both interior equipment and heat rejection[1]$(\mathrm{MJ/m^2\ Year})$.

The remainder of this section is organized as follows. In Section 3.1, an ACOR algorithm for solving (1) is detailed, while Section 3.2 discusses Nelder and Mead with the Extension of O'Neill algorithm, and Section 3.3 details PSOIW and PSO-HJ (chosen after thorough review of the literature). In Section 3.4, the building to be optimised is detailed along with two baseline design simulations.

3.1 Optimisation Algorithms: ACOR

Ant Colony Optimisation (ACO) is a metaheuristic which was inspired by observation of ant behaviour. This algorithm was first designed to solve discrete optimisation problems and later extended to continuous variables [16, 42]. This extension, called Ant Colony Optimisation for continuous domain (ACOR) [16], will be employed to optimise the building energy performance. In this paper, a strategy to deal with boundary constraints has been added to the original ACOR algorithm.

ACOR operates on a *solution archive* which is shown in Figure 1. This archive contains the values of the $\boldsymbol{N}$ decision variables $\mathbf{x}_j = \left[\boldsymbol{x}_j^{\mathbf{1}}, \boldsymbol{x}_j^{\mathbf{2}}, \dots, \boldsymbol{x}_j^{\boldsymbol{N}}\right]$ and the associated objective

[1] For the HVAC system considered, heat rejection is the energy consumption of cooling tower fan.

function values $\boldsymbol{f}(\mathbf{x}_j)$, obtained by simulating the building to obtain the annual energy consumption. Solutions in the archive are sorted from lowest to highest objective values, i.e.

$$f(\mathbf{x}_1) \le f(\mathbf{x}_2) \le \ \dots \ \le f(\mathbf{x}_j) \le \ \dots \ \le f(\mathbf{x}_M) \tag{3}$$

New candidate solutions are generated according to a Gaussian kernel probability density function (PDF) based on the solutions in the archive

$$G^i(x) = \sum_{j=1}^{M} \omega_j \, g_j^i(x) = \sum_{j=1}^{M} \omega_j \frac{1}{\sigma_j^i \sqrt{2\pi}} \, e^{-\frac{\left(x-\mu_j^i\right)^2}{2\sigma_j^{i2}}} \tag{4}$$

where $G^i(x)$ is the Gaussian kernel for the ith dimension of the solution, $g_j^i(x)$ is the jth sub-Gaussian function for the ith dimension while μ_j^i and σ_j^i are the jth dimensional mean value and the standard deviation, respectively. The *weights* ω_j are set so that solutions with lower objective values are preferred, since they likely indicate neighbourhoods where good solutions may be found. The weights are assigned based on the position of a solution in the archive

$$\omega_j = \frac{1}{qM\sqrt{2\pi}} \, e^{-\frac{(j-1)^2}{2q^2M^2}} \tag{5}$$

where q is a free parameter that controls the degree that to which the lowest objective solution is preferred. Low values of q increase the weights of the best solutions relative to the other solutions in the archive.

The mean and standard deviation of the of the sub-Gaussians are also set based on the archive solutions

$$\mu_j^i = x_j^i \tag{6}$$

$$\sigma_j^i = \xi \sum_{\ell=1}^{M} \frac{\left|x_\ell^i - x_j^i\right|}{M-1} \tag{7}$$

In other words, the standard deviation is set according to the average distance of $\mathbf{x}_j$ from the other $M-1$ solutions in the archive along dimension i in the parameter space. The free parameter ξ is simply a scaling factor which allows users to set the percentage of this average.

The new candidate solutions are generated according to the distribution in Eq. (4) via a two-stage process. First, a solution from the archive is randomly selected with probability

$$P_j = \frac{\omega_j}{\sum_{r=1}^{M} \omega_r} \tag{8}$$

Obviously, solutions with higher ω_j will be more probable. A new candidate solution, $\tilde{\mathbf{x}}$ is randomly generated according to the component-wise probability density functions

$$g_j^i(\tilde{x}^i) = \frac{1}{\sigma_j^i\sqrt{2\pi}} e^{-\frac{\left(\tilde{x}^i-\mu_j^i\right)^2}{2\sigma_j^{i2}}} \qquad i = 1,2,\dots,N \tag{9}$$

where j is the selected solution from the archive. The objective value of this solution is then evaluated and the generation procedure repeats until m candidate solutions are generated. The archive is then updated by selecting the best M solutions from the $M+m$ solutions. To do the optimisation with ACOR algorithm all variables are normalised between zero and one ($l_i = 0 \; and \; u_i = 1$). However, during the generation of new solutions, a variable (x_i) may violate the domain boundary constraint. If this occurs, x_i is repaired as follows:

$$\begin{aligned} &\text{if } x_i < 0 \;\rightarrow\; x_i = |x_i| \\ &\text{if } x_i > 1 \;\rightarrow\; x_i = 1 - (x_i - floor(x_i)) \end{aligned} \tag{10}$$

The overall algorithm is summarized below.

0. Select values for the parameters $q, \xi, M, m \leq M$

1. Initialize. Randomly generate $\mathbf{x}_j \;\; j = 1,2, \dots, M$ according to component-wise uniform distributions[2] between the upper and lower bounds. Compute the objective values.
2. Sort solutions in ascending order according to their objective values so that Eq. (3) is satisfied.
3. Calculate weights according to Eq. (5)
4. Generate a new solution.
    a. Select a solution j from the archive with probabilities from Eq. (8)
    b. Generate a solution according to Eq. (9)
    c. Adjust any variable values violating constraints according to Eq. (10)
5. Repeat step 4, m times
6. Evaluate objectives of m new solutions
7. Select the best M solutions from the $M + m$ solutions available
8. Check stopping criteria. If they are not satisfied, return to 2.

A key challenge in the application of any optimisation algorithm is striking the proper balance between exploration of the parameter space and intensification of the search near quality solutions. In ACOR this behaviour is controlled using the parameters q and ξ. Smaller values of q promote intensification by assigning relatively large weights to better solutions in the archive and thus generating more candidate solutions in the neighbourhood of the best solutions. Larger values of q increase exploration by assigning more uniform weights to solutions in the archive. The parameter ξ is a normalized width of the sub-Gaussians; higher values promote increased exploration around a given solution, while lower values increase intensification near it.

[2] One could also use a space-filling algorithm (e.g. Latin Hypercube) to conduct this step.

3.2 Optimisation Algorithms: Nelder and Mead with the Extension of O'Neill

The first benchmark algorithm is Nelder and Mead (NM) algorithm [43] which is a popular direct search method and can be applied for nonlinear optimisation problems. In a problem with n variables, this algorithm generates $n+1$ vertices to construct a simplex (i.e. a triangle with two variables), and then moves or reshapes this simplex to find the better solutions. To generate new vertices in a minimisation problem, the NM algorithm calculates the value of objective function associated with each vertex and replace vertex with highest value of objective function (worst vertex) with a new vertex. New vertices are generally constructed by reflecting the worst vertex to a new vertex. Additional mechanisms such as expansion of the simplex and contraction of the simplex may be performed which were detailed in [44]. As this algorithm may fail to converge, starting from different initial points could improve its efficiency [39].

3.3 Optimisation Algorithms: PSOIW and PSO-HJ

The next two benchmark algorithms which were selected from the literature are both based on Particle swarm optimisation (PSO), which is inspired by the social behaviour of birds. PSO is a metaheuristic optimisation algorithm introduced in [45]. PSO seeks the optimum solutions by changing the position of "particles" (which represent particular values of the building parameters in this study) to seek better solutions and avoid local optima.

The first benchmark algorithm will be Particle Swarm Optimisation with Inertia Weight (PSOIW) which was developed to improve the performance of the original PSO by better controlling the balance between global and local search [46, 47]. In PSOIW, the velocity and position of a particle are determined as follows:

$$\mathbf{v}_i(k+1) = \omega(k)\mathbf{v}_i(k) + c_1\rho_1(k)(\mathbf{p}_{l,i}(k) - \mathbf{x}_i(k)) + c_2\rho_2(k)(\mathbf{p}_{g,i}(k) - \mathbf{x}_i(k)) \tag{10}$$

$$\mathbf{x}_i(k+1) = \mathbf{x}_i(k) + \mathbf{v}_i(k+1) \tag{11}$$

Where $\mathbf{x}_i$ is the position of ith particle, k is the generation number, $\mathbf{v}_i$ is the particle velocity, ρ_1 and ρ_2 are uniformly distributed random numbers. The variable $\mathbf{p}_{l,i}(k)$ is the position of the particle with the best objective value observed so far for particle i, $\mathbf{p}_{g,i}(k)$ is the position or the particle with the best objective value so far[3], $\omega(k)$ is a non-increasing inertia weight, and c_1 and c_2 are algorithm parameters that control the relative influence of the “global” and local optima on the particle velocity update in Eq. (10). The interested reader is referred to [46, 47] for further details.

The last benchmark algorithm is the hybrid PSO-HJ algorithm. PSO searches globally to find near optimal solutions and then Hooke-Jeeves searches locally to refine the solutions. PSO stops in this hybrid algorithm after a finite number of iterations or generations and then Hooke-Jeeves refines the PSO solution and terminates when no improvement is found [31].

3.4 Building Simulation

In this paper, a ten-storey building called building “Type A” will be used as a case study. Australian Building Code Board (ABCB) [48, 49] has recommended this building to represent the typical large commercial building located in Australian Capital Business Districts (CBD). This building has been studied by many researchers [50-59]. However, different simulation assumptions and input values have been used in the literature which has resulted in different building simulation results. In this research, the building configuration, parameters, and assumptions (e.g. internal loads) are as specified in the ABCB recommendations [48, 49, 58]. The details of this configuration will now be discussed.

[3] Actually, the $\mathbf{p}_{g,i}$ is the best objective found amongst the particles in a neighbourhood of particle i, which could potentially be all particles.

Building Type A is an office building (tower) with the heavy-weight concrete construction and gross floor area of 9985 m^2. This building includes all features of real buildings including multiple thermal zones, internal loads of occupancy, lighting, equipment, auxiliary service equipment and HVAC system. The template VAV system of the EnergyPlus was selected to model a variable air volume system with water cooled chiller (COP = 3.7) and the heating and cooling sizing factors are 1.25. The prototypes and details of building Type A are given in Figure 2 and Table 1 and Table **2**. The schedules used for occupancy, lighting (limited control), equipment and HVAC working hour were the same as given by the National Australian Built Environment Rating System (NABERS) [56].

In this study, two different scenarios are used for comparison to the optimised results. Scenario A is Building Type A as specified. The second scenario, Scenario B, is identical to Scenario A, but adds four typical "rule of thumb" modifications to improve energy efficiency: 1) additional (0.5 meter) overhangs above windows, 2) double-pane ($\mathrm{U} = 2.678\ \mathrm{W/m^2\ K}$), Solar Heat Gain Coefficient (SHGC) = 0.427 and Visible Transmittance (VT) $= 0.308$) instead of single-pane windows, 3) using daylighting control for each perimeter zone with one reference point with 320 lux set point at a height of $0.8\ (m)$ from the floor and continuous lighting control (minimum electric power and light output $= 0$), and 4) removing temperature set back.

4 Results

In this section the energy performance of the baseline scenarios and optimised buildings are presented. Section 4.1 details the results for the baseline scenarios in a number of climates represented by four different Australian cities. The results are then compares the results to available data and literature. In Section 4.2 the ACOR-optimised building for each city is compared to the baseline scenarios and the benchmark algorithms.

4.1 Baseline Building Simulation Results

Figure 3 shows the simulation results for the annual energy consumption per unit floor area for building Type A for both Scenario A and Scenario B, and the average state energy intensity of office buildings for four cities. The annual energy consumption in Scenario B respect to Scenario A reduced by 32.5%, 30.2%, 35.2 % and 38.1% for Brisbane, Darwin, Hobart and Melbourne, respectively. All cities except Darwin, the simulation results of annual energy consumption are close to the corresponding state average (within one standard deviation of those reported in [60]). In addition, for all cities, simulation results of Scenario A of present study are very close to the existing study [58]. Some possible reasons for the discrepancy for Darwin results include: different building constructions in that climate, higher cooling set-point, or differences in occupant behaviour [58].

4.2 Optimisation Results

The simulation-based optimisation methods were applied to building Type A in four different Australian climates: Darwin, with hot humid summers and warm winters; Brisbane, with warm humid summers and mild winters; Melbourne with warm summers and cool winters; Hobart, with mild to warm summers and cold winters [51]. The objective function is to minimise the annual energy consumption of the building (Eq. 2) with respect to 15 listed in Table 3. The average number of variables in BOPs was selected here [13], and the feasible search intervals were determined according to other similar studies [13, 15, 31, 34-36].

To conduct the building optimisation, a MATLAB code was developed which connects EnergyPlus to the ACOR optimisation algorithm. In contrast, GenOpt optimisation software was used to perform optimisation with NM, PSOIW and PSO-HJ algorithms [44]. Ten optimisation runs of each method were conducted for each city. A High Performance Computing (HPC) cluster was used since between

3000 and 4600 building simulations were required for each run. The time required for each run with EnergyPlus 8.1.0 is between three and five days.

In order to provide a fair comparison among the different optimisation algorithms, the number of function evaluations (simulations) to achieve the optimised result should be the same. In the hybrid PSO-HJ algorithm, PSO stops after the pre-defined number of iterations (3000 building simulations). However, Hooke-Jeeves terminates when no improvement is found (not after a set number of iterations). Thus, the number of simulations for each run was set in the following way. At first, the PSO-HJ algorithm was run to completion and the number of function evaluations was calculated. This number was considered as the stopping criterion for ACORs, NM and PSOIW (though the exact number of function evaluations will vary slightly due to the specifics of each algorithm).

An important factor in optimisation algorithm performance is the values for the free parameters. The parameters used in NM are those recommended in [31] and are shown in Table 4. The parameters used in the PSOIW and PSO-HJ algorithms are shown in Table 5. These parameters were set based on recommendations from previous studies which analysed PSO performance on benchmark functions and BOPs [35, 61]. The values for inertia weight in PSOIW and the values of parameters in HJ algorithm selected here were recommended by [31]. Parameters used in the ACOR recommended in [16] and are also shown in Table 6.

The optimisation results are presented in Table 7. The normalized energy consumption per unit floor area is presented to provide an easier comparison of results. Table 7 shows the best parameter sets among all ten runs for each algorithm in each city. For Brisbane, Hobart and Melbourne, the best solutions were obtained by ACOR (1) after 3468, 4171 and 3372 building simulations, respectively. ACOR (2) found the best solution for Darwin after 3519 building simulations. In contrast, PSOIW found the worst solution for Hobart and Darwin after 3800 and 3600 building simulations, respectively. Likewise, NM found the worst solutions Brisbane and Melbourne, respectively.

Table 7 also shows that the best building orientations are approximately zero degrees for Darwin, Hobart and Melbourne and almost ten degrees relative to North (clockwise) for Brisbane. For all cities, the optimum wall has the minimum solar absorptance, and best roof has the maximum emissivity with minimum solar absorptance. The optimum wall insulation thickness is 0.01 ($U_{wall} = 1.88\ \mathrm{W/m^2K}$) while its value before optimisation was 0.1. The selection of the minimum allowable insulation thickness can be explained as follows. The HVAC system operates only during the daytime and the internal loads are fairly high. Due this combination of usage factors and the relatively mild Australian climates, the dominant mode of operation of the HVAC system is cooling, even in winter. Therefore, increasing the insulation thickness will lead to higher cooling loads in winter months, which more than offsets any reductions in the cooling load in the summer months [62]. For example, If the optimal insulation thickness increases $1cm$ (10% of the allowable range), the annual cooling loads increase 33 (GJ), 11.35 (GJ), 21 (GJ) and 16 (GJ) for Brisbane, Darwin, Hobart and Melbourne, respectively, while the heating loads decrease only 3.3 (GJ) for both Hobart and Melbourne. The optimum windows and overhangs values depend on city and building direction because of the trade-off between lighting, cooling and heating loads. These results can also be used to compute the optimal values for window-to-wall ratio. For example, Melbourne has window-to-wall ratios (excluding plenum) of 27.7%, 32.7%, 37.2% and 31.8% for the East, North, South and

West building faces, respectively. The minimum and maximum were selected for heating and cooling set-points for all cities, respectively. This is clearly expected when the building energy consumption is only minimised. It should be noted that Table 7 shows optimisation solutions with decimal points which are important in terms of solutions quality of optimisation algorithms but it might be impractical for some variables in buildings design. For example, the heating/cooling set points are likely be rounded to their nearest integer in buildings design.

From an energy point of view, the difference between optimised objective functions obtained by ACOR (e.g. $642.56\ MJ/m2$ (Brisbane)) and PSO-HJ (e.g. $642.74\ MJ/m2$ (Brisbane)) are small. As can be seen in table 7, despite of slight differences between optimised objective functions, significantly different sets of parameters have been obtained by each algorithm, showing that the building objective function is very multi-modal. This fact provides building designers with more options in designing low energy buildings.

In real world optimisation problems, it is very likely that few optimisation runs will be utilised due to the high computational cost. Therefore, an algorithm which leads to good solutions consistently is preferable. A low mean value with a small spread or variability in results suggests a more reliable algorithm in finding good solutions in any single run. Box–Whisker (BW) plots display the distribution of optimisation results of annual energy consumption ($\mathbf{MJ/m^2}$) for each city, based on ten runs. Comparing the median values in Figure 4 shows that ACOR (2) and ACOR (1) perform the best for all cites, respectively. Although the median value of ACOR (1) is very close to ACOR (2), it has a larger variability than the ACOR (2) which makes ACOR (1) less reliable than ACOR (2). In contrast to ACOR, in all cites the spread of the optimisation results in NM is much larger than others. In addition, the median values of NM are also greater than other algorithms except for Darwin which PSOIW is highest. Apart from NM, the spread of the optimisation results in PSO-HJ for Brisbane and Hobart is larger than others.

Figure 4: Algorithm comparison with Box-Whisker plots for 10 runs; a) Brisbane b) Darwin c) Hobart d) Melbourne

The Wilcoxon rank-sum test was applied to understand the statistical significance of the differences in the algorithms' performance. The Wilcoxon rank-sum is a non-parametric statistical hypothesis test used to understand the probability that the difference between two groups (here two algorithms) is significant. In this test, low p-values indicate a low probability that the results were obtained by random chance while high p-values indicate a significant probability that there is no difference between the algorithm performances. Table 8 shows that for all cities the differences between both ACOR algorithms and NM, PSO-HJ as well as PSOIW are very significant. There is, however, no significant difference between ACOR (2) and ACOR (1).

Another important metric for optimisation algorithms is the convergence rate. In building optimisation problems, the evaluation of objective function is time-consuming. And it is therefore crucial that the number of function evaluations is kept to a minimum. Comparing convergence speed of optimisation algorithms is particularly important when the overall performance is very close in terms of the objective value.

Figure 5 shows an example of the optimisation run (for a solution close to the median) for Brisbane. As can be seen, both ACOR (1) and ACOR (2) converge to their final solutions much faster than other metaheuristic algorithms. In early iterations, NM performance is better than PSOIW and PSO-HJ and quickly converges to a solution. However, its solution is quite far from the best found solution. It can also be seen in the hybrid PSO-HJ algorithm, the PSO stopped after 3000 building simulations and then HJ refined the PSO results. The overall convergence speed of optimisation algorithms after ten runs is shown in the boxplots in Figures 6 and 7.

Figure 6 compares the convergence speed in the final stages of optimisation when algorithms converge to a solution very close to the final (e.g. within 0.1%) for Brisbane and Darwin. As can be seen, NM produced highly inconsistent results. In the PSO-HJ results, the solutions were found when HJ algorithm started refining PSO solutions (after 3000 iterations). A comparison of median values shows that both ACOR (1) and ACOR (2) are between two to four and half times faster than NM, PSOIW and PSO-HJ. Figure 7 compares the convergence speed in the initial optimisation stages when algorithms converge to a solution close to the optimal (e.g. within in 1%) for Hobart and Melbourne. Both ACOR algorithms showed slightly faster convergence rates than NM and much faster performance than PSOIW and PSO-HJ. A comparison of median values shows that ACOR (1) is almost seven times faster than PSO-HJ in Melbourne, and although NM has a potentially fast convergence rate, this rate is inconsistent and the solutions found have significantly higher energy consumption than the ACOR solutions.

Figure 6. Number of building simulations required for each algorithm to converge to within $\mathbf{0.1}\%$ of the final solution, for a) Brisbane and b) Darwin

Figure 8. Building annual energy consumption for Scenario A, B, and after optimisation

Figure 8 shows the building annual energy consumption and the breakdown of energy consumption for Scenario A, B, and after optimisation. Figure 8 also shows that cooling loads in Scenario B respect to Scenario A reduced by 48.4%, 39.5%, 62.6% and 61.1% for Brisbane, Darwin, Hobart and Melbourne, respectively.

After applying simulation-based optimisation, the annual energy consumption (compared to Scenario B) was reduced by 13.9%, 12.9%, 12.9% and 11.47% for Brisbane, Darwin, Hobart and Melbourne, respectively. Comparison of energy breakdown between Scenario B and optimised building shows that optimisation has significantly reduced the fan and cooling loads (fan energy consumption fell 53.45%, 43.37%, 61.32% and 53.22% for Brisbane, Darwin, Hobart and

Melbourne, respectively). The optimised building design in Darwin saw the maximum fan energy reduction by $34.65\ \mathrm{MJ/m^2}$. More importantly, cooling loads, which have significant impacts on the building peak load, were reduced by 35.7%, 24.9%, 52.03% and 39.5% for Brisbane, Darwin, Hobart and Melbourne, respectively. Darwin and Hobart experienced the maximum and minimum cooling load reductions of $75.92\ \mathrm{MJ/m^2}$ and $42.79\ \mathrm{MJ/m^2}$, respectively. It should be noted that despite the use of daylighting control, lighting loads almost remain constant between Scenario B and the optimised result. Since minimising the cooling and lighting loads are conflicting objectives, it is noteworthy that the optimisation algorithm prioritises reduction of the cooling loads, which isn't surprising in Australia (where cooling loads are typically high). Since the optimisation seeks the best balance between the various building loads, it is highly likely that an attempt to further decrease the lighting or cooling load would lead to a corresponding increase of equal or greater magnitude in the other.

5 Conclusion and Future Work

In this study ACOR algorithm developed for solving building optimisation problems and was applied to optimise fifteen variables in a typical commercial building in four different climates in Australia. A comparison between ACOR and three benchmark algorithms, NM, PSOIW and PSO-HJ, established the supremacy of ACOR in solving BOPs. All algorithms found good solutions. However, the two different parameter settings for ACOR (ACOR (1) and ACOR (2)) found results which are closer to global optimum than PSOIW and PSO-HJ. In terms of consistency (spread of results), ACOR (2) showed less variation in results and was by far more consistent than other algorithms. Importantly, both ACOR (1) and ACOR (2) converged much faster to their final solutions than the PSOIW and PSO-HJ. Indeed, since computational cost is a key issue limiting BOP practicality, this represents a significant result. Wilcoxon rank-sum test confirmed that the superior performance of ACOR over the two other algorithms was statistically significant. Overall, ACOR (2) is recommended for solving

BOPs due to finding more precise solutions, greater consistency in results and a fast convergence rate.

This paper also highlights the importance of using simulation-based optimisation for commercial buildings in Australia. The results show that building optimisation can achieve energy reductions of at least 11.47% and up to 13.9%, even after implementing the energy saving measures of Scenario B. This reduction was achieved largely by reducing the cooling load without significantly altering the lighting requirements (see Figure 8). Applying a simulation-based optimisation on an Australian typical commercial building identifies the potential energy saving solutions, provides a better understanding of optimal values of design variables, and help building designers set up future building codes to design high performance buildings in Australia.

In this paper, it was assumed 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 (e.g. uncertainties in thermophysical properties or building user behaviour). These uncertainties are likely to cause changes in the building optimised design. Therefore, future studies will consider uncertainties during the optimisation process to select a reasonable compromise between the expected energy consumption and the robustness to uncertainty, potentially using multi-objective approaches.

In addition, single-objective optimisation problem was considered in this paper (i.e. annual energy consumption), while other objectives have been not been considered, e.g. thermal comfort, which will be the subject of future studies.

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x_1^1	x_1^2	$\cdots$	x_1^i	$\cdots$	x_1^N
x_2^1	x_2^2	$\cdots$	x_2^i	$\cdots$	x_2^N
$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$
x_j^1	x_j^2	$\cdots$	x_j^i	$\cdots$	x_j^N
$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
x_M^1	x_M^2	$\cdots$	x_M^i	$\cdots$	x_M^N

$f(\mathbf{x}_1)$	ω_1
$f(\mathbf{x}_2)$	ω_2
$\vdots$	$\vdots$
$f(\mathbf{x}_j)$	ω_j
$\vdots$	$\vdots$
$f(\mathbf{x}_M)$	ω_M

Figure 1: Solution archive for ACOR (adapted from [16])

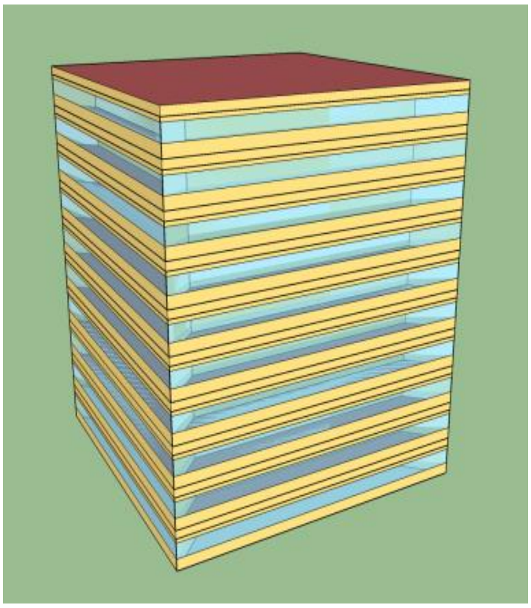

Figure 2: Ten-storey building Type A (ABCB) [48, 49]

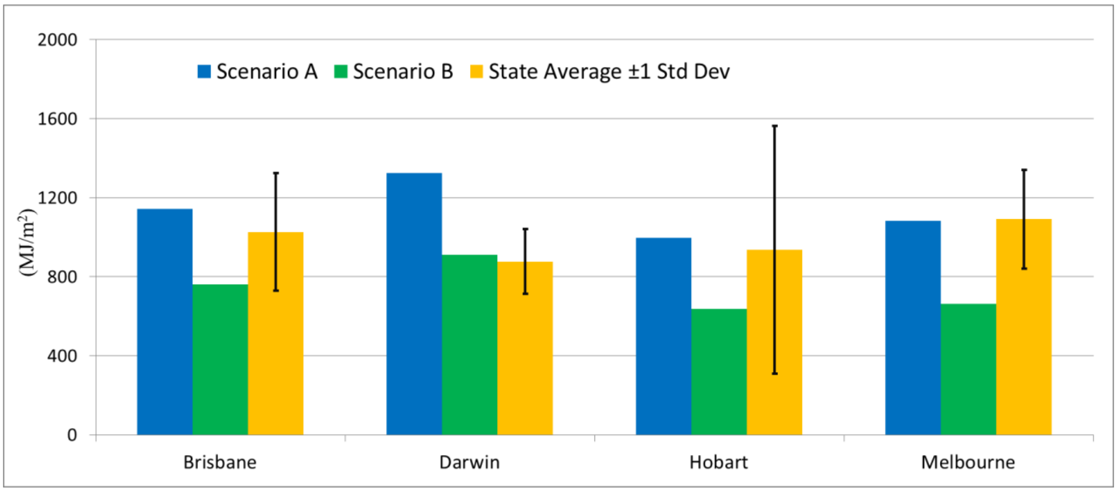

Figure 3: Annual energy consumption for building Type A scenarios A and B, and the average state energy consumption for commercial office buildings [60]

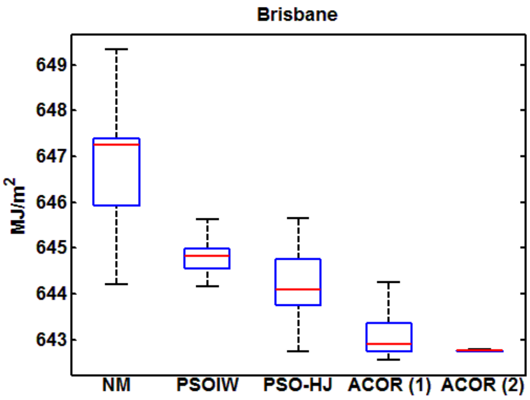

Figure 4a

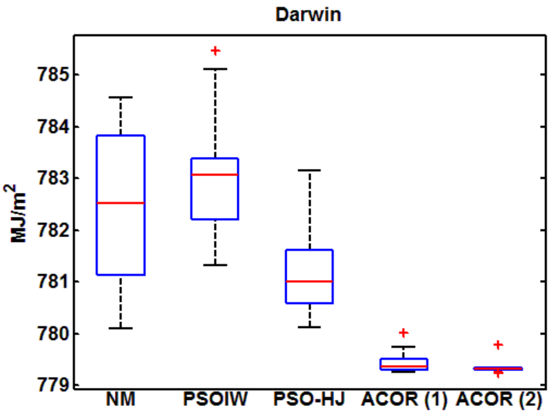

Figure 4b

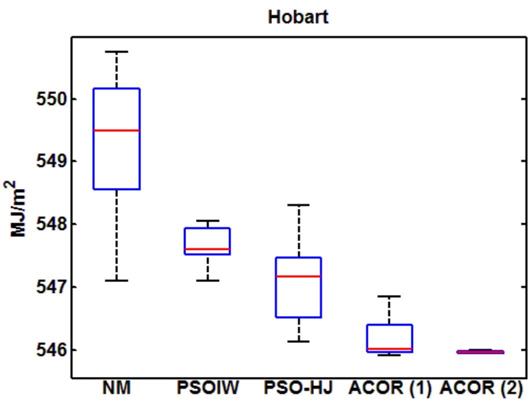

Figure 4c

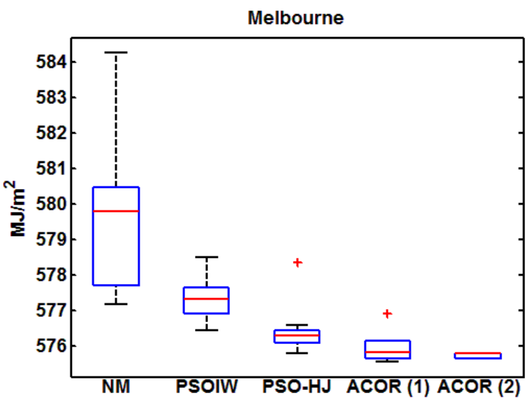

Figure 4d

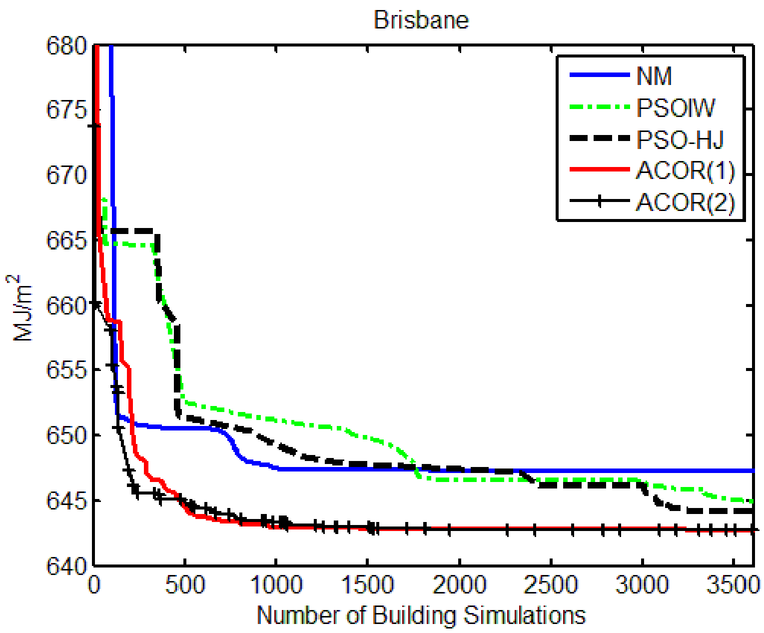

Figure 5: Convergence speed for the solution close to median in Brisbane

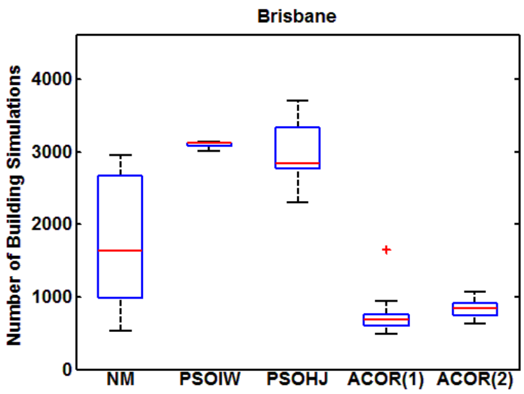

Figure 6a

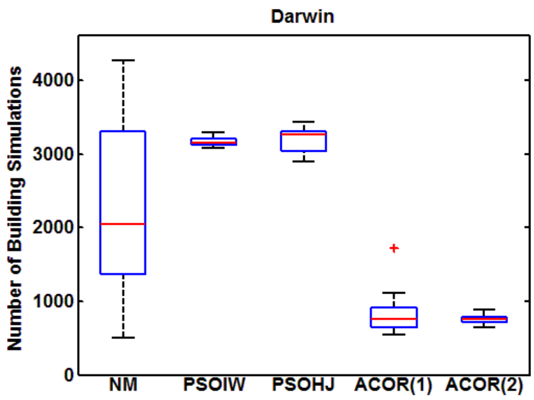

Figure 6b

Figure 6. Number of building simulations required for each algorithm to converge to within 0.1% of the final solution, for a) Brisbane and b) Darwin

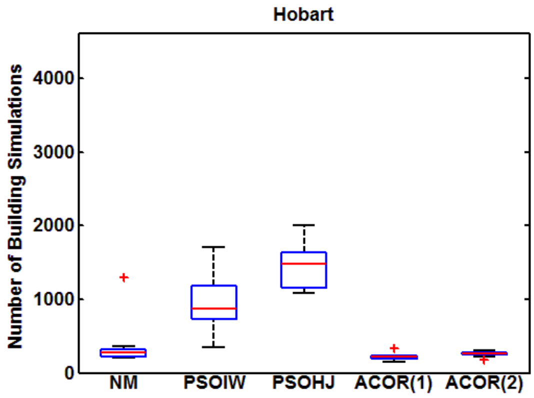

Figure 7a

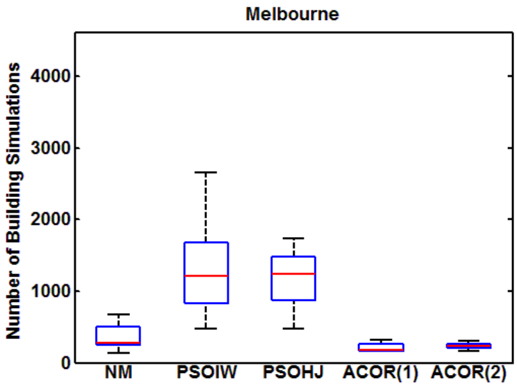

Figure 7b

Figure 7. Number of building simulations required for each algorithm to converge to within **1**% of the final solution, for a) Hobart and b) Melbourne

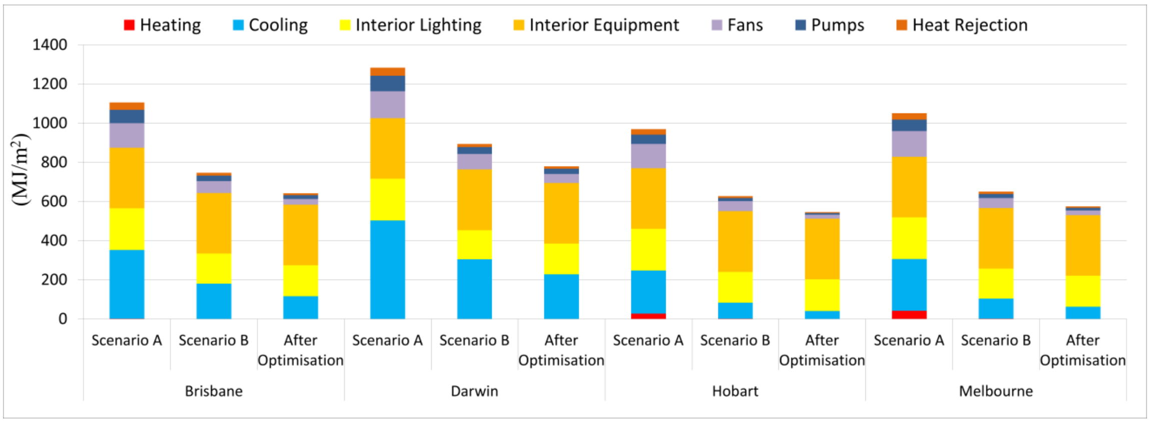

Figure 8. Building annual energy consumption for Scenario A, B, and after optimisation

Table 1. Building Type A construction details [48, 49]

	Construction Materials	Overall U-Value (W/m2-K)
Wall	200 mm heavy weight concrete R1.5 batts, 10mm plasterboard (absorption coefficient (AC) = 0.6)	0.557
Roof	Metal deck, air gap, 150mm HW concrete, roof space, R2.0 batts, 13mm acoustic tiles (AC= 0.6)	0.231
Floors	175 mm concrete, carpet 2.7 cm	1.351
Windows	6 mm clear glass (SHGC = 0.818, VT= 0.88)	5.89
Window to wall ratio	38 %	

Table 2. Building geometry details and assumptions used in building modelling

Parameters	Values
Total floor area (m^2)	9985.6
Geometry (m)	31.6 × 31.6
Number of floors	10
Floor to floor height (m)	3.6
Floor to ceiling height (m)	2.7
Lighting load	15 W/m^2
Equipment load	15 W/m^2
Lifts and auxiliary service equipment	1 W/m^2
Occupancy	0.1 Person/m^2
Temperature set-point	20-24 °C
Temperature set-back	28 °C (18pm-7am, business days)
Infiltration	1 ACH outside HVAC operating hours, 0 ACH during HVAC hours
HVAC system	VAV system, water cooled AC, Gas boiler, COP=3.57 (no heat recovery and economy cycle)

Table 3.Optimisation variables and their ranges

Variables	Description	Variable Range
X_1	Roof emissivity	[0.5-0.9]
X_2	Roof solar absorptance	[0.3-0.85]
X_3	Wall insulation (m)	[0.01-0.1]
X_4	Wall solar absorptance	[0.3-0.9]
X_5	East window height (m)	[0.5-1.5]
X_6	North window height (m)	[0.5-1.5]
X_7	South window height (m)	[0.5-1.5]
X_8	West window height (m)	[0.5-1.5]
X_9	East overhang depth (m)	[0-1]
X_{10}	North overhang depth (m)	[0-1]
X_{11}	South overhang depth (m)	[0-1]
X_{12}	West overhang depth (m)	[0-1]
X_{13}	Heating setpoint (°C)	[18-22]
X_{14}	Cooling setpoint (°C)	[23-27]
X_{15}	Building orientations (degree)	[0-45]

Table 4.Parameters used for NM

NM parameters	
Accuracy	0.01
Step size factor	0.1
Block restart check	10
Modify stopping criterion	TRUE

Table 5.Parameters used for PSOIW and PSO-HJ

	PSOIW	PSO-HJ
Topology	Von Neumann	Von Neumann
Number of particles	100	100
Cognitive acceleration	2.05	2.05
Social acceleration	2.05	2.05
Constriction gain	-	1
Max velocity gain	0.2	0.2
Initial inertia weight	1.0	-
Final inertia weight	0	-
Mesh size divider	-	2
Initial mesh size exponent	-	0
Mesh size exponent increment	-	1
Number of step reductions	-	4

Table 6.Parameters used for ACOR (1) and ACOR (2)

	ACOR (1)	**ACOR (2)**
No. of new solutions used in each iteration (ants)	5	5
q parameter	0.0001	0.1
Speed of convergence (ξ)	0.85	0.85
Archive size	50	50

Table 7.Optimisation results, best solution of each algorithm

	Algorithm	**Objective Function (MJ/m^2)**	**x_1**	**x_2**	**x_3**	**x_4**	**x_5**	**x_6**	**x_7**	**x_8**	**x_9**	**x_{10}**	**x_{11}**	**x_{12}**	**x_{13}**	**x_{14}**	**x_{15}**
Brisbane	**NM**	644.21	0.66	0.49	0.01	0.30	0.75	0.75	0.86	0.74	0.57	0.94	0.54	0.88	21.58	27.00	19.65
	PSOIW	644.17	0.69	0.33	0.01	0.30	0.78	0.87	1.04	0.68	0.71	0.62	0.63	0.95	20.08	26.98	4.77
	PSO-HJ	642.74	0.90	0.30	0.01	0.30	0.75	0.79	0.93	0.75	1.00	0.60	0.58	1.00	18.00	27.00	2.60
	ACOR (1)	**642.56**	**0.90**	**0.30**	**0.01**	**0.30**	**0.75**	**0.75**	**0.95**	**0.75**	**1.00**	**0.65**	**0.72**	**1.00**	**18.43**	**26.99**	**10.00**
	ACOR(2)	642.74	0.90	0.30	0.01	0.30	0.86	0.83	0.94	0.75	0.74	0.71	0.71	1.00	19.04	26.99	11.66
Darwin	**NM**	780.11	0.69	0.30	0.01	0.30	0.75	0.70	0.88	0.74	1.00	0.78	0.75	0.97	18.64	27.00	15.29
	PSOIW	781.32	0.84	0.31	0.01	0.30	0.69	0.67	0.93	0.74	1.00	0.89	0.71	0.92	21.31	26.98	36.72
	PSO-HJ	780.11	0.90	0.30	0.01	0.30	0.75	1.00	0.75	0.75	1.00	0.79	0.57	1.00	20.50	27.00	13.44
	ACOR (1)	779.25	0.90	0.30	0.01	0.30	0.73	0.75	0.91	0.75	1.00	1.00	0.69	1.00	21.92	26.99	2.01
	ACOR(2)	**779.24**	**0.90**	**0.30**	**0.01**	**0.30**	**0.72**	**0.75**	**0.90**	**0.75**	**1.00**	**1.00**	**0.68**	**1.00**	**21.18**	**26.99**	**0.02**
Hobart	**NM**	547.10	0.90	0.39	0.01	0.30	1.00	0.67	1.36	0.88	0.76	0.53	0.60	0.76	18.02	27.00	18.28
	PSOIW	547.10	0.74	0.48	0.01	0.30	1.11	0.92	1.16	0.93	0.81	0.76	0.47	0.77	18. 00	27.00	17.95
	PSO-HJ	546.13	0.90	0.30	0.01	0.30	0.95	1.07	1.34	1.02	0.78	0.80	0.52	0.77	18.00	27.00	7.25
	ACOR (1)	**545.92**	**0.90**	**0.30**	**0.01**	**0.30**	**0.75**	**1.02**	**1.26**	**0.92**	**1.00**	**0.77**	**0.25**	**0.70**	**18.00**	**27.00**	**0.00**

	ACOR(2)	545.95	0.90	0.30	0.01	0.30	0.89	1.05	1.27	0.92	0.77	0.80	0.28	0.77	18.00	27.00	8.85
Melbourne	**NM**	577.19	0.67	0.62	0.01	0.30	0.74	0.89	0.96	0.79	0.56	0.56	0.59	0.69	18.57	26.99	4.84
	PSOIW	576.44	0.83	0.37	0.01	0.30	0.86	0.80	1.03	0.82	0.70	0.65	0.45	0.71	18.20	27.00	13.27
	PSO-HJ	575.82	0.90	0.30	0.01	0.30	0.78	0.75	0.99	0.75	0.68	1.00	0.28	1.00	18.50	27.00	9.60
	ACOR (1)	**575.58**	**0.89**	**0.30**	**0.01**	**0.30**	**0.75**	**0.88**	**1.01**	**0.86**	**1.00**	**0.76**	**0.39**	**0.74**	**18.30**	**27.00**	**0.00**
	ACOR(2)	575.64	0.90	0.30	0.01	0.30	0.88	0.87	0.99	0.75	0.76	0.75	0.38	1.00	18.30	27.00	19.70

Table 8.Wilcoxon rank-sum test results. Bold numbers indicate $\boldsymbol{p}$-values that are below the conventional 0.05 significance level

	Brisbane (P-value)	**Darwin (P-value)**	**Hobart (P-value)**	**Melbourne (P-value)**
ACOR (2) VS NM	(**0.0001**)	(**0.0001**)	(**0.0001**)	(**0.0001**)
ACOR (2) VS PSOIW	(**0.0001**)	(**0.0001**)	(**0.0001**)	(**0.0001**)
ACOR (2) VS PSO-HJ	(**0.0022**)	(**0.0001**)	(**0.0001**)	(**0.0003**)
ACOR (2) VS ACOR (1)	(0.2730)	(0.1405)	(0.1405)	(0.4274)
ACOR (1) VS NM	(**0.0002**)	(**0.0001**)	(**0.0001**)	(**0.0001**)
ACOR (1) VS PSOIW	(**0.0002**)	(**0.0001**)	(**0.0001**)	(**0.0003**)
ACOR (1) VS PSO-HJ	(**0.0173**)	(**0.0001**)	(**0.0022**)	(**0.0173**)