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Building energy optimization using Grey Wolf Optimizer (GWO)

Mehdi Ghalambaz [a], Reza Jalilzadeh Yengejeh [a,*], Amir Hossein Davami [b]

[a] Department of Environmental Engineering, Ahvaz Branch, Islamic Azad University, Ahvaz, Iran
[b] Department of Environmental Management-HSE, Ahvaz Branch, Islamic Azad University, Ahvaz, Iran

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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

* Corresponding author.
E-mail addresses: ghalambaz.mehdi@gmail.com (M. Ghalambaz), r.jalilzadeh@iauahvaz.ac.ir (R. Jalilzadeh Yengejeh), ah.davami@iauahvaz.ac.ir (A.H. Davami).

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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

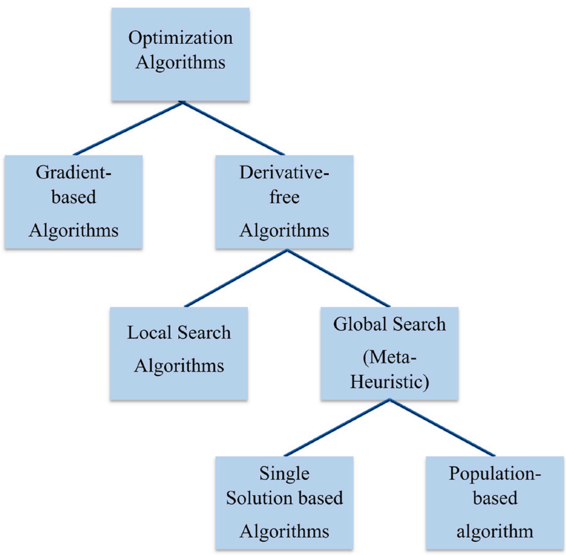


Fig. 1. Classification of optimization algorithms for BOPs.

and the optimization algorithm. However, the neural network is just an approximation of the building energy consumption behaviour. The results showed that the optimization approach could reduce the building energy consumption by 35%. Keivan et al. [33] proposed a new sampling strategy for approximate models (surrogate models) to reduce the uncertainty of such models. Bui et al. [34] improved building energy efficiencies by optimizing the façade design of buildings. They employed a Python toolkit (Eppy) to connect the energyplus to a modified firefly algorithm. They examined two case studies of a typical single office room and a medium office building. The simulation results showed that employing an adaptive façade system can reduce the energy consumption of a medium office building by 14.2–22.3% compared to the static façades. Ke et al. [35] utilized improved crow search algorithm to optimize buildings energy consumption in Australia. Using overhangs and duble glazing windows were some of the important parameters, which could reduce the energy consumptions. The results showed that an 11.8% of energy consumption can be reduced by employing energy-saving actions. Waibel et al. [36] performed a comprehensive investigation and analyzed the performance of various optimization methods for BEOs. They pointed out that a fast convergence could lead an optimization method to be entrapped in a local optimum. Moreover, no optimization method could dominate all investigated performance metrics for all BEO problems.

Recently, several optimization algorithms have been proposed in the literature, which have shown superior performance compared to the state-of-art optimization algorithms, which are currently employed in BOPs. However, such novel optimization algorithms have never been employed in BOPs, and hence, their performance in BOPs is unknown. Thus, an investigation into adapting and applying novel optimization approaches to BOPs is warranted.

The Grey Wolf Optimizer (GWO) algorithm is a new meta-heuristic optimization method, which was inspired by the foraging social behavior of grey wolfs. The GWO was first proposed by Mirjalili et al. [37] in 2014. The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves, such as alpha, beta, delta, and omega, are employed for simulating the leadership hierarchy.

Very recently, Faris et al. [38] reviewed the scientific applications of GWO. They reported that GWO had shown promising results in a wide variety of optimization problems. The high degree of GWO success in dealing with optimization problems in the literature could be due to the impressive characteristics of this method over other swarm intelligence methods. This review highlights that GWO requires no derivation information of the search space, and the algorithm also has only a few parameters. Besides, GWO is scalable, flexible, easy to use, and straightforward. The algorithm benefits from a balance between exploration and exploitation through the search process, which results in an excellent convergence. Thus, the GWO has attracted the attention of researchers in various scientific and engineering fields. Since 2014, GWO algorithm has been extensively used in the optimization of many scientific areas such as engineering (61%), machine learning (20%), medical and bioinformatics (6%), networking (5%), environmental applications (5%), and image processing (3%) [38]. The application of GWO in computational fluid dynamic investigations has also been reviewed by Mirjalili et al. [39].

The GWO and its modified versions have been employed in various engineering aspects such as feature selection methods for classification [40,41], path planning [42,43], groundwater remediation [44], improving biodiesel production [45], machining of multiwall carbon nanotube/polymer nanocomposites [46], wireless sensor network coverage optimization [47], optimization of construction duration and schedule robustness [48], prediction of soil electrical conductivity [49], a favorable reservoir of oil field [50], and concrete strength [51], are some of the environmental applications of GWO.

As seen, the literature review shows that GWO has been very successful in various engineering fields. However, the capability of GWO has not been tested in building optimization problems. The present study aims to investigate the performance of GWO in minimizing the energy consumption of a building for the first time. Moreover, a coupling interface was developed to directly connect the optimization algorithm to the energyplus in a two-way approach and perform building optimization.

2. Methods and materials

The present study aims to investigate the optimization performance of GWO in building optimization. Hence, a benchmark building with a Seattle weather conditions profile was adopted as a benchmark case. Then, the GWO algorithm was employed to optimize the energy consumption of the building. The Building Energy Optimization (BEO) problem consists of three parts. The first part is the energy modeling of the buildings, which simulates the energy model of a building and computes the energy consumption. The second part is the optimization method, which utilizes the simulation data to control the building parameters and reach an optimized solution. The third part is the coupling of the simulations and optimization algorithm. These three parts will be discussed later in this section.

2.1. The building models

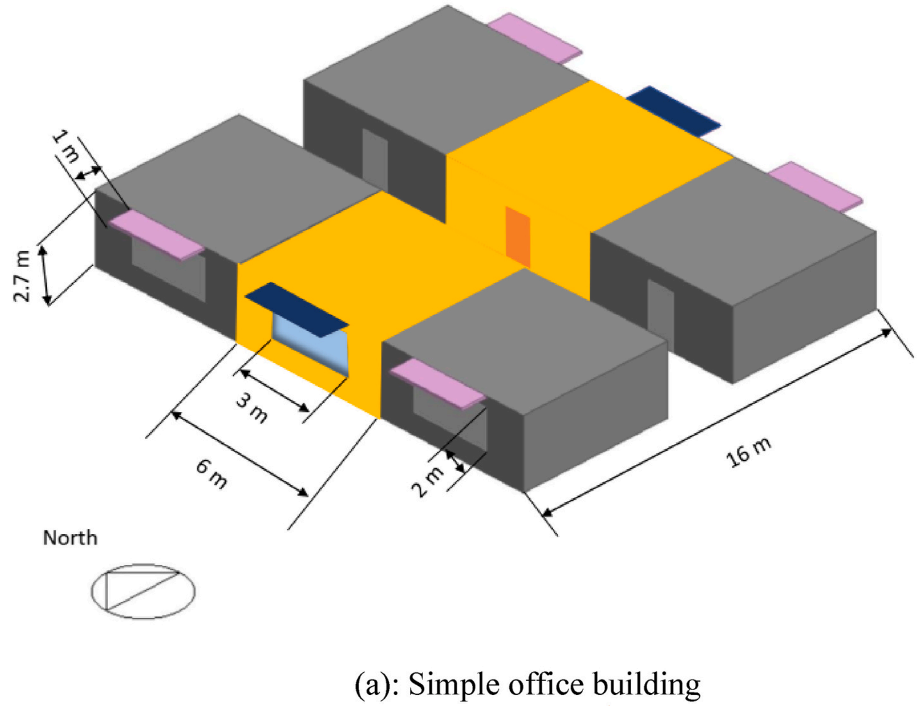
In order to perform a case study, a benchmark building of an office with four decision variables was adopted. Two buildings were

Table 1
The decision variables of the simple office building.

Variables	Description	Bounds	Units
X_1	Building orientation	[−180, 180]	°
X_2	Window width West	[0.1, 5.9]	m
X_3	Window width East	[0.1, 5.9]	m
X_4	Shading transmittance	[0.2, 0.8]	–

adopted here as case studies. The first building was previously investigated in many literatures works such as [25], and here it was adopted from [36]. The decision variables are summarized in Table 1. These variables are the shading transmittance, the widths of the windows for the East and West façades, and the building orientation.

The exterior walls have a U-value of 0.25 W/(m^2K) and are made of concrete (20 cm), insulation (10 cm), and wood siding (1 cm). The floor and ceiling are made of carpet, concrete (5 cm), padding, and concrete (18 cm). The interior walls are made of brick with a



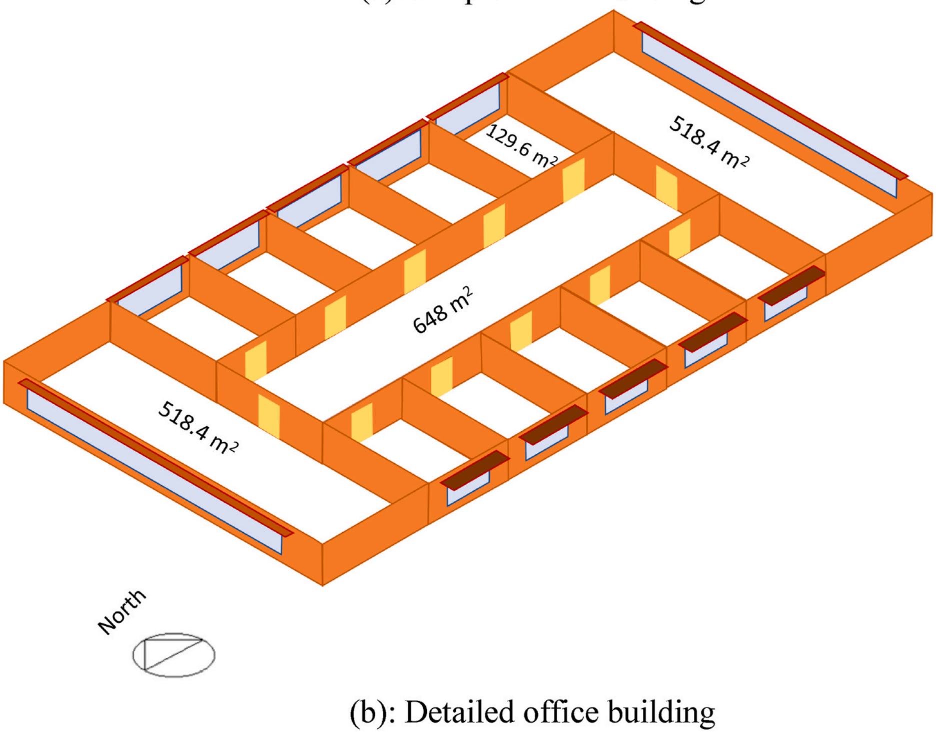


Fig. 2. The schematic view of the office buildings, adopted from the study of Wetter and Wright et al. [25]. The detail of building material and interior space has been provided in the dataset of the current study at https://doi.org/10.17632/v358nd5f7k.1.

thickness of 12 cm. The double-panel windows are with low-emissivity filled with Krypton gas, and there is an exterior shading device. The windows are made of double panel glass with 8 mm of Crypton gas and 3 mm of clear space. Following [25,36], the aim is to minimize the energy consumption of the building, represented by the following equation:

$$\min\left[F\left(X\right)=\left(\frac{Q_h\left(X\right)}{\eta_h}+\frac{Q_c(X)}{\eta_c}+\ PEF\times\ E(X)\right)\Big/A\right],\quad X=\ \{X_1,\ X_2,\ X_3,\ X_4\} \tag{1}$$
$$180\leq X_1\leq 180;\ 0.1\ \leq X_2\leq\ 5.9;\ 0.1\ \leq X_3\leq\ 5.9;\ 0.2\leq X_4\leq\ 0.8$$

where $Q_c(.)$, $Q_h(.)$, and $E(.)$ denote the annual (kWh/a) heating, cooling, and lighting energy consumptions, respectively. Here, A is the conditioned surface area of the building. A primary energy factor (*PEF*) of 3.0 was applied for electricity. The plant cooling and heating efficiencies of $\eta_h = 0.44$ and $\eta_c = 0.77$ were employed [25,36]. Generally, the coefficients of performances are a function of load and weather conditions and could be changed. However, following the literature studies [25,36], these values have been assumed fixed so that the present optimization results can be compared with the literature results and other optimization approaches.

Finally, the energy consumption was accounted for per floor area. Thus, Eq. (1) shows the primary annual energy consumption per unit of the floor in kWh/m^{2}a, which should be minimized. The details of design variables X_1-X_4 are specified in Table 1. A schematic view of the building model simulated in the EP is illustrated in Fig. 2(a). This objective function can be written in the form of a two objective function:

$$\min\begin{cases}F_1\left(X\right)=\left(PEF\ \times E\left(X\right)\right)/A\\[2ex] F_2\left(X\right)=\left(\dfrac{Q_h\left(X\right)}{\eta_h}+\dfrac{Q_c(X)}{\eta_c}\right)\Big/A\end{cases},X=\ \{X_1,\ X_2,\ X_3,\ X_4\} \tag{2}$$
$$180\leq X_1\leq 180;\ 0.1\ \leq X_2\leq\ 5.9;\ 0.1\ \leq X_3\leq\ 5.9;\ 0.2\leq X_4\leq\ 0.8$$

where $F_1(X)$ represents the energy consumption by lightings, and $F_2(X)$ indicates the energy consumption due to heating and cooling. The aim is to minimize both $F_1(X)$ and $F_2(X)$ simultaneously.

The second building is a more detailed model of the first building. This building was studied in [25] and later was adopted by [36]. Here, we took the building model from [36]. The building consists of a large zone, located to the West and East, surrounded by five smaller zones on each side, oriented towards the North and South. The floors and ceilings are well insulated (adiabatic). A view of the building model is depicted in Fig. 2(b). This building involves 13 decision variables, including external shading setpoints, overhang depths, window widths, the HVAC system's supply air temperature, and setpoints for the zone air temperature for night cooling during winter and summer. The decision variables and their range are summarized in Table 2. The aim is to minimize the annual primary energy consumption of the office per unit area per year (kWh/m^{2}a). The energy consumption involves energy demand for cooling coils, fans, heating, and zone lighting. The BOP can be formulated as follows:

$$\min\left[F(X)=\left(PEF_{\rm el}\left(E_{\rm el}(X)+E_{\rm c}(X)\right)+PEF_{\rm gas}E_{\rm h}(X)\right)/A\right],\quad X=\{X_1,\ X_2,\ ...,\ X_{13}\} \tag{3}$$

where the fans and zone's lighting energy consumption ($E_{\rm el}$), the heating coil ($E_{\rm h}$), and the cooling coil ($E_{\rm c}$) were taken into account. Here, the primary energy factors for gas ($PEF_{\rm gas} = 1$) and electricity ($PEF_{\rm el} = 3$) are also taken into account. The objective function of Eq. (3) can be written in the form of a two objective function as:

$$\min\left[\begin{cases}F_1(X)=\left(PEF_{\rm el}\times E_{\rm el}(X)\right)/A\\ F_2(X)=\left(PEF_{\rm el}\times E_{\rm c}(X)+PEF_{\rm gas}E_{\rm h}(X)\right)/A\end{cases}\right],\quad X=\{X_1,\ X_2,\ ...,\ X_{13}\} \tag{4}$$

Table 2
The decision variables of the detailed office building.

Variables	Description	Bounds	Units
X_1	Window width North	[1.224, 5.8321]	m
X_2	Window width West	[7.344, 25.668]	m
X_3	Window width East	[7.344, 25.668]	m
X_4	Window width South	[1.224, 5.8321]	m
X_5	Overhang depth West	[0.05, 1.05]	m
X_6	Overhang depth East	[0.05, 1.05]	m
X_7	Overhang depth South	[0.05, 1.05]	m
X_8	Shading setpoint West	[100, 600]	W/m^2
X_9	Shading setpoint East	[100, 600]	W/m^2
X_{10}	Shading setpoint South	[100, 600]	W/m^2
X_{11}	Night cooling summer, set point	[20,25]	°C
X_{12}	Night cooling winter, set point	[20,25]	°C
X_{13}	Supply air temperature cooling	[12,18]	°C

where $F_1(X)$ and $F_2(X)$ represent the energy consumption by lightings and the energy consumption due to heating and cooling, respectively. The goal is to simultaneously minimize both $F_1(X)$ and $F_2(X)$.

The details of the constructive materials and model of these two office buildings can be found in the supplementary files in the following address: https://doi.org/10.17632/v358nd5f7k.1.

2.2. Building energy simulation software

In the current study, EnergyPlus (EP) simulation program is adopted to simulate the thermal behavior of the building and estimate the corresponding energy consumption. EnergyPlus is capable of simulating the energy analysis of a whole building, which was developed by the US Department of Energy, DOE [52]. The EP does not have a graphical interface, and it reads the input data through a text file and computes the energy consumption. Then, it reports the outcomes in an output text file. EP computes the essential heating and cooling loads of a building for defined thermal control setpoints during the building simulations. The loading conditions include the energy consumption of the primary plant equipment and conditions throughout the secondary HVAC system and coil loads. The computations of EP are accurate and fast as they are based on the legacy programs of DOE-2 and BLAST [52]. The initial conditions were computed through warm-up until the building reaches a steady-state condition for the beginning of the transient computations. The boundary conditions for the outside walls and roof were a combination of convection and radiation using the weather data. The conduction transfer function with a time step of 15 min was used to solve the transient energy equation. The shading information was updated monthly. The computations were performed for a full year period.

2.3. Grey Wolf Optimizer

The Grey Wolf Optimizer (GWO) is a meta-heuristic optimization algorithm, which was first proposed by Mirjalili et al. [37] in 2014. The GWO mimics the leadership hierarchy and hunting strategy of grey wolfs. The leadership hierarchy is consisting of four types of wolves, namely, alpha (the fittest solution), beta (the second-best solution), delta (the third-best solution), and omega (the rest of the candidate solutions). Moreover, the algorithm follows the three major hunting steps, which are: searching, encircling, and attacking prey.

In practice, the grey wolves encircle prey and march during the hunt, which was modeled using the following relationship:

$$\begin{aligned} \vec{D} &= \left|\vec{C}.\vec{X}_p\left(t\right) - \vec{X}\left(t\right)\right| \\ \vec{X}|\left(t+1\right) &= \vec{X}_p\left(t\right) - \vec{A}\,.\,\vec{D} \end{aligned} \tag{5}$$

where t denotes the current iteration, $\vec{D}$ shows the movement vector, $\vec{X}_p$indicates a prey's position vector, $\vec{A}$ and $\vec{C}$ denote coefficient vectors, and $\vec{X}$ represents a grey wolf's position vector. The coefficient vectors ($\vec{A}$ and $\vec{C}$) are computed using the following relationships:

$$\vec{A} = 2\vec{a}\,.\,\vec{r}_1 - \vec{a} \tag{6a}$$

$$\vec{C} = 2\,.\,\vec{r}_2 \tag{6b}$$

where r_1, r_2 are selected randomly in the normal range of zero to unity. Over the course of iterations, the components of $\vec{a}$ are linearly decreased from 2 to 0. Using Eq. (5), a grey wolf can approach the prey by changing its position around the prey randomly.

In the next step, the knowledge of alpha (best candidate solution) beta, and delta are used to update the location of other search agents (including the omegas) using the following relationships:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|,\ \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|,\ \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{7a}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\,\vec{D}_\alpha,\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\,\vec{D}_\beta,\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\,\vec{D}_\delta \tag{7b}$$

$$\vec{X}\left(t+1\right) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{7c}$$

where the subscripts of α, β, δ denote the alpha, beta and delta wolfs. In order to finish the hunt with a final attack. The final attack is modeled by reducing the $\vec{a}$ values from 2 to zero while $\vec{A}$is a random value in the range of -2$\vec{a}$ and 2$\vec{a}$. Thus, reducing $\vec{a}$ would also reduce $\vec{A}$. $\left|\vec{A}\right|<1$ forced the wolfs to attach to the prey. To search for prey, grey wolves follow the leader wolfs and diverge from each other to search for prey and converge to attack. $\left|\vec{A}\right|$ with a random value higher than unity allows divergence of wolfs to seek a prey.

The GWO algorithm consists of two important setting parameters: the number of wolfs (N_W) and the generation number (N_G). Each generation represents a wolf's decision movement, and the number of wolfs indeed represents the function evaluations in each generation. Thus, the total objective function evaluations (OFEs) will be equal to the number of wolfs times the generation number, i.e., OFEs $= N_W \times N_G$.

The details of the GWO and multi-objective GWO could be found in the original study of Mirjalili et al. [37,53], and they have not been repeated here for the sake of brevity. The engine of the GWO code was provided by Mirjalili et al. [37,53] on the Mathworks website. We adopted the raw source code of GWO from [54,55], and then we modified it into a general optimization function to be linked to EP. The final GWO code, which was utilized for computations, was stored as a supplementary file here: https://doi.org/10.17632/v358nd5f7k.1.

2.4. Coupling EP and GWO algorithm

A coupling subroutine was written to couple the GWO optimization function with EP. Fig. 3 shows the framework of the optimization process, and Fig. 4 illustrates the flowchart of the coupling between the EP and GWO through the coupling procedure. As mentioned, the communication with EP is through its input and output files. Hence, a subroutine was developed to define the building model, alter the building control parameters, and execute the EP along with a weather profile for simulation and estimation of the annual energy consumption of the building. Then, the subroutine will wait for the EP to complete the computation and write the output results in the output file. After that, the subroutine will read the estimated energy consumptions of the building. The optimization code alters the control parameters (optimization variables) and, through the subroutine, passes them into the input file of the EP. Then, it excites the EP and reads the energy consumptions (objective), and it passes the outcomes to the GWO algorithm. The GWO decides on the new set of optimum design values and, through the subroutine, passes them into the input file of EP. This way, the interaction

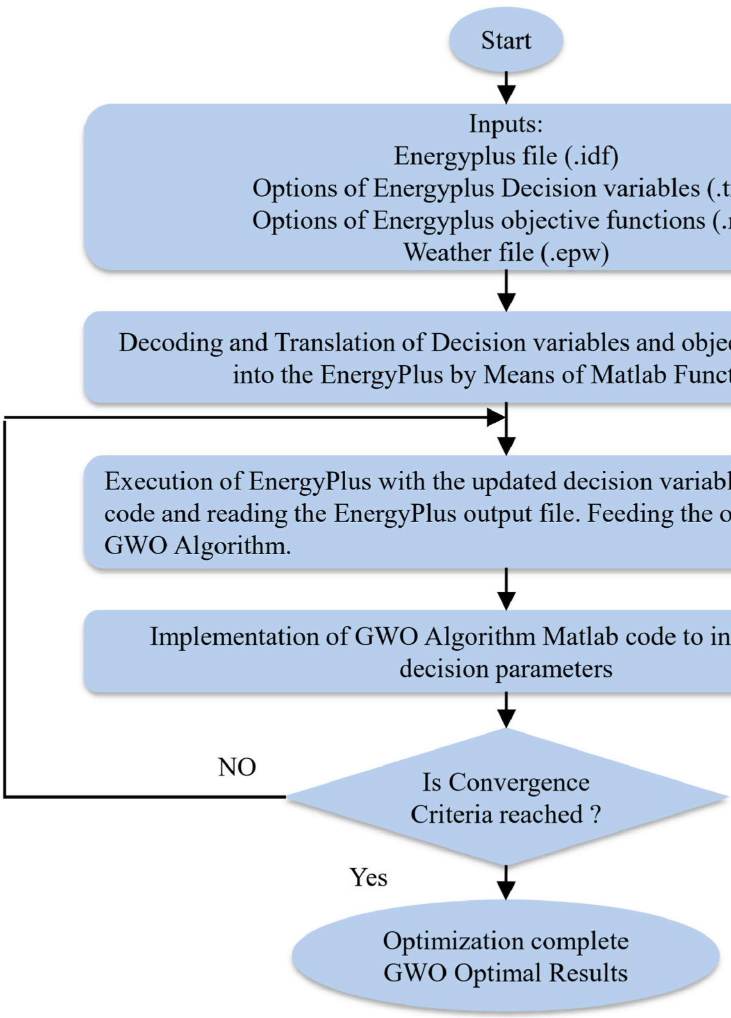


Fig. 3. The framework of the optimization process.

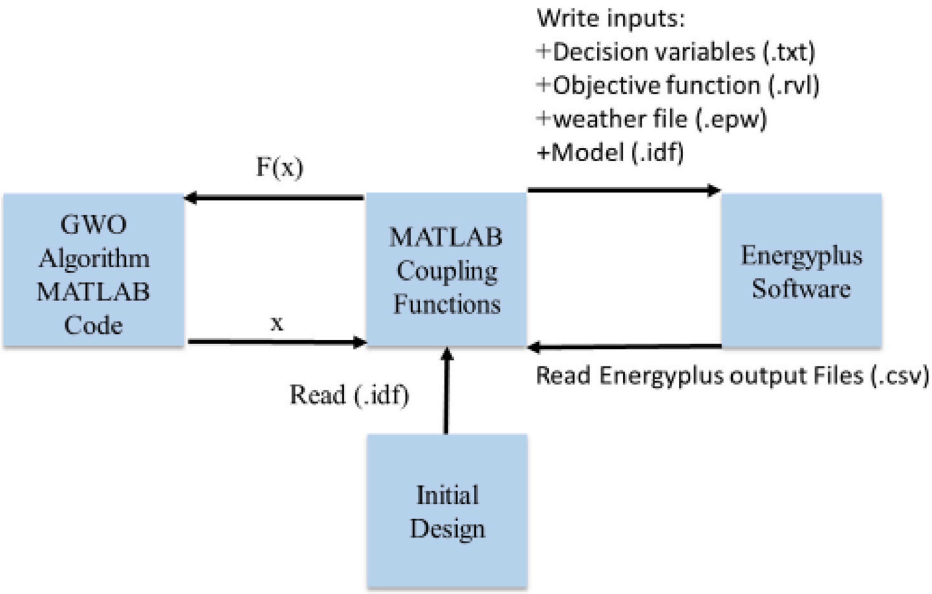


Fig. 4. The coupling process between the EP and GWO.

between the GWO algorithm and EP continues.

3. Results and discussion

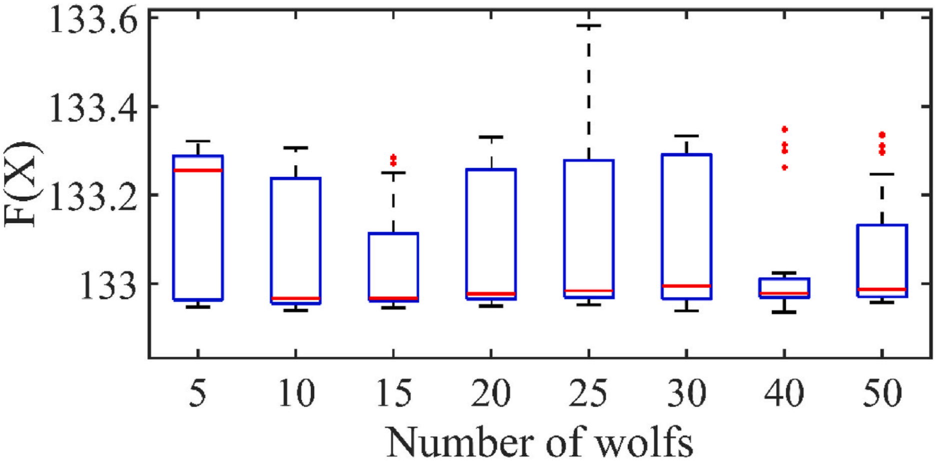
In this section, the GWO was employed to optimize the energy consumption of the buildings described in section 2.1. As mentioned before, these two buildings were also optimized in [36]. In [36], the function evaluations were fixed to 100 × (*dim*+1) evaluations for all optimization algorithms to perform a fair comparison between various algorithms. Here, *dim* is the number of decision variables where for the first problem is 4 and for the second problem is 13. Following [36], here we also fix the number of the OFEs (EP computation calls) similarly to perform a fair comparison between the GWO algorithm and the literature algorithms. Since the number of OFEs is equal to wolfs number times generation number, the number of generations (N_G) can be represented as $N_G = \text{OFEs}/N_W$ where OFEs is the fixed number of function evaluations, and N_W is the number of wolfs. Moreover, following [36], each set was repeated 20, and the outcomes were reported in the box plot format. In multi-objective optimization, the OFEs was multiplied by ten to better allow search of the non-dominant optimum solutions.

Since the selection of the number of wolfs could change the convergence and capability of the GWO, we executed the GWO for the various number of the wolfs. The results were plotted in the box plot format in Fig. 5(a) and (b) for the simple and the detailed buildings, respectively. The dots show the outlier data. As seen, the number of wolfs has a notable impact on the capability of the GWO algorithm. Using 40 wolfs leads to a very good optimized solution for both the simple and detailed office buildings. After that, 50 and 15 wolfs could lead to good optimizations for a simple office building while five wolfs lead to the worst results. In the case of detailed office, using 100 wolfs leads to the worst results. This is since the function evaluations are fixed, OFEs = 1400, and using too many wolfs reduce the impact of encircling prey and attacking mechanisms. Moreover, using only a few wolfs could lead to the worst results because adopting a few wolfs cannot adequately represent the leadership hierarchy and explore the search space. A reasonable number of wolfs (40 wolfs) not only can adequately explore the search space but also fairly benefit from encircling the prey and attacking mechanisms.

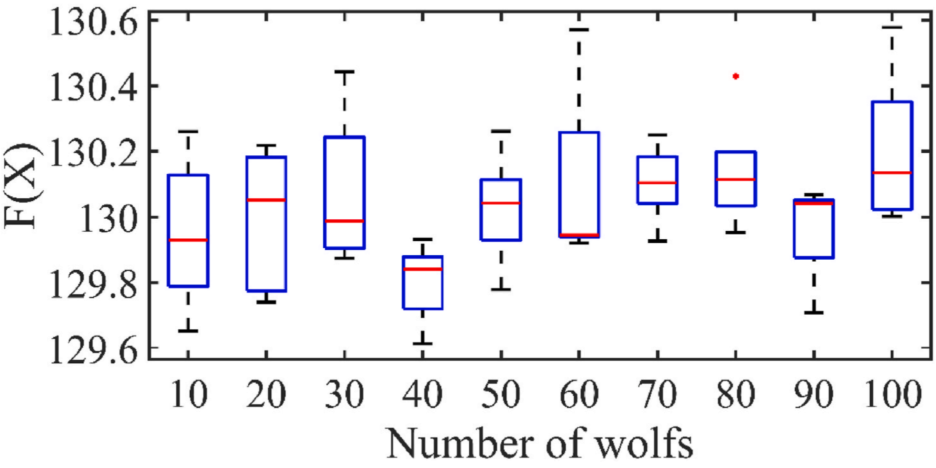
3.1. Validation and comparison

Fig. 6 shows a comparison of the obtained results by GWO in the present study and the literature results of various optimization methods reported by [36]. The box plot results of GWO are plotted for the best and worst cases of Fig. 5. As seen, the worst case of GWO ($N_W = 5$ for simple office and $N_W = 100$ for detailed office) could provide acceptable results compared to the literature algorithms. Moreover, the best case of GWO ($N_W = 40$) could provide outstanding performance in finding the optimized solution. One of the best literature approaches is the PSO approach, which gives the optimum solution in the range of 132.9–133.5 for the simple office. This is while the Best GWO provides the optimum solution in the range of 132.9–133 with a few points out of the range. Thus, the worst optimum case of PSO can be considered as 133.5, while GWO leads to 133.

As mentioned, the algorithm was repeated 20 times for each setting. For example, Tables 3 and 4 provide the optimized control parameters obtained for each run and the corresponding objective functions for the simple office. Table 3 shows the decision variables for the best case (40 wolfs), while Table 4 depicts the same outcomes for the worst case (5 wolfs). Considering the decision parameters,



(a): Simple office building



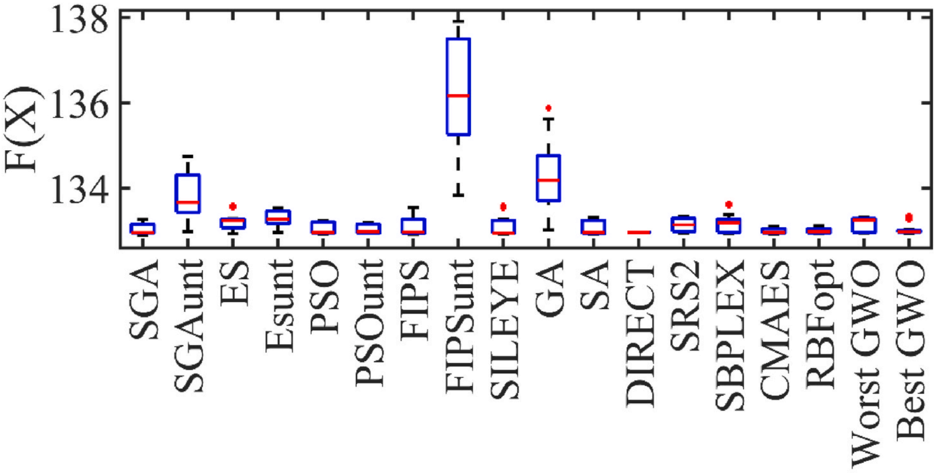
(b): Detailed office building

Fig. 5. The box plot of the optimized objective function for various numbers of wolfs (N_W).

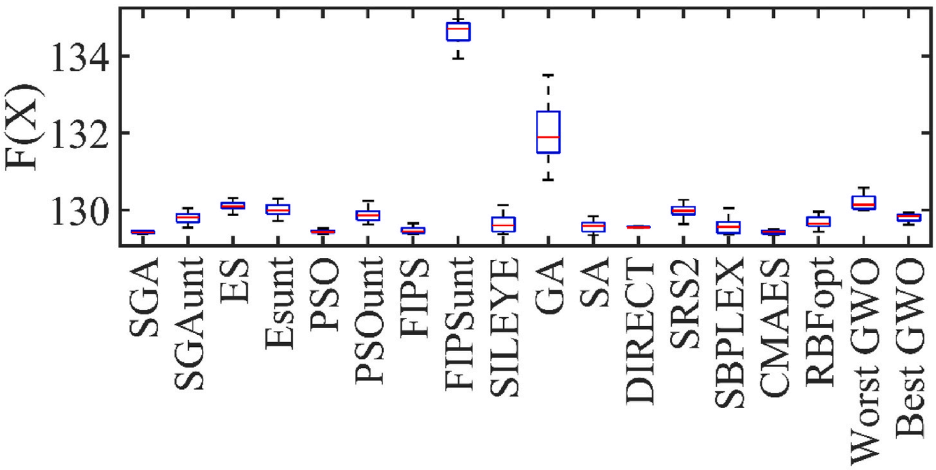
as seen, X_1 fluctuates about two values of -73.5 and 70.5 but an almost similar value of the objective function. Thus, it could be concluded that there are two major minimums in the search space, which are quite far away from each other. When the number of wolfs is comparatively high ($N_W = 40$), the wolfs can see both extremums and move toward the real global extremum. However, when the number of wolfs is too small, they cannot adequately explore the search space, and they could be easily entrapped in a local optimum. Table 5 shows the values decision parameters (X_1-X_{13}) for the detailed office. These values correspond to the best single objective solution with energy consumption of $F(X) = 129.6142$ kWh/m^{2}a.

3.2. Impact of GWO parameters on the optimization performance

The detailed behavior of the algorithm has been investigated as a function of generation evaluations in Fig. 7 for the simple office. This figure illustrates the convergence history of the algorithm for the worse case of 5 wolfs, and the best case of 40 wolfs as well as the best cases of the intermediate number of wolfs ($N_W = 10$ and 20). As seen, when the number of wolfs increases, the number of generations decreases to maintain a fixed number of 500 OFEs. It is interesting that in the case of 5 wolfs, the pack of the wolfs finds a local optimum and establishes circulation around it until another wolf finds a better optimum, and hence, step by step, the value of



(a): Simple office building



(b): Detailed office building

Fig. 6. The comparison of the results with the literature works [36] for a fixed objective function evaluation of 500. The worst-case corresponds to 5 wolfs, and the best case corresponds to 40 wolfs in a generation.

objective function decreases.

However, as the number of wolfs increases, they easily find a better optimum point, and then they quickly circulate it and attack. Thus, a sufficient number of wolfs is essential for finding a good optimum design and escaping the local optimum. Moreover, in most cases, only 200 function evaluations are adequate for reaching almost an optimum point.

Fig. 8 (a) and (b) draw the objective function values for each function evaluation. Fig. 8 shows the evaluation history for the best case of $N_W = 40$ and the worth case of $N_W = 5$, respectively. As seen in Fig. 8(a), the minimum of the curves drops quickly for the first 200 runs (first five generations) and then remains constant, which is in complete agreement with the results of Fig. 7. There are also many maximums in Fig. 8(a). These maximums are denser at initial times, and then they decay as the number of the function evaluations increases. These maximums are indeed the wolfs that scout the search space for a possible better prey (a minimum objective function). However, when they select their prey, they circulate it, and hence, the number of maximum fluctuations reduces. At the final function evaluations where they attack the prey (refining the objective function), there are no large fluctuations, which shows that all wolfs have been focused on the prey (final optimum). The fluctuations in Fig. 8(b) are scattered since there are only a few wolfs

Table 3
Summary of the selected 40 wolfs runs and the corresponding control parameters and the objective functions for the simple office: the case of 40 wolfs as the best number of the wolfs.

Iteration	X_1	X_2	X_3	X_4	$F(X)$
1	71.4945	5.8854	5.9	0.2921	132.9986
2	70.7521	5.9	5.5671	0.2873	132.9754
3	70.7434	5.9	5.9	0.2835	132.9610
4	-73.5092	5.9	5.9	0.2888	133.2996
5	71.5268	5.9	5.9	0.2876	132.9933
6	70.8659	5.9	5.9	0.2959	132.9593
7	70.5021	5.9	5.9	0.2870	132.9724
8	71.9335	5.9	5.6289	0.2993	132.9356
9	70.6854	5.9	5.9	0.2965	132.9596
10	72.2714	5.9	5.9	0.2921	132.9754
11	72.1803	5.9	5.9	0.3025	132.9929
12	70.4004	5.9	5.6168	0.3080	132.9718
13	70.6194	5.8734	5.9	0.2813	132.9828
14	72.2496	5.9	5.9	0.2975	132.9782
15	-73.4735	5.9	5.9	0.3309	133.3486
16	72.0744	5.9	5.9	0.3164	133.0248
17	-73.2355	5.9	5.9	0.3058	133.3140
18	70.7613	5.9	5.9	0.2998	132.9674
19	70.7180	5.9	5.9	0.3025	132.9783
20	-73.2478	5.6219	5.9	0.3160	133.2624

Table 4
Summary of the 20 runs and the corresponding control parameters and the objective functions for the simple office: the case of 5 wolfs as the worst number of the wolfs.

Iteration	X_1	X_2	X_3	X_4	$F(X)$
1	71.7627	5.9	5.6124	0.3130	132.9631
2	70.6467	5.9	5.9	0.2918	132.9691
3	-72.7492	5.6220	5.9	0.2907	133.3218
4	-73.0804	5.6123	5.9	0.3213	133.2844
5	-73.7652	5.9	5.9	0.3011	133.2559
6	-73.7455	5.7895	5.9	0.2953	133.2754
7	-73.5885	5.9	5.9	0.2798	133.2997
8	70.8246	5.8978	5.8833	0.2792	132.963
9	70.6887	5.9	5.9	0.2803	132.9631
10	-73.7008	5.8367	5.9	0.3091	133.2756
11	-73.4696	5.5680	5.8831	0.3419	133.3130
12	-73.5114	5.5987	5.8838	0.3140	133.2615
13	72.2076	5.9	5.8457	0.3038	132.9797
14	70.7285	5.9	5.9	0.2766	132.9617
15	-73.5594	5.8528	5.9	0.2896	133.2915
16	-73.3739	5.5789	5.9	0.3133	133.2539
17	72.1936	5.9	5.8317	0.2918	132.9654
18	-73.5985	5.5807	5.9	0.3199	133.2559
19	-73.6404	5.8459	5.9	0.2687	133.3129
20	70.8742	5.9	5.5927	0.2906	132.9481

Table 5
The best single objective optimum solution for the detailed building and its objective function value.

X_1	X_2	X_3
5.8320	21.8539	19.7773
$\boldsymbol{X_4}$	$\boldsymbol{X_5}$	$\boldsymbol{X_6}$
5.8320	0.4023	0.3967
$\boldsymbol{X_7}$	$\boldsymbol{X_8}$	$\boldsymbol{X_9}$
0.7907	174.9786	284.8660
$\boldsymbol{X_{10}}$	$\boldsymbol{X_{11}}$	$\boldsymbol{X_{12}}$
240.1304	23.8009	24.8993
$\boldsymbol{X_{13}}$	**F(X)**	–
12	129.6142	

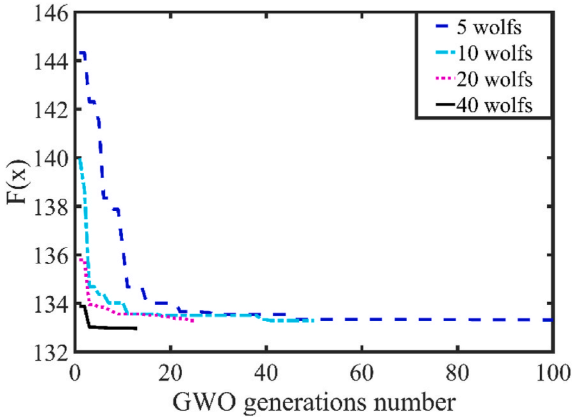
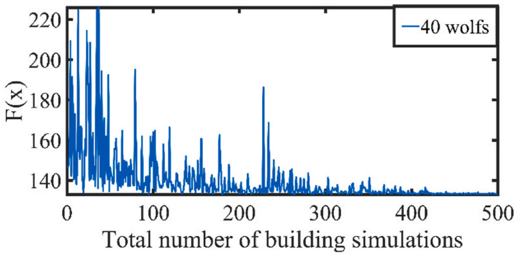
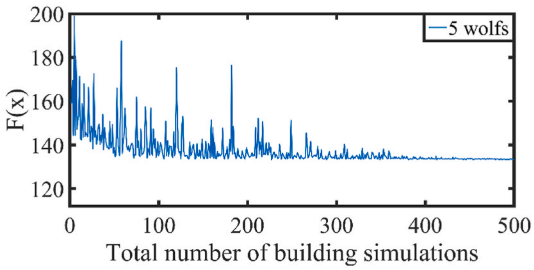


Fig. 7. The convergence history of GWO as a function of generation number for the selected number of wolfs: the case of simple office.



(a)



(b)

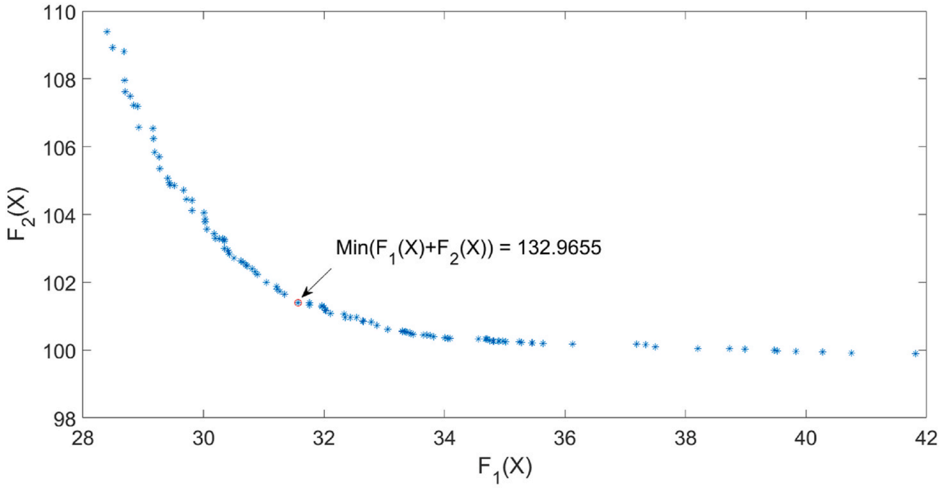
Fig. 8. The convergence toward the optimized value based on the function evaluations for the simple office (a): the case of 40 wolfs and (b): the case of 5 wolfs.

searching for better prey, while other wolfs step by step follow the minimum that they have already found.

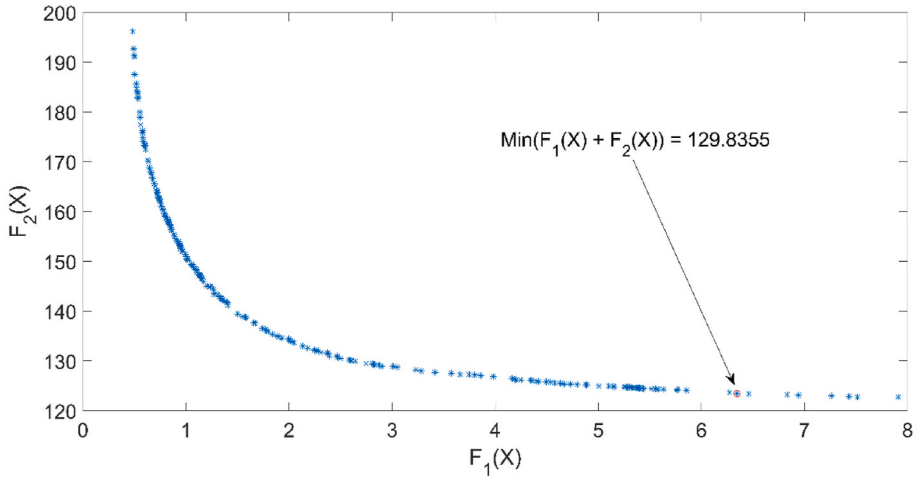
Fig. 9(a) and (b) show the parato-front of non-dominant solutions of multi-objective GWO algorithm for the simple and detailed office building designs. As seen, multi-objective GWO has found a nice parato of non-dominant solutions for heating/cooling ($F_1(X)$) energy consumption against the lighting/fans ($F_2(X)$) energy consumption for both buildings. In the case of the simple office, the minimum value of $F_1(X) + F_2(X)$ was obtained as 132.9655 kWh/m^{2}a, which is in excellent agreement with the results of single-objective optimization reported in Table 2. In the case of the detailed office building, the minimum value of $F_1(X) + F_2(X)$ was obtained as 129.8355 kWh/m^{2}a, which is also in excellent agreement with the results of single-objective optimization, i.e., 129.6142 kWh/m^{2}a. Thus, the parato front curve of the multi-objective GWO algorithm can robustly find the non-dominant designs with a good variety. Such non-dominant optimum designs add options to engineers to select an optimum solution with minimal energy consumption and consider other design aspects such as the building architect and construction aspects when selecting an optimum design.

4. Conclusion

The grey wolf optimizer algorithm was coded and coupled with the EnergyPlus software. The coupled system of the optimization algorithm and the EP were successfully employed to a building optimization problem. The impact of the number of wolfs on the optimization behavior of the GWO was explored. It was found that using 40 wolfs could lead to the best optimization behavior for both cases of simple (four decision variables) and detailed offices (13 decision variables) while using too few wolfs (5 wolfs) or too many wolfs (100 wolfs) could notability reduce the performance of the algorithm to deal with the energy building optimization problem. The



(a): Simple office building



(b): Detailed office building

Fig. 9. The parato-front of non-dominant optimum designs for two studied office buildings.

box plots of the best case and the worst case were compared with the literature optimization method, while all of the optimizations were performed for 500 (simple office) and 1400 (detailed office) function evaluations.

The outcomes showed that the GWO could easily find the optimum solution in most cases. The worst case of 5 wolfs or 100 wolfs could provide results better than many of the optimization algorithms in the literature. Thus, the case study of the present research demonstrates the capability of GWO in the optimization of building optimization problems. Finally, the details of the behavior of GWO were investigated for generation evaluations and function evaluations. The results show that using an adequate number of wolfs could help the algorithm to find the best optimum solution and skip the local minimums. Later, the algorithm will easily focus on refining the optimum solution.

The multi objective GWO could obtain the non-dominant optimum solutions robustly. For both simple and detailed office cases, the minimum value of $F(X)$ discovered by the multi objective GWO was in complete agreement with the cases of single-objective optimization results.

Author statement

M. Ghalambaz: Conceptualization, Methodology, Software, Validation, Data Curation, Writing- Original draft preparation, Writing - Review & Editin. R. Jalilzadeh Yengejeh: Investigation. Formal analysis, Supervision, Writing- Original draft preparation, Writing - Review & Editing. A.H. Davami: Conceptualization, Writing- Original draft preparation, Writing - Review & Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper..

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