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RESEARCH ON ENERGY CONSUMPTION CONTROL METHOD FOR THE LIFECYLE OF PUBLIC GREEN BUILDINGS BASED ON MULTI OBJECTIVE OPTIMIZATION

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Abstract. In the operation process of public green buildings, traditional optimization algorithms require a lot of time and computational resources to solve complex models, and may even get stuck in local optimal solutions, unable to find the global optimal solution, resulting in high energy consumption costs. Therefore, a multi-objective optimization based energy consumption control method for the lifecyle of public green buildings is proposed. Firstly, an optimization model for energy consumption control throughout the entire lifecyle of public green buildings is developed with the goal of maximizing energy efficiency and minimizing incremental costs. During the operation of public green buildings, it helps to reduce energy consumption and minimize the impact on the environment. Next, constraints such as building envelope structure, heating, ventilation, and air conditioning (HVAC) systems, roof structure, and maximum incremental cost are defined. Finally, the improved genetic algorithm is used to solve the constructed model and output the lifecyle energy consumption control optimization results for public green buildings. The experimental results show that through the verification of the energy consumption control scheme with 10 sets of differentiated building envelope parameter combinations, the lifecyle cost of this method is reduced by 29.5%, carbon emissions are reduced by 29.0%, and the response time is controlled within 6 s. This study innovatively adopts a multi-objective optimization framework and an improved genetic algorithm to construct a lifecyle energy consumption control model for public green buildings. By synchronously optimizing key parameters such as building envelope and HVAC system, the dual improvement of energy efficiency and environmental benefits can be achieved under the constraint of incremental cost, opening up a new path for intelligent operation and management of green buildings, which has significant comprehensive economic and environmental value.

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1. Introduction

Green building as a focus on environmental protection, energy saving and sustainable development of the building concept [1], more and more people's attention and attention. In the field of public buildings, the

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implementation of green building strategies is particularly important due to the large scale of buildings, high frequency of use, and high energy consumption [2]. The lifecyle energy consumption control of public green buildings is an important part of the green building implementation process [3]. Through the reasonable control and optimization of energy consumption in various stages of building planning, design, construction, and operation, not only can reduce the operating costs of the building, but also reduce the impact on the environment [4], and achieve a win–win situation in terms of economic and environmental benefits. The traditional lifecyle energy consumption control methods for public green buildings often rely on experience and practice [5], and lack of systematic and scientific. Additionally, the energy consumption of buildings is affected by many factors, such as climatic conditions, building type, equipment performance, which makes energy consumption control a complex multi-objective optimization problem [6]. Thus, identifying scientific and effective methods to optimize and control the lifecyle energy consumption of public green buildings has become a key research focus and challenge [7]. Genetic algorithm is a kind of optimization algorithm that simulates the mechanism of natural selection and genetics, which can deal with complex and nonlinear optimization problems, and has the advantages of strong global search ability and wide applicability [8]. The improved genetic algorithm is applied to the lifecyle energy consumption control of public green buildings to realize the optimization and control of building energy consumption.

Many researchers have studied methods for controlling building energy consumption: Verma *et al.* apply data-driven methods to optimize building energy efficiency [9]. This approach monitors and optimizes building energy consumption, adjusts indoor environmental parameters such as temperature, humidity, and lighting, and improves occupant comfort. Although this method reduces unnecessary waste and lowers operational costs, it struggles to handle nonlinear factors such as sudden changes in building usage patterns and abnormal climate conditions, leading to insufficient adaptability in long-term energy consumption control and compromising the sustainability and stability of optimization effects. Idrissi *et al.* develop a numerical method to study the impact of coupled heat and moisture transfer on energy consumption in residential buildings [10]. By employing numerical simulations, they comprehensively analyze heat and humidity transfer, accounting for factors such as temperature, humidity, and airflow, to more accurately assess their influence on energy consumption. While this method reduces experimental costs, its reliance on idealized modeling necessitates oversimplifications of real-world building environments, particularly when addressing multi-physics coupling effects. Such simplifications weaken the dynamic interactions between key parameters, introducing systematic deviations between simulated and actual energy consumption results. Sayary *et al.* construct a net-zero energy residential building using BIM-based energy consumption templates [11]. BIM technology enables 3D visualization of the design process, facilitating better structural and performance understanding for designers, thereby improving energy efficiency. The templates provide detailed building information, including materials, structures, and equipment, supporting more accurate energy consumption calculations and aiding in achieving net-zero energy goals. However, this method relies on static building information models, limiting its ability to adapt in real-time to operational changes, occupant behavior, or climate variations, which undermines its effectiveness in dynamic lifecycle energy management. Neto *et al.* develop a building energy consumption model using smartphone-based user interfaces [12]. By analyzing energy data displayed on these interfaces, they aim to better understand consumption patterns and optimize energy use. However, inconsistencies in data collection standards and transmission delays compromise the model's completeness and real-time performance, making it difficult to accurately reflect actual energy consumption characteristics and diminishing the reliability of optimization decisions. Goli *et al.* propose a scheduling method based on an efficient multi-objective metaheuristic algorithm [13]. They design a mixed-integer linear programming model to minimize production time and total energy consumption, employing algorithms such as multi-objective ant lion optimizer (MOALO), multi-objective Keshtel algorithm (MOKA), and multi-objective hybrid social engineering optimizer (MOHSEA). However, in long-term dynamic scenarios like building energy control, this method lacks adaptive optimization direction adjustment, often converging to local optima, and fails to ensure sustained optimal energy configurations throughout the building lifecycle. Goli and Tirkolaee introduce a supply chain network control method using an accelerated Benders decomposition (ABD) algorithm [14]. To address model complexity, they implement ABD alongside multi-objective techniques such as weighted sum method (WSM), augmented ε-constraint (AEC), and fuzzy multi-objective programming (FMOP). However, for high-dimensional, nonlinear problems like building energy optimization, this method requires excessive iterations, leading to exponentially growing computational complexity, which hinders real-time control feasibility and limits its practical applicability. Existing energy control methods exhibit notable strengths in specific contexts: data-driven approaches enable monitoring and optimization, numerical methods reduce experimental costs, BIM supports detailed modeling, smart terminals facilitate data collection, and multi-objective algorithms address complex optimization. However, they share critical limitations: static models lack dynamic adaptability, data quality and latency constraints persist, and computational inefficiencies arise, impeding sustained lifecycle optimization. To address these shortcomings, an improved genetic algorithm-based optimization method is proposed, enhancing global optimization through dynamic search strategies, adaptive mechanisms for environmental variations, and integration with lifecycle assessment models for long-term optimization. Compared to existing methods, it offers superior capabilities in multi-objective coupling, dynamic adaptability, and computational efficiency, making it better suited for public green building energy control requirements.

The problem of energy consumption control in the lifecycle of public green buildings involves multiple optimization objectives. While pursuing energy-saving performance, this article further considers minimizing incremental costs. This means that while achieving energy-saving goals, the increase in building construction and operating costs can be effectively controlled, ensuring the economic feasibility of public green buildings. At the same time, constraints such as building envelope, HVAC system, roof construction, and maximum incremental cost are set. Therefore, a multi-objective optimization method is studied to control the lifecycle energy consumption of public green buildings, aiming to achieve energy optimization throughout the entire lifecycle of public green buildings. The multi-objective optimization method comprehensively considers multiple objectives and constraints, providing a more comprehensive and scientific decision-making basis. This helps to reduce subjectivity and uncertainty in the decision-making process while improving the scientific rigor and rational nature of decision-making. The experimental results show that the cost reduction achieved by the method proposed in this paper reaches 29.5%; the highest carbon emission reduction reaches 29%, which is significantly higher than that of the comparison method. It can effectively improve the energy utilization efficiency of buildings and reduce energy waste in public buildings.

2. Optimization of energy consumption control throughout the entire lifecycle of public green buildings

2.1. Simulation of energy consumption in the lifecyle of public green buildings

A green building refers to a structure that maximizes resource conservation, protects the environment, and reduces pollution throughout its entire lifecycle, while providing people with healthy, comfortable, and efficiently utilized spaces in harmony with nature [15]. Green building design should aim to meet energy-saving and emission-reduction objectives to achieve a balance between thermal comfort and carbon emission reduction in buildings. Due to the substantial energy required to regulate the thermal environment of buildings, current research primarily focuses on improving building thermal performance efficiency [16]. However, other aspects of the building, such as the lighting system, also significantly influence the total energy consumption. The physical properties of buildings mainly include the thermal environment, lighting environment, sound environment, and wind environment, among which the thermal and lighting environments exert the most substantial impact on building energy consumption [17]. The lighting environment primarily encompasses the illumination system of buildings. When designing green buildings, priority should be given to optimizing the thermal environment and lighting system.

2.1.1. Simulation of lighting systems in public green buildings

In the lighting system of public green buildings, daylighting coefficient and total natural daylighting rate are two important evaluation indicators. When these two indicators meet the prescribed standards, it can be considered that the building's lighting system meets the requirements of the building's lighting environment [18]. The daylighting coefficient refers to the ratio of indoor illuminance generated by diffuse light on a completely cloudy day at a specific indoor point on a horizontal plane to the simultaneous outdoor illuminance generated by diffuse light under the same conditions on an unobstructed horizontal plane [19]. The illumination time of artificial light sources in public green buildings is:

$$T_{el-l} = (1 - \mathrm{DA}_{500}) \times T_{\mathrm{day}} \times T_{\mathrm{hour}}. \tag{1}$$

In equation (1), T_{el-l} represents the illumination time of the artificial light source. T_{day} indicates the number of days worked per year. T_{hour} indicates the number of hours worked per day.

The artificial lighting in public green buildings consumes electricity, and the annual electricity consumption is expressed as:

$$Q_{el-l} = \sum_{n=1}^{N} (T_{el-l} \times P_{lit})_n. \tag{2}$$

In equation (2), Q_{el-l} represents the annual electricity consumption of artificial lighting. P_{lit} represents the power of a single lamp; N represents the number of lighting fixtures in the tested area, calculated as follows:

$$N = E_{av} \times A/(u \times k \times \phi). \tag{3}$$

In equation (3), E_{av} represents the actual average illuminance of the tested working surface; A represents the area of the tested working surface (m^2); u represents the utilization coefficient; k represents the maintenance coefficient; ϕ represents the luminous flux of artificial lighting sources.

2.1.2. Simulation of building thermal environment performance

When simulating the thermal environment performance of public green buildings, it is assumed that the HVAC system operates continuously throughout the year to provide the required thermal environment for the building and achieve thermal comfort in the indoor environment. The thermal environment performance of a building is reflected in the energy consumption of the HVAC system required to maintain indoor thermal comfort. The higher the energy consumption, the worse the thermal performance of the building [20]. Thermal environment simulation mainly calculates the energy required to maintain a constant indoor temperature in a building, and then calculates the annual energy consumption. To calculate the cooling and heating energy consumption of public green buildings [21], COP (Coefficient of Performance) is introduced to represent the energy efficiency ratio, which is the ratio of the rated cooling or heating capacity to the rated power (electricity consumption). The calculation formula for annual electricity consumption to maintain the comfort performance of building thermal environment is as follows:

$$Q_{el-t} = Q_{\mathrm{cool}}/\mathrm{COP}_{\mathrm{cool}} + Q_{\mathrm{heat}}/\mathrm{COP}_{\mathrm{heat}}. \tag{4}$$

In equation (4), Q_{cool} represents the annual cooling load; Q_{heat} represents annual heat load; $\mathrm{COP}_{\mathrm{cool}}$ represents the refrigeration energy efficiency ratio; $\mathrm{COP}_{\mathrm{heat}}$ represents the heating energy efficiency ratio.

After completing the simulation of public green building lighting system and thermal environment performance [22], the annual total energy consumption of public green buildings can be expressed as:

$$Q_{el-s} = Q_{el-l} + Q_{el-t} = \sum_{n=1}^{N} (T_{el-l} \times P_{lit})_n. \tag{5}$$

2.2. Construction of an optimization model for energy consumption control throughout the entire lifecycle of public green buildings

Based on the simulation results of energy consumption throughout the entire lifecycle of public green buildings, while considering the energy-saving investment and benefits over the building lifecycle, this study conducts a quantitative analysis of both factors to establish a dual-objective optimization problem that simultaneously minimizes the lifecycle cost and maximizes energy-saving benefits for public green buildings. The study proposes the concept of energy-saving design efficiency, defined as maximizing the incremental benefits generated per unit incremental cost, which serves as the evaluation index for the objective function solution set to determine the optimal lifecycle energy consumption control scheme for public green buildings.

2.2.1. Multi-objective small function construction

(1) Establishing the objective function.
The energy-saving technology adopted by public green buildings aims to maximize energy-saving benefits, expressed as:

$$\max Z_1 = \Delta s = \sum_{i}^{m}\sum_{j}^{n} \Delta Q_{ij} x_i x_{ij} [P_2 + \delta \cdot \varepsilon + P_3] \cdot P(\Delta S_a, i_0, n). \tag{6}$$

The incremental benefits of the lifecycle of public green buildings mainly include three components: first, the direct economic benefits generated by energy conservation; second, the environmental benefits brought by energy conservation and emission reduction; third, the social benefits from reduced power investment and power shortage losses. By systematically summarizing the energy-saving effects of various energy-saving technology solutions, the annual energy-saving benefits can be accurately calculated, and future incremental benefits can be scientifically discounted to determine the present value of incremental benefits.
While pursuing maximum efficiency, energy-saving technologies used in public green buildings also need to strictly control incremental costs. The mathematical expression for minimizing incremental costs as an important optimization objective is:

$$\min Z_2 = \Delta C_d + \Delta C_c = P_1 + \sum_{i=1}^{m}\sum_{j=1}^{n_i} \Delta C_{ij} x_i x_{ij}. \tag{7}$$

In equations (6) and (7), Z_1 represents incremental benefits; Z_2 represents incremental cost; Δs represents the incremental benefits during the calculation period (including economic, environmental, and social benefits of energy conservation); ΔQ_{ij} represents the energy savings generated by the ith technology and the jth energy-saving plan; P_1 represents the electricity price at the location of the project; δ represents the coefficient for converting electrical energy into standard coal; ε represents the value of energy conservation and carbon reduction, which is obtained by summarizing the emission reduction values of various pollutants; P represents the discount coefficient; ΔS_a represents the annual incremental rate of return; i_0 represents the benchmark rate of return; n represents the calculation period (in years); ΔC_d and ΔC_c represent the incremental costs during the decision-making period and the construction period, respectively; P_2 represents the consultation fee during the decision-making period; ΔC_{ij} represents the incremental cost generated by the j-th energy-saving scheme of the i-th technology; X_i and X_{ij} respectively represent the i-th energy-saving plan in the j-th energy-saving technology measure, including exterior wall enclosure structure, air conditioning and heating system, lighting system, renewable energy, roof energy-saving, etc; n_j represents the number of measures and plans for the j-th energy-saving technology.

(2) Efficiency evaluation of energy-saving design.
The energy consumption control results of public green buildings throughout their lifecycle obtained through optimization algorithms usually form a Pareto optimal solution set. To facilitate decision-making, this study proposes an energy-saving design efficiency index that maximizes the incremental benefits per unit

incremental cost. Its mathematical expression is given by:

$$\max Z = \frac{f_{Z_1}(Z_1, Z_2)}{f_{Z_2}(Z_1, Z_2)}. \tag{8}$$

In equation (8), $f_{Z_1}(Z_1, Z_2)$ and $f_{Z_2}(Z_1, Z_2)$ respectively represent the incremental benefits and incremental costs corresponding to a set of Pareto optimal solutions $f(Z_1, Z_2)$. Through comparing the incremental benefits and incremental costs of each solution in the Pareto optimal solution set, the solution yielding the maximum incremental benefit per unit incremental cost is selected as the final optimized energy consumption control strategy for the entire lifecycle of public green buildings.

2.2.2. *Constraint conditions*

(1) Envelope constraints.
Taking into account the construction characteristics of the enclosure structure of public green buildings, it is divided into two parts: exterior wall windows and roof energy-saving, and the constraint conditions are determined separately. The thermal performance of the enclosure structure needs to effectively reflect the energy-saving effect. The scoring criteria are as follows: 5 points for optimizing the building load by 5% compared to the benchmark building, and 10 points for reducing it by 10%. The constraint condition expression is:

$$a_1 = \begin{cases} 5, & 5\%\, Q_L \le \sum_{j=1}^{n_i} x_1 x_{1j} \Delta Q'_{1j} < 10\%\, Q_L \\ 10, & \sum_{j=1}^{n_i} x_1 x_{1j} \Delta Q'_{1j} \ge 10\%\, Q_L. \end{cases} \tag{9}$$

In equation (9), $\Delta Q'_{1j}$ represents the reduced building load of optimization plan X_{1j} compared to the benchmark building, Q_L represents the total load of the benchmark building, and a_1 represents the energy-saving plan score.

(2) Constraints of air conditioning and heating system.
For public green buildings employing different air conditioning and heating systems, their energy consumption varies. The evaluation scores differ according to the energy consumption reduction ranges. Based on the evaluation standard of public green buildings, the scoring method is appropriately simplified to create abstract content, which can be divided into three categories: for a 5%∼10% reduction in energy consumption in the design scheme, the score is 12 points; for a 10%∼15% reduction range, the score is 28 points; and for an energy consumption reduction of 15% or more, the score is 37 points.

(3) Roof structure constraints.
The roof structure is a main factor affecting building energy consumption, and different roof structures can lead to significant differences in energy-saving effects. Based on the variations in energy-saving performance, the assigned scores vary accordingly. Following the evaluation criteria of public green buildings, the following scoring method is adopted: for a 5% reduction in total energy consumption compared to the reference building, 5 points are awarded; for a 10% reduction, 12 points are given.

(4) Maximum incremental cost constraint.
Incremental cost control serves both as the objective function and the constraint function in selecting the optimization scheme. When determining the optimal energy consumption control strategy, energy managers must consider the maximum incremental cost they can accommodate. The expression for establishing the maximum incremental cost constraint is as follows:

$$P_1 + \sum_{i=1}^{m} \sum_{j=1}^{n_i} C_{ij} x_i x_{ij} \le w. \tag{10}$$

In equation (10), w represents the maximum incremental cost acceptable for energy consumption control optimization.

2.3. Model solution based on improved genetic algorithm

2.3.1. Standard genetic algorithm solution mechanism for energy consumption control optimization

The core idea of genetic algorithm is that in any population, the dominant individuals in each generation will show an exponential growth trend, indicating that the algorithm has convergence and can be well applied in practice. This algorithm is an adaptive random search optimization method, which requires a relaxed optimization object and does not require the objective function to be continuous or differentiable. Therefore, it has good robustness and parallel search ability. Genetic algorithms do not require initial solution settings, and any initial population can obtain the final solution through iteration. This algorithm adopts a probability selection strategy, retaining dominant individuals to enter the next generation, and then performing genetic operations such as crossover and mutation until the algorithm converges. Genetic algorithms use evolutionary mechanisms to achieve global search, even if the fitness function is discontinuous or irregular, the algorithm can still find the global optimal solution. This algorithm has excellent parallel computing performance and is particularly suitable for large-scale, widely distributed public building lifecycle energy consumption optimization control problems.

For the purpose of optimizing the lifecyle energy consumption control of public green buildings, the implementation process of genetic algorithm is shown in Figure 1.

Figure 1 illustrates the genetic algorithm-based optimization of lifecycle energy consumption control for public green buildings, comprising the following components:

(1) Chromosome representation (encoding).
Assign numerical codes to the lifecycle energy consumption control plans for public green buildings, thereby generating chromosomes. Due to the limited processing capability of genetic algorithms for spatial data, the problem must be transformed into a chromosome (gene string) data format compatible with the algorithm. Each chromosome represents a possible energy consumption control solution, and each gene within the chromosome corresponds to a specific parameter or strategy within the solution.

(2) Population initialization.
Initialize a random population of N individuals ($N = 100$), where each individual represents a chromosome encoding an optimized energy consumption control solution for the lifecycle of a public green building.

(3) Fitness function evaluation.
The maximum energy-saving design efficiency is designated as the fitness value in the genetic algorithm. Each chromosome in the population (representing each energy consumption control scheme) is evaluated by the fitness function to assess its performance characteristics, and this fitness value is then utilized for subsequent selection, crossover, and mutation operations.

(4) Selection of superior individuals.
Within genetic algorithms, superior chromosomes from the previous generation are selected based on their fitness values. The roulette wheel selection method is employed to assign selection probabilities to individuals. This process of selecting superior chromosomes from the previous generation, which contain favorable genes, plays a crucial role in generating improved offspring.

(5) Crossover for new individual generation.
New chromosomes are generated through gene crossover operations applied to the selected chromosomes (*i.e.*, individuals). Crossover operations generally consist of randomly pairing selected chromosomes and randomly choosing crossover points for gene segment exchange, thereby producing new and potentially superior energy control solutions.

(6) Mutation for new individual generation.
The mutation operation involves randomly selecting a subset of chromosomes and applying random changes to specific genes within them, thereby enhancing population diversity and preventing the algorithm from converging to local optima. Through mutation operations, new chromosomes potentially possessing advantageous characteristics can be generated.

(7) Iteration process.

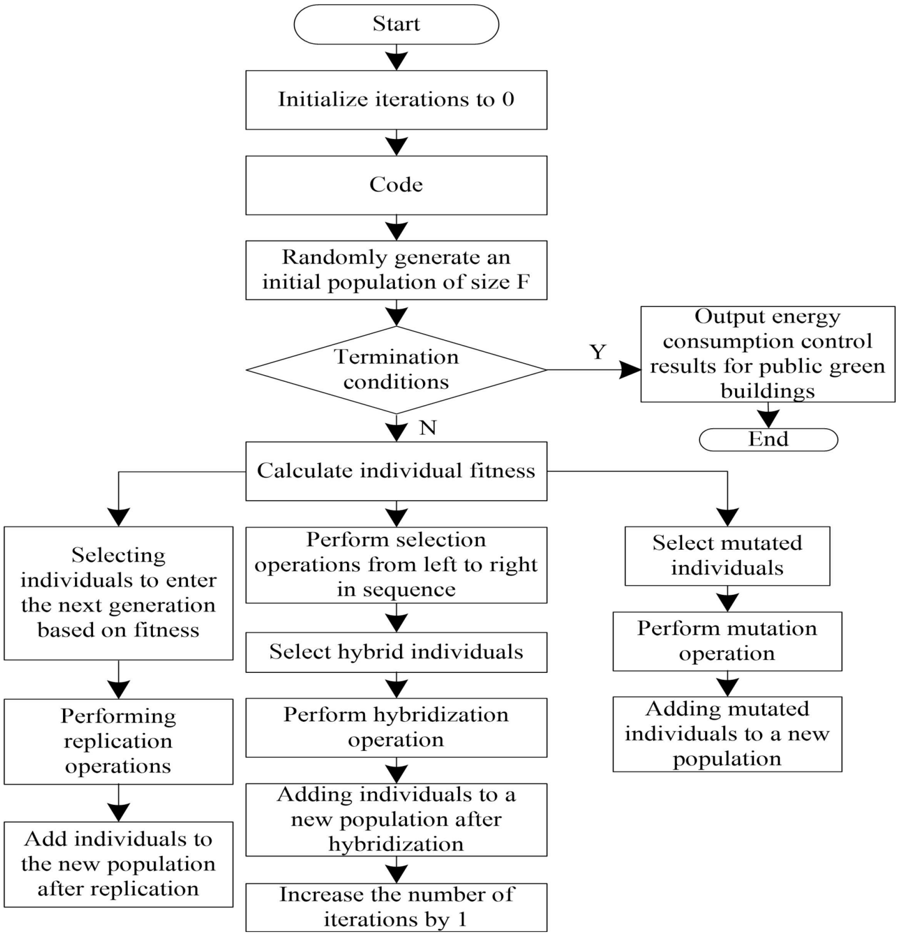

FIGURE 1. Genetic algorithm operation process.

The algorithm iteratively executes steps 4 to 6 until reaching the maximum iteration count (set at 100), upon which the algorithm terminates.

(8) Result output.
The algorithm outputs the optimal chromosome in the final population (representing the optimal energy consumption control scheme) and its corresponding fitness value. This optimal solution can serve as either a reference for practical applications or a basis for further optimization.

2.3.2. Improvement of genetic algorithm based on population grouping and adaptive strategy

This study proposes to improve the genetic algorithm through population grouping strategy combined with adaptive population ratio adjustment, while implementing different crossover and mutation strategies for different populations to enhance the algorithm's convergence speed. Additionally, an elite retention strategy is introduced to preserve high-fitness individuals and ensure the preservation of excellent individuals' gene sequences.

(1) Encoding method. This study employs integer encoding, though it is not applicable to the traveling salesman problem (TSP), where node sorting cannot be directly encoded. Considering the characteristics of energy consumption control in the lifecycle of public green buildings, all relevant elements (such as different functional areas, equipment systems, and energy-saving measures) are systematically numbered and organized,

with their combinations forming encoded representations of possible energy consumption control schemes for public green buildings' lifecycle.

(2) Population initialization. Following the encoding process, a random strategy is applied to generate initial energy consumption control schemes for the building lifecycle. The initial population size is determined not by pipeline segments or nodes, but through comprehensive analysis of energy consumption control factors, including the variety of functional areas in public green buildings, equipment system complexity, and available energy-saving measures.

(3) Fitness function design. The individual fitness value serves as the core metric for chromosome evaluation. This research adopts a multi-objective optimization framework that simultaneously addresses lifecycle benefit maximization and cost minimization for green buildings. Consequently, the fitness function is formulated as follows:

$$f(i) = \alpha \cdot \frac{\varphi_{\text{benefit}}}{\varphi_{\max}} + \beta \cdot \left(1 - \frac{C_{\text{total}}}{C_{\max}}\right). \tag{11}$$

In equation (11), φ_{benefit} represents the comprehensive benefits of the building lifecycle; $\varphi_{\max}$ represents the maximum potential benefit benchmark value; C_{total} represents the total lifecycle cost; $C_{\max}$ represents the upper limit of cost constraints; α and β represent weight coefficients used to balance the relative importance of benefits and costs.

(4) Adaptive population grouping strategy. To enhance the algorithm's computational speed and global search capability, this study proposes an adaptive population grouping approach that classifies the population into two subpopulations based on fitness values, with the size of each subpopulation adaptively adjusted according to iteration count. The dynamic proportion variation between high-fitness and low-fitness subpopulations is governed by the following equation:

$$pop_{\text{high}}/pop_{\text{low}} = \begin{cases} 1:2, T \in [0, T_{\max}/3] \\ 1:1, T \in (T_{\max}/3, 2T_{\max}/3] \\ 2:1, T \in (2T_{\max}/3, T_{\max}]. \end{cases} \tag{12}$$

In equation (12), $pop_{\text{high}}/pop_{\text{low}}$ represents the ratio of high fitness population to ground fitness population; T represents the current number of iterations; $T_{\max}$ represents the maximum number of iterations.

(5) Elite retention strategy implementation. To maintain the high-quality individuals in the original population, we implement an elite retention strategy where the top-fitness individuals across all populations are exempt from subsequent crossover and mutation operations and instead directly propagate to the next generation.

(6) Adaptive crossover and mutation. This study introduces adaptive crossover probability p_c and mutation probability p_m that vary according to the fitness level of the grouped populations.
The adaptive crossover probability formulation is:

$$p_c = \begin{cases} p_{c1} - \frac{(p_{c1}-p_{c2})\left(f_i - \overline{f}\right)}{f_{\max}}, & f_i \in pop_{\text{high}} \\ p_{c1}, & f_i \in pop_{\text{low}}. \end{cases} \tag{13}$$

The equation for adaptive mutation probability is:

$$p_m = \begin{cases} p_{m1} - \frac{(p_{m1}-p_{m2})\left(f_i - \overline{f}\right)}{f_{\max} - \overline{f}}, & f_i \in pop_{\text{high}} \\ p_{m1}, & f_i \in pop_{\text{low}}. \end{cases} \tag{14}$$

In equation (14), p_{c1} represents the maximum crossover probability; p_{c2} represents the minimum crossover probability; p_{m1} represents the maximum mutation probability; p_{m2} represents the minimum mutation probability; f_i represents the fitness value of the current individual; $\overline{f}$ represents the average fitness value of the current population; $f_{\max}$ represents the maximum fitness value in the population.

The proposed adaptive crossover and mutation strategy depends on both individual fitness and population group classification. For high-fitness populations and individuals, reduced crossover and mutation probabilities are applied to preserve high-quality genes. Conversely, for lower-fitness populations and individuals, elevated crossover and mutation probabilities are implemented to facilitate the generation of new individuals.

(7) Crossover operation. Different crossover strategies are implemented for populations with varying fitness levels. In single-point crossover, a random position is selected to divide and exchange the right segments of two chromosomes, producing two distinct offspring chromosomes while causing minimal gene disruption and effectively preserving favorable chromosome segments. In multi-point crossover, multiple crossover positions are randomly established along the chromosomes, followed by segment exchange. This approach significantly modifies individuals and enhances population diversity. Thus, high-fitness populations utilize single-point crossover, whereas low-fitness populations employ multi-point crossover.

(8) Mutation operation. The exchange mutation randomly selects two gene positions on the chromosome to swap their values, imposing relatively minor structural modifications. The reverse mutation randomly identifies two positions and inverts the gene sequence between them, resulting in substantial structural changes. Accordingly, high-fitness populations adopt exchange mutation to conserve superior individuals, while low-fitness populations apply reverse mutation to maximize the acquisition of improved individuals.

In order to solve the problem that the global optimization results of improved genetic algorithms may deviate from engineering practice, the DeST (Designer's Simulation Toolkit) model is introduced. DeST, as a professional tool for simulating building energy consumption, can dynamically simulate and quantitatively analyze building energy consumption with high precision based on building physical characteristics, meteorological parameters, and usage patterns. This model can verify the actual energy-saving effect of the energy consumption optimization scheme generated by genetic algorithm, and accurately reflect the temporal characteristics of energy consumption through its hourly simulation ability, making up for the limitations of static optimization of genetic algorithm. The combination of the two realizes a collaborative mechanism of "theoretical optimization engineering verification", which retains the global search advantage of genetic algorithm and combines the refined simulation ability of DeST, ultimately improving the engineering feasibility and reliability of the energy consumption optimization scheme for the entire lifecyle of public green buildings.

For solving the energy consumption control optimization model, the DeST model is employed to process the building's parameter information, construct an energy consumption simulation model, and analyze the simulation results to formulate an objective function characterizing the energy consumption optimization targets. The objective function is computed as follows:

$$f_{obj} = \min(E_{\text{total}}(x)). \tag{15}$$

In equation (15), f_{obj} denotes the objective function; $E_{\text{total}}(x)$ represents the total energy consumption value under a given energy consumption control strategy x. The optimization goal of this formulation is to identify the energy consumption control strategy x that minimizes the total energy consumption.

Next, use an improved genetic algorithm to generate a new solution, with the specific formula being:

$$L_{\text{accept}} = \exp\left(-\frac{E}{\delta}\right). \tag{16}$$

In equation (16), L_{accept} denotes the acceptance probability of a new solution; E represents the energy consumption difference between the new and old solutions; δ indicates the current annealing temperature. The obtained new solution is then input into the DeST model for energy consumption simulation to obtain the corresponding energy consumption values. The solution quality is evaluated based on the energy consumption values, and the algorithm's convergence to an optimal solution is assessed. The convergence criterion is expressed as:

$$E_{\text{best}}^{k+1} - E_{\text{best}}^{k} \leq \varepsilon. \tag{17}$$

In equation (17), E_{best}^{k+1} and E_{best}^{k} represent the optimal energy consumption values during $k+1$ and k iterations, respectively; ε represents a preset small positive number. When the difference between the optimal energy consumption values from two consecutive iterations falls below the preset threshold, the algorithm is considered to have converged to the optimal solution region. Based on the DeST model simulation results, the parameters of the improved genetic algorithm are then adaptively adjusted to enhance solution efficiency and quality. Subsequently, the algorithm checks whether the convergence criteria are satisfied. If satisfied, the optimal solution is output as the final energy consumption control strategy; otherwise, the iterative search process continues.

The improved genetic algorithm demonstrates significant optimization efficiency improvements through population grouping strategy and adaptive adjustment framework. The integer encoding method precisely characterizes the combinatorial relationships of energy consumption control elements in green buildings, while the multi-objective fitness function optimally balances benefit and cost optimization requirements. The adaptive population grouping strategy dynamically regulates the proportion of high- and low-fitness populations, complemented by the elite retention mechanism for preserving high-quality genes. The differentiated crossover-mutation strategy maintains equilibrium between population diversity and optimal gene inheritance. High-fitness populations employ mild single-point crossover and exchange mutation, whereas low-fitness populations utilize aggressive multi-point crossover and reversal mutation to strengthen exploration capability. The integration with the DeST model establishes a closed-loop system for theoretical optimization and engineering verification. Dynamic simulation validates the engineering feasibility of algorithm results, and hourly simulation addresses the limitations of static optimization. This enhanced scheme provides a comprehensive energy consumption control solution for public green buildings that integrates global optimality with engineering practicality.

2.4. Space exploration and convergence guarantee strategy for energy consumption control optimization solution

(1) Generation of population individuals based on the crossover model.

A specialized crossover model is developed to cluster each generational population within the genetic algorithm, accounting for genetic operations among both similar and dissimilar individuals to produce new population members. The implementation process proceeds as follows:

(a) The population in the genetic algorithm is clustered using a minimum spanning tree approach. First, the Euclidean distance between all pairs of individuals in the population is computed to construct the adjacency matrix D. Next, the minimum spanning tree T of D is generated using the Prim algorithm. Then, the average weight $\overline{W}$ of T is calculated, and the threshold V is defined as the maximum weight in T that satisfies $V < \delta \times \overline{W}$. Subsequently, T is traversed to identify and remove all edges with weights greater than V. This process yields disconnected subgraphs, each representing a subclass, which are then numbered and stored.

(b) An individual p_{i1} is selected for crossover based on the crossover probability roulette. Its category C_i is then determined. For intra-class crossover, the highest-fitness individual p_{i2} from C_i is selected as the mating partner. For inter-class crossover, the class C_j most distant from C_i is identified, and an individual p_{j1} is randomly chosen from it. Crossover is performed between p_{i1}/p_{i2} and p_{j1} to leverage their genetic differences. From the resulting offspring, the most promising individuals are selected for the lifecycle energy control optimization of public green buildings.

(c) The algorithm checks whether the target population size has been achieved. If so, the process terminates; otherwise, it returns to step (b).

The proposed algorithm exhibits two key characteristics: first, intra-class individuals demonstrate minimal differences, enabling same-class crossover to preserve elite gene patterns, maintain superior traits, and accelerate convergence; second, inter-class individuals display significant differences, allowing cross-class crossover to enhance population diversity. This dual-crossover mechanism optimally balances convergence speed and diversity maintenance.

(2) An improved selection operator.

Table 1. Overview of public green building projects.

Indicator name	Result
Number of building floors	6th floor
Building exterior area	$6584.85\,\mathrm{m}^2$
Building height	$20.8\,\mathrm{m}$
Building volume	$20\,645.85\,\mathrm{m}^3$
Building area	$6538.5\,\mathrm{m}^2$
Body shape coefficient	0.29
North angle	108°

Notes. Some of the planes of the standard floor plan of the building are shown in Figure 2.

The selection operation selects individuals from the old population for inclusion in the new population based on specified probabilities. To preserve high-quality individuals, this work proposes a novel selection operator that combines proportional selection (where each individual's selection probability equals $\frac{f(x_i)}{\sum f(x_i)}$ with an elite retention strategy. Specifically, $\alpha \times M$ individuals are retained from the previous generation, while the remaining $(1-\alpha) \times M$ individuals are chosen from the parent population in fitness-descending order, yielding a final offspring population of size M. Here, α is the selection factor.

(3) Population renewal strategies based on population similarity.
A key challenge in genetic algorithms lies in accelerating the discovery of optimal solutions while preventing premature convergence. To ensure global convergence, it is essential to preserve population diversity to safeguard valuable genetic material. Conversely, accelerating convergence requires rapid population transition toward optimal states, which inherently reduces diversity and increases susceptibility to local optima. The proposed population updating mechanism leverages group similarity to maintain enhanced diversity, thereby improving algorithmic performance. The group similarity-based population updating strategy operates as follows:
  (a) Calculate the average distance among M individuals in the population:

$$T(M) = \frac{1}{M} \sum T_i(M). \tag{18}$$

  In equation (18), $T_i(M)$ is the path length of the i-th individual.
  (b) If $\sum |T_i(M) - T(M)| \le A$, generate P new individuals, resulting in a total population size of $M+P$; otherwise, proceed to the next generation operation.
  (c) Select M individuals with higher fitness to form the next-generation population of size M.

3. Algorithm testing

To validate the effectiveness of the proposed method for lifecycle energy consumption control in public green buildings, a six-story office building located in a hot-summer-and-cold-winter region is selected as the case study. The building, primarily comprising office spaces, serves as the testbed for algorithm verification. The project overview is presented in Table 1.

Figure 2 depicts the standard floor plan of a six-story public green office building located in a region with hot summers and cold winters. The overall layout is neat and the functional zones are clearly defined. The central area features an open public office space, facilitating communication and collaboration among staff. On one side, there is an independent conference room to meet meeting requirements. On the other side, multiple offices provide relatively independent workspaces. The building's dimensions are clearly marked, reflecting a certain degree of planning rationality, which helps to enhance office efficiency and space utilization.

The parameter settings of the improved genetic algorithm are shown in Table 2.

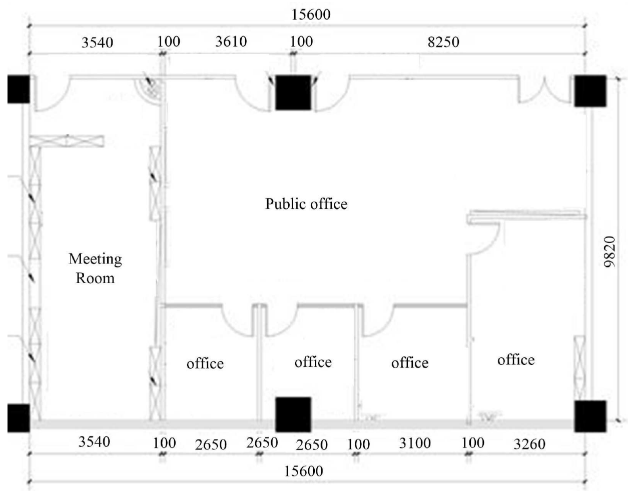

FIGURE 2. Standard floor plan of public green buildings.

TABLE 2. Parameter settings for improved genetic algorithm.

Parameter name	Parameter results
Population size	120
Variable dimension	20
Encoding length for each dimension	20
Cross probability	1.0
Mutation probability	1.0
Cluster coefficient	0.98

Using a larger population size of 120 ensures population diversity and avoids premature convergence. For 20-dimensional variables, a coding length of 20 bits per dimension is adopted, providing sufficient precision in the solution space. Both the crossover probability and mutation probability are set to 1.0, indicating that the algorithm adopts a radical global search strategy. This, combined with a clustering coefficient of 0.98, ensures both global exploration capability and maintains local optimization performance of the solution. This parameter combination is particularly suitable for handling complex optimization problems.

To determine the optimal energy-saving scheme for public green buildings, a reference building is established as the benchmark. All energy-saving schemes are evaluated against this benchmark to quantify building energy savings, thereby providing the foundation for the genetic algorithm's optimization process. The reference building's parameter design is detailed in Table 3.

Table 3 serves as the parameter benchmark for the reference building and adopts the exact same parameter settings as the improved genetic algorithm. A population size of 120 ensures sufficient solution space coverage, and a 20 dimensional variable combined with a 20 bit encoding length provides accurate algorithm resolution. The crossover and mutation probabilities are both 1.0, indicating that the reference model also adopts a strong global search strategy, combined with a high clustering coefficient of 0.98, to achieve full exploration while maintaining population convergence. This high-precision parameter setting establishes a reliable baseline for comparing subsequent energy-saving solutions.

The DeST model is employed to simulate energy consumption variations in the public green building. All parameter information for the reference building is input into the DeST software, while unspecified building

Table 3. Parameter design of reference buildings.

Parameter name	Parameter results
Population size	120
Variable dimension	20
Encoding length for each dimension	20
Cross probability	1.0
Mutation probability	1.0
Cluster coefficient	0.98

Table 4. Sub item energy consumption of reference buildings.

Sub item name	Load/(kWh/m^2·a)	Investment/(yuan/m^2)
Enclosure structure	175.64	External wall: 336.15 Roof: 186.51
Air conditioning system	87.16	195.75
Lighting system	56.25	52.64
Hot water system	5.16	0.47
Total energy consumption of buildings except for enclosure structures	148.57	–

parameters adopt default DeST values. The reference building's energy consumption values, derived from software calculations, are presented in Table 4.

As presented in Table 4, the reference model's energy consumption data for public green buildings reveals that the enclosure structure accounts for the largest proportion at 175.64 kWh/m^2·a, accompanied by higher initial investment costs (336.15 RMB/m^2 for exterior walls and 186.51 RMB/m^2 for roofing). The HVAC system represents the second-largest energy consumer at 87.16 kWh/m^2·a with a 195.75 RMB/m^2 investment. The lighting system consumes 56.25 kWh/m^2·a (52.64 RMB/m^2 investment), while the hot water system has the lowest consumption (5.16 kWh/m^2·a). The total energy use for non-enclosure structures reaches 148.57 kWh/m^2·a, confirming that enclosure structures are the primary focus for energy-efficient retrofits.

The variations in air-conditioning and heating loads for the exterior walls, windows, and roof of the public green building are analyzed across different heat transfer coefficients, with the statistical results presented in Figure 3.

Figure 3 illustrates that the building's cumulative total load increases proportionally with rising heat transfer coefficients for exterior walls and windows. At a heat transfer coefficient of 1.4 W/(m^2·K), the wall load measures 134 kWh/m^2 whereas the window load registers 157 kWh/m^2. The roof's cumulative load demonstrates a convex trend, achieving its minimum value of 131 kWh/m^2 at 0.8 W/(m^2·K). This thermal behavior stems from the heat transfer coefficient's fundamental control over a building's heat exchange capacity, which directly governs HVAC load magnitudes. A low coefficient signifies limited heat exchange, promoting stable indoor temperatures and consequently reducing HVAC loads. Conversely, elevated coefficients facilitate greater thermal exchange, amplifying the external environment's influence on indoor temperatures and necessitating increased HVAC loads. Effective public green building design must integrate local climate conditions with indoor-outdoor temperature differentials through optimal selection of insulation materials and window-to-wall ratios to minimize heat transfer coefficients and associated energy consumption. Supplementary passive strategies including natural ventilation and solar energy utilization can be strategically implemented across varying regional climates to further diminish energy demands while enhancing overall sustainability.

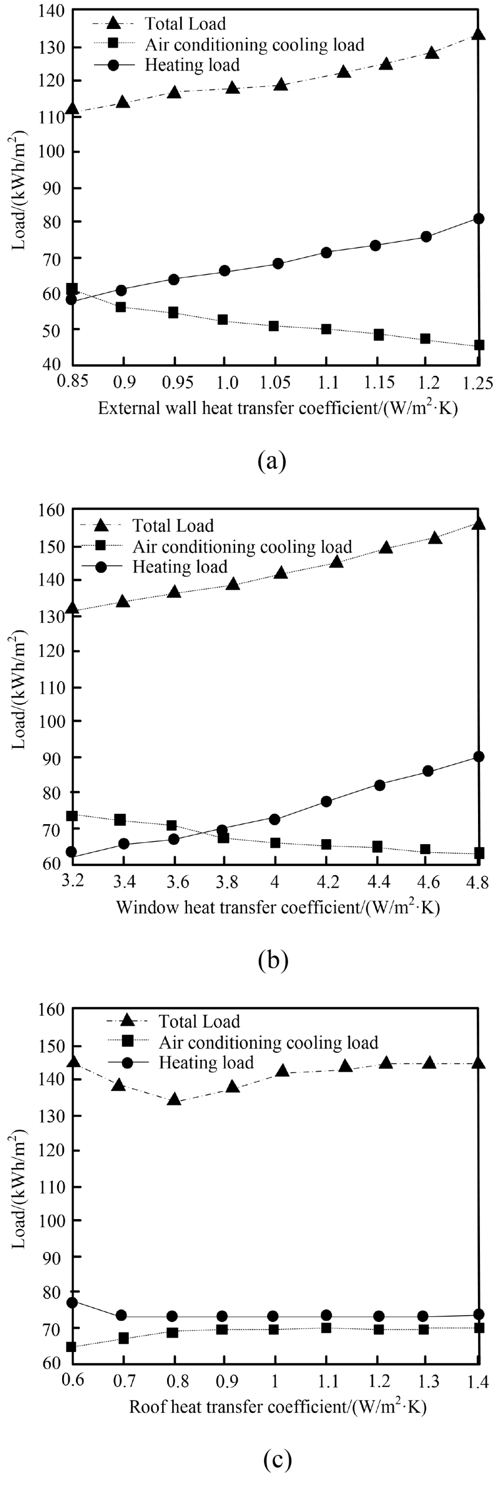

Figure 3. Effect of heat transfer coefficient on load variation. (a) Exterior wall. (b) Window. (c) Roof.

TABLE 5. Optimization plan for energy consumption control of public green buildings.

Optimization plan	Wall type	Window to wall ratio	External shading width/m	Glass type	Building orientation/°
1	Reinforced concrete walls	0.152	0.168	Single layer transparent glass	215
2	Aerated concrete block wall	0.415	1.251	Double layer transparent glass	182
3	Lightweight brick wall	0.524	1.168	Three layer insulating glass	172
4	Reinforced concrete walls	0.615	1.254	Double layer green glass	258
5	Aerated concrete block wall	0.421	1.065	Coated glass	176
6	Lightweight brick wall	0.284	0.685	Single layer transparent glass	226
7	Reinforced concrete walls	0.164	0.842	Double layer transparent glass	154
8	Aerated concrete block wall	0.358	0.264	Three layer insulating glass	64
9	Lightweight brick wall	0.418	1.645	Double layer green glass	190
10	Reinforced concrete walls	0.385	1.085	Coated glass	270

For this public green building, 10 public green building energy consumption control optimization schemes are designed as shown in Table 5.

Table 5 presents the key parameter configurations of ten energy consumption control optimization schemes for public green buildings. Each scheme exhibits diversity in wall material selection, including reinforced concrete walls, aerated concrete block walls, and lightweight brick walls, each with distinct thermal performance characteristics. The window-to-wall ratio ranges from 0.152 to 0.615, with Scheme 1 having the lowest ratio and Scheme 4 the highest, representing a significant contrast. Notable variations exist in external sunshade width: Scheme 3 and Scheme 9 employ wide sunshades of 1.168 m and 1.645 m respectively, while Scheme 8 uses a narrow 0.264 m sunshade. The glass types demonstrate considerable diversity, encompassing single-layer transparent glass, triple-layer insulated glass, double-layer green glass, and coated glass, representing various energy-efficient glazing options. Building orientations range from 64° to 270°, providing multiple perspectives for passive building energy-saving design. These schemes systematically investigate the influence of different building envelope parameter combinations on energy consumption, establishing a comprehensive dataset for subsequent genetic algorithm optimization.

The energy consumption control scheme for public green buildings fully considers energy-saving requirements by optimizing building layout design to maximize natural lighting and ventilation, thereby reducing reliance on artificial lighting and mechanical ventilation. The scheme incorporates high-efficiency, energy-saving equipment such as variable-frequency air conditioners, LED lighting systems, and elevators. Equipment quantity and capacity are carefully configured to avoid excessive redundancy and energy waste. Additionally, energy recovery technologies, including building exhaust air recovery and condensation heat recovery systems, are employed to recycle otherwise wasted energy, further minimizing energy consumption.

The methods from references [9–12] are selected as benchmark approaches to evaluate the optimization performance of the proposed energy consumption control method. Different schemes are applied to the energy consumption control of public green buildings, and five methods are validated in terms of their effectiveness in reducing full lifecycle costs and full lifecycle carbon emissions. The statistical results are presented in Table 6.

Table 6 presents a comparative performance analysis of five methods for energy consumption control in public green buildings. The proposed method demonstrates superior performance compared to the four reference methods, achieving 29.5% and 29.0% optimization in lifecycle cost reduction and carbon emission reduction respectively. In contrast, the best-performing reference methods achieve 27.2% cost reduction (Ref. [11]) and

TABLE 6. Energy consumption control results of different schemes.

Different methods	Cost reduction/%	Carbon reduction/%
Reference [9] method	26.1	23.5
Reference [10] method	24.9	25.6
Reference [11] method	27.2	24.8
Reference [12] method	25.5	25.4
Proposed method	29.5	29.0

TABLE 7. Response time contrast.

Iteration times/times	Reference [9] method/s	Reference [10] method/s	Reference [11] method/s	Reference [12] method/s	Proposed method/s
10	15	9	20	19	6
20	14	10	22	18	5
30	15	9	21	15	6
40	14	8	23	14	4
50	16	6	20	15	6
60	15	8	21	16	5
70	18	9	20	18	6
80	17	7	21	15	4
90	15	8	22	14	4
100	16	9	24	16	6

25.6% carbon reduction (Ref. [10]). The results indicate that the proposed method improves cost control by 2.3% and carbon reduction by 3.4% compared to the best reference methods. This comprehensive performance advantage demonstrates significant progress in building energy consumption optimization, effectively balancing economic and environmental objectives. The improved genetic algorithm enhances optimization efficiency and accuracy through adaptive population grouping and differentiated crossover-mutation strategies. Integer encoding precisely represents energy consumption control element combinations, while the multi-objective fitness function effectively balances cost and emission targets. The elite retention mechanism preserves high-quality solutions, and dynamic adjustment of crossover-mutation probabilities maintains global exploration and local exploitation capabilities. Validated by precise DeST model simulations, the algorithm adaptively generates optimal solutions that balance economic and environmental considerations, ultimately achieving 29.5% cost reduction and 29.0% carbon reduction.

To further validate the method's effectiveness, a comparative analysis of algorithm response times was conducted, with the results presented in Table 7.

The results demonstrate that the proposed method achieves the shortest response time, with a maximum of only 6 s, while the comparison methods exhibit significantly longer maximum response times of 18 s, 10 s, 24 s, and 19 s respectively. This indicates that our method enables high-performance energy consumption control in green buildings with practical applicability. The improved genetic algorithm enhances computational efficiency through adaptive population grouping, while differentiated crossover-mutation operations reduce invalid searches without compromising optimization quality. The elite retention mechanism eliminates redundant calculations of high-quality solutions, and the integer encoding scheme coupled with the multi-objective fitness function facilitates rapid convergence to feasible solutions. When integrated with the DeST model for precise energy consumption prediction, the algorithm completes optimization calculations within 6 s, representing a response speed improvement exceeding 67% compared to conventional methods, thereby offering an efficient solution for real-time energy consumption control.

4. Conclusion

With growing societal emphasis on environmental protection and energy conservation, effective energy consumption control in public green buildings has become crucial for construction industry development. This research investigates a multi-objective optimization approach for lifecycle energy consumption management in public green buildings. The study establishes an optimization model targeting maximal energy efficiency and minimal incremental costs, formulates relevant constraints, and employs an improved genetic algorithm to solve the model, thereby achieving comprehensive lifecycle energy consumption control. The experimental results demonstrate the algorithm's excellent performance in building energy management, achieving 29.5% cost reduction and up to 29% carbon emission reduction. These outcomes effectively decrease building energy consumption while improving energy utilization efficiency, providing substantial support for sustainable development of green buildings.

Data availability statement

No new data/codes were created or analyzed in this study.

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