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Building energy optimization using Grey Wolf Optimizer (GWO)

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ABSTRACT

In the present research, the Grey Wolf Optimizer (GWO) was used to minimize the yearly energy consumption of an office building in Seattle weather conditions. The GWO is a meta-heuristic optimization method, which was inspired by the hunting behavior of grey wolfs. The optimization method was coded and coupled with the EnergyPlus codes to perform the building optimization task. The impact of algorithm settings on the optimization performance of GWO was explored, and it was found that GWO could provide the best performance by using 40 wolfs. The optimized solutions of GWO were compared with other optimization algorithms in the literature, and it was found that the GWO could lead to an excellent optimum solution efficiently. One of the best optimization methods in the literature was Particle Swarm Optimization (PSO), which led to an optimum objective function of 133.5, while GWO resulted in the optimum value of 133. The multi-objective building optimization was also examined by GWO. The results showed that it could provide an excellent archive of non-dominant optimum solutions.

1. Introduction

In recent years, there has been a vast increase in worldwide energy demand because of industrial development and population growth. The United Nations Environment Program reported that the buildings consume around 40% of the global energy, and they are responsible for 36% of the world's carbon dioxide emission [1,2]. If no measures are taken to reduce buildings' energy consumption, greenhouse gas emissions from buildings will be almost double by 2030 [1]. In addition, fossil fuels are the source of energy for most buildings, which boosts the emission of greenhouse gases. The US Energy Information Administration reported that about 57% of the energy consumption of buildings is for heating, air conditioning (HVAC) and ventilation, and lighting [3]. Thus, improving the energy efficiency of the building is a crucial issue for researchers to reduce energy consumption [4,5]. Very recently, strategic approaches such as using load shift [6], battery storage [7], thermal energy storage [8], window size [9], ventilation heat recovery [10], passive solar air heater [11], and new materials [12] have been proposed.

Currently, the typical approach for the design of low-energy buildings is based on using computer simulation software and the sensitivity analysis of design parameters. In such an approach, first, a designer builds a building model, including the base design parameters. Then, the impact of variation of each of the parameters on the energy consumption of the building will be investigated while the other parameters are constant. This way, the effect of all of the design parameters could be explored independently. This approach not only demands a large number of building simulations but also neglects the possible considerable interactions between the

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Nomenclature

Latin symbol

A	the conditioned surface area of the building (m^2)
$\overrightarrow{A}$	coefficient vectors
$\overrightarrow{a}$	a linearly decreasing vector from 2 to 0
$\overrightarrow{C}$	coefficient vectors
$\overrightarrow{D}$	wolfs movement vector
dim	the number of decision variables
E	annual lighting energy (kWh/a)
E_c	annual energy consumed by cooling coils (kWh/a)
E_{el}	annual lighting energy consumption (kWh/a)
E_h	annual energy consumed by heating coils (kWh/a)
F	objective function, annual energy consumption per unit of area (kWh/m^2a)
F_1, F_2	objective function components (kWh/m^2a)
N_G	the generation number
N_W	the number of wolfs
PEF	primary energy factor
PEF_{el}	primary energy factor for electricity
PEF_{gas}	primary energy factor for gas
Q_c	annual cooling (kWh/a)
Q_h	annual heating (kWh/a)
r_1, r_2	random values in the range [0, 1]
t	current iteration
X	vector of decision variables
$\overrightarrow{X}$	a grey wolf's position vector
X_1, X_2, …	components of the decision variables
$\overrightarrow{X}_p$	a prey's position vector

Greek symbols

α	alpha wolf
β	beta wolf
δ	delta wolf
η_c	plant cooling efficiency
η_h	plant heating efficiency

design parameters. As a result, some potential energy-saving measures could be lost through the design process. For example, in a building with a daylighting system, the optimized window and shading sizes can hardly be estimated. This is since natural light reduces the energy use of artificial lighting and the HVAC system (i.e., heat generation of lights) while increasing solar heat gains simultaneously. Considering more variables (e.g., building orientation) makes the design problem highly complex for the maximum energy saving estimation.

With more stringent energy performance requirements and high demand for low-energy buildings, improved methods are required to achieve maximum potential energy savings in building designs. An efficient building design demands considering a combination of design parameters in the design process simultaneously, rather than merely investigating one parameter each time.

Building Optimization Problems (BOPs) provide a more rigorous framework for exploring new designs that manage complex trade-offs in ways that are not possible when using traditional methods. Methods for solving BOPs are primarily software-in-the-loop methods (coupling building simulation software with a mathematical optimization algorithm). These methods seek to find the near-optimal design by intelligently exploring the candidate design values to find promising solutions and evaluating their suitability using building simulations. The review of the literature works shows that the energy consumption of buildings could be reduced significantly [2,5,13,14].

First, commonly used simulation-based optimization algorithms are the Genetic Algorithms (Ga) and Particle Swarm Optimization (PSO) method. These sophisticated methods use stochastic search strategies that require hundreds to thousands of time-consuming building simulations to converge. The optimization cost and time depend on many parameters, such as the number of objective function computations, the number of design variables, and the adopted optimization algorithm. With current computing power, some optimization runs may take several weeks or months [15]. Additionally, the buildings' thermal behavior and the energy consumption are nonlinear, and hence, the optimization algorithm could be entrapped in a local minimum [16]. Accordingly, it is necessary to develop an optimization method that can address these computational challenges.

The conventional method for solving BOPs is simulation-based optimization, in which a building simulation software would be coupled with an optimization algorithm (e.g., Genetic Algorithm). Thus, the building simulation software computes the objective function (e.g., thermal comfort, energy consumption), and an optimization algorithm controls the design parameters.

The performance of the simulation-based optimization designs depends strongly on the optimization algorithms. Fig. 1 indicates a classification of the most-used optimization algorithms in BOPs, according to the method of operation. Optimization algorithms can be generally classified into two categories: Gradient-based algorithms and Derivative-Free (DF) algorithms.

The Gradient-based methods like the Levenberg–Marquardt algorithm or Discrete Armijo algorithm use the gradient of the function to find the optimal solutions. Although these methods benefit from fast convergence and guarantee a local minimum, they are susceptible to discontinuities in the objective functions and multi-modal functions, which cause these algorithms to be inappropriate for BOPs [15–17].

The second category is DF algorithms (e.g., stochastic optimization algorithms), which do not necessitate calculating the objective function derivatives. However, these algorithms often need many objective function evaluations and cannot guarantee the local optimality of the solution due to their derivative-free search mechanisms. However, the term 'optimization' in BOPs does not necessarily mean searching for the global optima, as it may be infeasible due to the nature of either the optimization problem or the simulation software itself [16,18].

DF algorithms are capable of dealing with both linear and nonlinear problems with discontinuities. These features make these algorithms suitable for BOPs [15–17,19]. DF optimization algorithms have been largely used in building optimization studies. Peippo et al. [20] applied the Hooke and Jeeves pattern search method to identify the optimal design variables for solar energy buildings. Bouchlaghem [21] used the simplex method of Nelder and Mead and the non-random complex method to optimize building envelopes.

Despite the many studies on BOPs, no unique optimization algorithm could be selected as the best algorithm since its performance depends on the nature of the optimization problem [22]. Wetter and Wright [23] analyzed the capability of GA and the Hooke–Jeeves (HJ) algorithms in minimizing building energy consumption. The outcomes revealed that the GA could find an optimum with a low computational effort while HJ could be entrapped into a local optimum. Zhou et al. [24] developed an optimization module integrated with EnergyPlus and compared the performance of Nelder Mead Simplex, Quasi-Newton, SA, and a hybrid algorithm, including GA, Tabu search and Scatter search. It was observed that Nelder Mead Simplex is the best choice for optimizing a three-floor office.

Wetter and Wright [25] investigated the capability of nine different optimization algorithms to deal with BOPs. They found that the PSO-HJ could lead to the lowest building energy consumption while the Nelder and Mead method could be easily entrapped in a local minimum. Wright and Ajlami [26] tested the robustness of the GA in the selection of control parameters in an unconstrained BOP. It was found that the GA was not sensitive to the choice of its control parameters.

Tuhus-Dubrow and Krarti [27] performed a comparative investigation on the capability of PSO and GA for BOPs. The results showed that the GA could find an optimum solution with a lower computational cost compared to the PSO. The BOPs have also been investigated by Hamdy et al. [28], and Chegari et al. [29]. Futrell et al. [30] investigated the capability of four optimization algorithms for the optimization of daylighting performance in buildings. Very recently, Sajadi et al. [31] coupled Energyplus and NSGA-II optimization algorithm to actively optimize the smart windows of a building considering the thermochromic and electrochromic effects. The coupling was performed through software called jEPlus. A notable decrease in building energy consumption was found by using optimized smart windows. Ilbeigi et al. [32] employed a combination of an artificial neural network (a multi-layer perceptron model) and a genetic algorithm optimization method to optimize the energy consumption of an office building. Indeed, the neural network is used as a function approximator to estimate the energy consumption of the building without the need for direct link to building simulation software. This approach removes the requirement of direct twoway link between the building simulation software

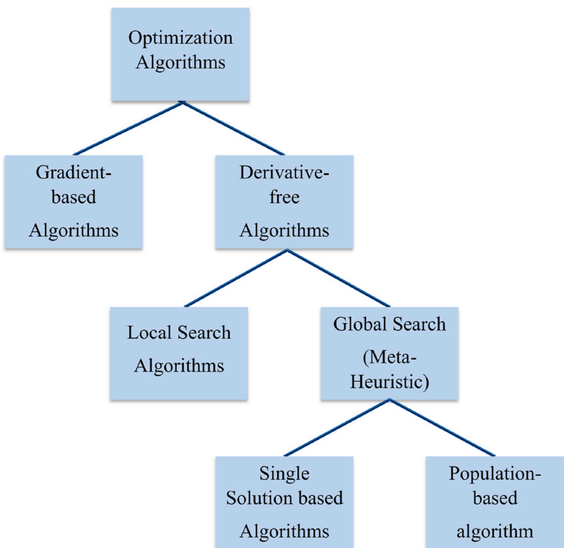

Fig. 1. Classification of optimization algorithms for BOPs.