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*Research Article*

# Research on Green Building Design Optimization Based on Building Information Modeling and Improved Genetic Algorithm

**Fengtao Liu, Ting Ouyang, Bingzhang Huang, and Jiehong Zhao**

*Liuzhou Institute of Technology, Liuzhou City, Guangxi Province, China*

Correspondence should be addressed to Ting Ouyang; ouyangt@hotmail.com

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The energy consumption of the construction industry has been increasing year by year, posing a huge challenge to China's dual carbon goals of peaking carbon emissions and achieving carbon neutrality. The Chinese construction industry has huge potential for energy conservation and emission reduction, and the government has therefore put forward requirements for constructing green buildings and formulated strict evaluation standards. The carbon emissions of the construction industry involve various stages of the entire life cycle and are closely related to the green building design standards that meet the requirements. This article sets multiple objective functions based on the two dimensions of the carbon emissions of the entire life cycle of buildings and green building evaluation and uses the NSGA-II algorithm in genetic algorithms to optimize ten indicators selected from the two objectives. Based on this, building information modeling (BIM) modeling was carried out for an office building project in Southwest China, and energy consumption analysis and evaluation were conducted based on the project's multidisciplinary model. The dialectical relationship between the carbon emissions of the entire life cycle of buildings and the green building evaluation values was discovered, and the optimized parameter combination scheme corresponding to the Pareto solution set was obtained, providing a reference for using improved genetic algorithms and BIM technology to optimize green building design.

## 1. Introduction

In recent years, the global construction industry is undergoing a transformation process toward sustainability and efficiency [1]. In 2023, the Asia-Pacific Conference on Sustainable Built Environment proposed that the green building development model of collaborative innovation promotes the organic connection between the built environment and natural ecology and promotes more innovative construction methods to reduce the energy consumption of buildings [2]. In China, the construction industry, as an important part of the national economy, is undergoing significant expansion and evolution [3]. However, this growth brings unprecedented challenges, especially the increasing energy consumption in the process of building. Statistics shows that China's construction industry accounts for about 28% of the country's total energy consumption, of which nearly 50% is attributed to energy utilization during material production and construction [4, 5]. Most new and existing buildings lack comprehensive measures to improve energy efficiency [6]. Therefore, the high-quality development of green, informationization, and intensification is the inevitable trend of China's construction industry development.

In the whole life cycle of a building, the design stage of a green building is a key link that affects building energy efficiency, environmental friendliness, and sustainability [7]. Design decisions without comprehensive evaluation and planning can lead to subsequent phases of building operation with high energy consumption and high emissions [8]. In this case, the building may have high energy consumption, low efficiency, and high environmental burden during the use phase, which not only increases operating costs but also compromises environmental sustainability. Therefore, Roberts et al. [9] pointed out that the design stage of green buildings is a critical period to ensure that buildings achieve sustainability and reduce the environmental impact of the whole life cycle. By fully considering green standards and strategies in the design phase, more sustainable solutions can be provided for the whole life cycle of the buildings, reducing resource waste and environmental burden.

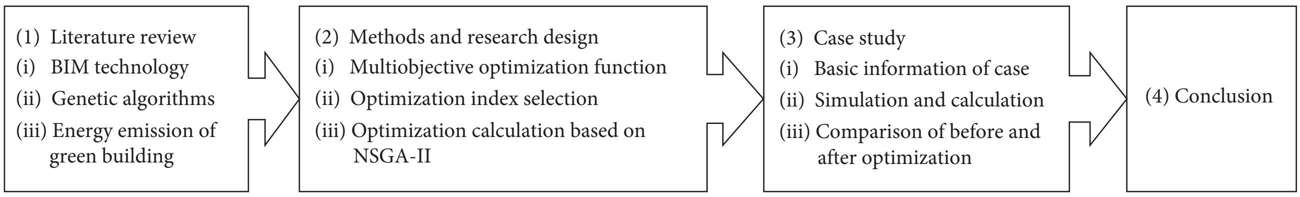


Figure 1: Research path and structure.

At present, the optimization of green building design has attracted the attention of some scholars. Multiobjective optimization methods are used to balance and optimize multiple contradictory design objectives, such as energy consumption, material selection, and environmental impact [10, 11]. Compared with single-objective optimization, multiobjective optimization can provide comprehensive and diversified design choices to meet the multifaceted needs of green buildings [12]. For example, NSGA-II (Nondominated Sorting Genetic Algorithm-II), as a commonly used multiobjective optimization algorithm, has been applied in green building design, which can effectively generate a series of ideal nondominated solution sets in the design decision [13]. Parameter analysis methods, by changing specific parameters in the design and assessing their impact on building performance, identify the most influential parameters [14]. This analysis provides insight into design vulnerabilities and critical factors. In addition, genetic algorithm and particle swarm optimization algorithm are widely used in architectural design to solve complex multivariable and multiobjective problems [15, 16]. The contributions of this paper are as follows: (1) Highlighting the deep application of building information modeling (BIM) technology in architectural design. Taking green building as the research object, the deep integration mode of BIM and green building design is explored. (2) A new method of multiobjective management of integrated building information data domain. With building information data as the core, this paper studies the relationship between the carbon emission of green buildings in the whole life cycle and the evaluation index of green buildings by improving genetic algorithm. (3) Enrich green building evaluation indicators. It focuses on the research content of carbon emission control and green building index evaluation in green buildings, and focuses on the relationship between carbon emission and green building evaluation index in the design stage of green buildings, so as to provide reference for the green development of the building industry.

Building energy efficiency is one of the key areas for China to achieve its 2030 carbon reduction targets. Green building is considered to be an effective way to solve the building energy consumption, and the green building evaluation system is an important basis for the development of green building. In order to meet the requirements of building resource conservation standards and summarize China's practical experience and research achievements in green building in recent years, on the premise of drawing on international advanced experience, China put forward the "Green Building Evaluation Standards" (GB/T50378-2019) in 2019, which is the core document of China's comprehensive evaluation standards for green buildings. At the same time, it provides a reference for the quantitative index of China's green building evaluation [17, 18].

This paper follows the path of "literature review–research design–case study–result, and discussion" (as shown in Figure 1). The remaining chapters are arranged as follows: The second section is literature review. The third section introduces the methods and research design, including research methods, model building, and simulation. The fourth section is the case analysis, combined with the digital cultural creative industry park office building project in a province in Southwest China, to form a green building design strategy with improvement direction. The fifth section gives the discussion and conclusion.

## 2. Literature Review

The main work of green buildings is to construct a scientific and reasonable evaluation index system and collect a large amount of building energy consumption data to analyze and optimize the methods and paths of improvement. Therefore, some experts and scholars mainly use energy consumption simulation methods to analyze green building energy consumption indicators. For example, Alves et al. [19] estimated the energy consumption intensity of Brazilian commercial buildings using a reference building model. Ko et al. [20] used BEMS for data acquisition and simulation prediction and established a benchmark prediction model based on cluster inversion technology. Dong et al. [21] used statistical theory to analyze building energy consumption and its related influencing factors in temperate zones of Singapore.

China has been conducting systematic research on the energy consumption of green buildings since the 1980s and has developed this area for over 30 years now [22]. The rise of green building in China is closely related to the process of urbanization and differs markedly from the context in which green building has been developed in other countries during the process of urbanization [23, 24]. A Chinese scientific research organization researched 31 projects for an operational energy consumption assessment study, which showed that green buildings have a positive effect on urban environmental improvement, but the actual operational energy consumption is not significantly related to star rating certification [25]. Jin et al.'s [26] study compared the US LEED and China's Green Building Evaluation Standard, pointing out the problems in China's green building evaluation. At the same time, puts forward suggestions such as the division of the whole life cycle and the content of economic evaluation parameters [26]. Currently, the world's mainstream green building evaluation standards include BREEAM (building research establishment environmental assessment method), CASBEE (comprehensive assessment system for building environmental efficiency), LEED, and China's "Green Building Evaluation Standard." Among the above standards, none of them has a clear economic evaluation subcomponent, except for GBC, which has some focus on the economics of buildings. This is partly due to the fact that green building studies are usually based on a full life cycle timeframe and buildings are implemented for a shorter period of time, resulting in insufficient data [27, 28].

BIM is an emerging digital design approach that was first proposed in the 1970s and gradually applied as a technical means in engineering design and construction management [29, 30]. Zhang et al. [31] used BIM to build a model, combined with green building design calculation and assessment, to clarify the advantages of BIM in achieving green and sustainable design. Not only that, BIM technology has significant advantages in analyzing green conditions and building performance, helping to maximize the use of natural resources, reduce energy consumption, and achieve the goal of building energy efficiency [32]. The application of BIM technology throughout the life cycle of a green building also provides effective recommendations for improving economic [33]. Xu [34] explained the use of BIM-related software to analyze the data of energy, material, and water saving schemes from design optimization and simulation experiments in the design stage. In addition, the optimization and improvement of the indoor environment have been simulated in the operation stage to improve the work efficiency. BIM can store all relevant parameters in the model and simplify data analysis through data exchange modes, providing a boost to building ecology and energy simulation [35]. Through the accumulation and comparative analysis of data in the BIM model of the whole life cycle can solve the problems of information silos in traditional project management [36, 37].

To sum up, the existing research has the following shortcomings: Firstly, there is insufficient research on the in-depth application of BIM technology in architectural design. Although the research emphasizes the deep integration mode of BIM and green building design, the actual deep integration research is still lacking, and more in-depth exploration and empirical research are needed. Second, there is a lack of comprehensive exploration of the relationship between building information data, green building life cycle carbon emissions, and evaluation indicators, especially the deep correlation between green building evaluation indicators and life cycle carbon emissions. Third, although existing studies focus on green building evaluation indicators and carbon emissions, the direct relationship between carbon emissions in the design stage and green building evaluation indicators has not been fully demonstrated.

## 3. Methods and Research Design

*3.1. Methods.* According to Darwin's theory of natural selection, it is proposed that living beings evolve through continuous reproduction and iteration. Each individual produced in reproduction inherits traits from their parents, with most being similar to the previous generation, while a few may have slight variations that gradually lead to the formation of new traits. As the number of individuals in a population increases due to reproduction, competition among individuals for limited resources results in the survival and reproduction of those with stronger adaptive abilities, while weaker individuals are eliminated. This process, known as "survival of the fittest," drives the evolution of species and promotes the superiority of the population, while the less favorable individuals are eliminated. This is the basic principle of genetic algorithms.

Genetic algorithms were first developed by Professor Holland to simulate biological systems in computer analysis and construct the technology for genetic algorithms [38]. Subsequently, the basic principles of genetic algorithms, the concept of genetic programing (GP), neural networks, and other related topics were proposed. These principles and basic operations have been widely applied in various fields for performance evaluation and target optimization and have received positive feedback, further promoting the development of target optimization research methods [39]. In recent years, with the advancement of computer technology, the theory of genetic algorithms has been continuously deepened and widely used to solve various decision optimization problems.

Traditional genetic algorithms, based on the principles of Darwinian evolution, assume the existence of an initial population. By setting certain mutation parameters and using selection, crossover, and mutation operators, a new population is generated. The fitness of the population is evaluated based on the objective function, and the process is repeated iteratively until the optimal solution is obtained [40]. Gu et al. [41] used a modular analysis approach in the genetic algorithm process, combining multiple modules for optimization. Tuhus-Dubrow and Krati [42] used genetic algorithms to simulate and calculate building energy consumption, analyzing the impact of building envelope structure design optimization on building energy consumption. Figure 2 illustrates the basic structure and process of the optimization design model proposed in this paper.

Machine learning techniques are widely used to optimize the performance of traditional optimization algorithms, including improved genetic algorithms (GA). The application of machine learning can automatically optimize the parameter setting, search strategy, and operator selection of genetic algorithms by training models [43]. The machine learning model can analyze a large number of algorithm operation data, learn the best parameter configuration and search strategy from it, and improve the performance and convergence speed of genetic algorithms [44]. Combining machine learning techniques to improve genetic algorithms can make genetic algorithms more suitable for complex, high-dimensional, and multiobjective optimization problems.

This article focuses on the optimization of green building design problems, considering multiple influential variables, setting multiple objective functions, and making it a multiobjective optimization problem. Considering the efficiency

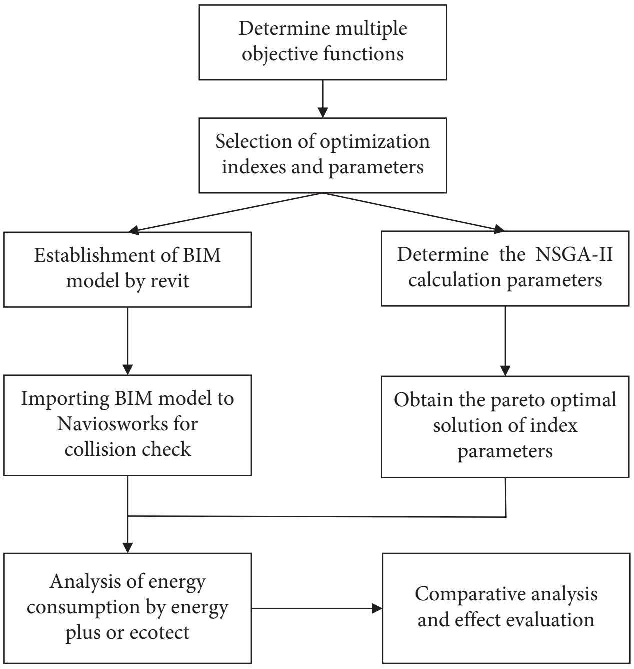


FIGURE 2: Basic structure and process of optimization design model.

and limitations of genetic algorithms in solving multiobjective optimization problems, this article establishes a green building design optimization algorithm model based on NSGA-II (nondominated sorting genetic algorithm) and proposes corresponding coding, initial population generation, crossover and mutation operators, and selection methods to determine the final optimization solution [45].

NSGA-II is a multiobjective optimization method that was developed by Deb et al. [46] in 1994 as an improvement to their previous method, NSGA, which was proposed in 2000. The main drawbacks of NSGA were high computational complexity, lack of elite preservation strategy, and the need to set sharing parameters. To eliminate these drawbacks, NSGA-II not only performs better in terms of computational complexity than traditional methods but also uses a more reasonable fitness allocation method to improve computational efficiency. At the same time, after multiple iterations, NSGA-II algorithm maintains population diversity, prevents the loss of excellent individuals, and increases the retention rate of population diversity, making it more suitable for multiobjective optimization research based on green building design optimization in this article.

*3.1.1. Multiobjective Optimization Problems.* BIM technology is widely used and has a significant impact on detecting design errors by conducting clash detection during the architectural design phase. However, for green building design, it not only needs to meet the requirements of traditional building design parameters and standards but also requires stricter design parameter constraints related to green building [47].

In a multiobjective optimization problem, different objectives are interrelated and affect each other, and even under certain conditions, conflicts may arise. Therefore, it is highly likely that in order to achieve a certain objective, the optimal solution for other objectives must be sacrificed, making it difficult to find an optimal solution that achieves optimal performance for all objectives [48]. Therefore, multiobjective optimization problems require a compromise between objectives to achieve a relatively optimal performance for each subobjective. The basic approach to solving multiobjective optimization problems is to set up a $m\,(m>1)$ dimensional objective space under multiple constraints and continuously optimize $n$-dimensional decision variables to find the optimal solution set [49]. Multiobjective optimization problems include two types of solving the maximum and minimum values of the objective function. Based on the research of this paper, a multiobjective optimization problem is used to solve the minimum value of the objective function, and it can be described by the following mathematical model:

$$\min y = F(x) = (f_1(x), f_2(x), \ldots f_m(x))^T, \tag{1}$$

$$s.t. \begin{cases} g_i(x) \le 0, i = 1, 2, \ldots, k \\ h_j(x) = 0, j = 1, 2, \ldots, l \end{cases}, \tag{2}$$

$$x = (x_1, x_2, \ldots, x_n)^T, \quad x_i \in [x_{\min}, x_{\max}], \quad i = 1, 2, \ldots n, \tag{3}$$

where $\min y$ is the optimal solution, $F(x)$ is a vector function, $f(x_n)$ is the component of the objective function, that is, the target value, $x$ represents the vector in which the decision variable is mapped to the target space, $g_i(x)$ is an inequality constraint, $h_j(x)$ is an equality constraint, $m$ is the number of target dimensions, and $n$ is the number of decision variable dimensions.

The traditional approach to multiobjective optimization is to assign different weights to different objectives and transform them into a single-objective optimization problem, which can be solved using dynamic programing. Weighted method, $\varepsilon$ constraint method, goal programing method, and extremum method can be used to allocate weights. It should be noted that the optimal combination solution of multiple single-objective optimization problems may not be unique. If multiple optimal solutions are obtained through multiple runs not only the optimization time is increased but also the optimization processes are independent of each other and lack parallelism, which cannot provide a reference value for the optimal solution. In 1986, French economist Pareto [50] proposed the Pareto optimal theory to solve multiobjective optimization problems, which outputs a set of Pareto optimal solution sets through Pareto optimization, solving the problem of traditional multiobjective optimization. The application of Pareto theory in multiobjective optimization problems mainly includes the following core concepts [51]:

(1) Feasible solution and feasible solution set. A decision vector $x$ satisfies $g_i(x) \le 0$ and $h_j(x) = 0$, then $x$ is a feasible solution. The set of all feasible solutions is called the feasible solution set.

(2) Optimal solution and optimal solution set. For a feasible solution $x^*$, if there is no $x \in X_f$ that satisfies $x \prec x^*$, then $x^*$ is a Pareto optimal solution, and the set of all Pareto optimal solutions is called the Pareto optimal solution set.

(3) Pareto optimal frontier. The surface of Pareto optimal solution set mapped from decision space to object space is called Pareto optimal frontier surface.

*3.1.2. Optimization by NSGA-II.* With the improvement of multiobjective optimization theory and swarm intelligence evolutionary algorithms, multiobjective optimization algorithms have become an important tool for researching multiobjective optimization problems due to their advantages of good operation parallelism, strong global search ability, wide applicability, robustness, and fast convergence speed. Currently, common multiobjective optimization algorithms include vector evaluated genetic algorithm (VELA) [52], multiobjective genetic algorithm (MOGA) [53], niched Pareto genetic algorithm (NPGA) [54], nondominated sorting genetic algorithm (NSGA), Nondominated Sorting Genetic Algorithm-II (NSGA-II) [55], strength Pareto evolutionary algorithm (SPEA) [56], and Strength Pareto Evolutionary Algorithm-II (SPEA-II) [57]. First, NSGA-II adopts the nondominated sorting technique, which can generate a set of nondominated solution sets and provide more options. Second, it has good convergence and diversity in finding solution sets, which can simultaneously maintain the balance and diversity of the solutions to avoid falling into the locally optimal solutions. Third, the parameter setting is relatively simple, which improves the computational efficiency; and last, NSGA-II is applicable to multiple domains of multiobjective optimization problems without the limitation of problem complexity. Thus, NSGA-II not only retains excellent individuals from the parent population and maintains population diversity but also has advantages such as strong global search ability, fast convergence speed, high execution efficiency, and good robustness. NSGA-II has been widely used in fields such as electric power, chemical industry, logistics, line scheduling, and architectural design. In the past decade, more and more different professional design optimization problems in the field of architecture have used NSGA-II for multiobjective optimization. This study is based on the two dimensions of green building energy consumption and green evaluation value, the application of NSGA-II involves the selection of key parameters, which include the number of generations and mutation rate. The choice of the number of generations directly affects the number of iterations and search space of the NSGA-II algorithm, and the choice of the mutation rate involves the understanding of the problem and experimental tuning. Through experiments and analyses, the mutation rate is adjusted to ensure that sufficient variation is introduced in the genetic operation. The specific process includes the following steps:

*(1) Initializing Population $P_t(t = 0)$.* Initialize a parent population $P_t(t=0)$ with a size of $N$. For each randomly generated chromosome, it needs to be compared with all previously generated individuals. If it is different, it is added to the initial population. If it is the same, it is discarded to ensure the diversity of the population.

Currently, there are many methods for initializing populations, and the most widely used is random initialization. Random initialization method is easy to execute, and the generated population has good diversity and distribution. In this study, random initialization method is used to initialize the population.

*(2) Rank Separation and Crowding Distance Calculation.* Perform nondominated sorting on the population, with higher levels indicating higher fitness. Use crowding distance to measure the fitness of individuals in the same nondominated level. The crowding distance of an individual is calculated as follows: set the crowding distance of individuals on the sorting edge to infinity, and the crowding distance of individuals in the middle is calculated using the Formula (4):

$$i_d = \sum\left(\overset{i+1}{f}_j - \overset{i-1}{f}_j\right)\left(\overset{\max}{f}_j - \overset{\min}{f}_j\right), \tag{4}$$

where $\overset{i+1}{f}_j$ represents the value of the $j$th objective function of point $i+1$ and $\overset{\max}{f}_j$ and $\overset{min}{f}_j$ are the maximum and minimum values of the $j$th function, respectively.

After the fast nondominated sorting and crowding distance calculation, each individual $i$ in the population has a nondominated rank $i_{\mathrm{rank}}$ and a crowding distance $i_d$ determined by the nondominated sorting. Therefore, a crowding comparison operator can be defined to compare individual $i$ with another individual $j$. If any of the following conditions is true, individual $i$ wins:

(i) If the nondominated layer of individual $i$ is superior to the nondominated layer of individual $j$, then it is $i_{\mathrm{rank}} < j_{\mathrm{rank}}$. If they have the same rank and individual $i$ has a larger crowded distance than individual $j$, then it is $i_{\mathrm{rank}} < j_{\mathrm{rank}}$ and $i_d > j_d$.

(ii) The first condition ensures that the selected individual belongs to a better nondominated level. The second condition selects the individual with a larger crowding distance among two individuals located in the less crowded area and belonging to the same nondominated level. The winning individual enters the next operation.

*(3) Binary Tournament.* The tournament selection strategy in genetic algorithm selects a certain number of individuals (with replacement) from the population each time, and then selects the best individual among them to enter the offspring population. Repeat this operation until the new population size reaches the original population size. A $k$-way tournament selects several individuals from the population at once and selects the best individual from them to enter the set reserved for the next generation. As shown in Figure 3, the specific steps are as follows:

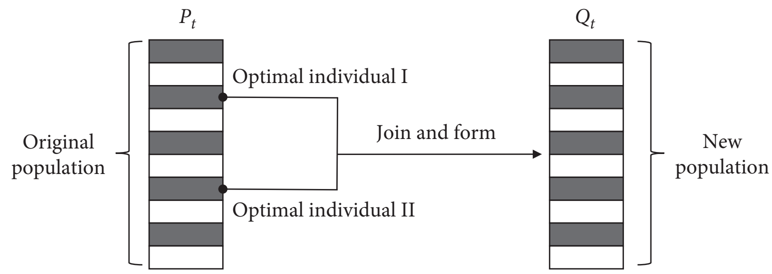


FIGURE 3: Concept of binary tournament selection.

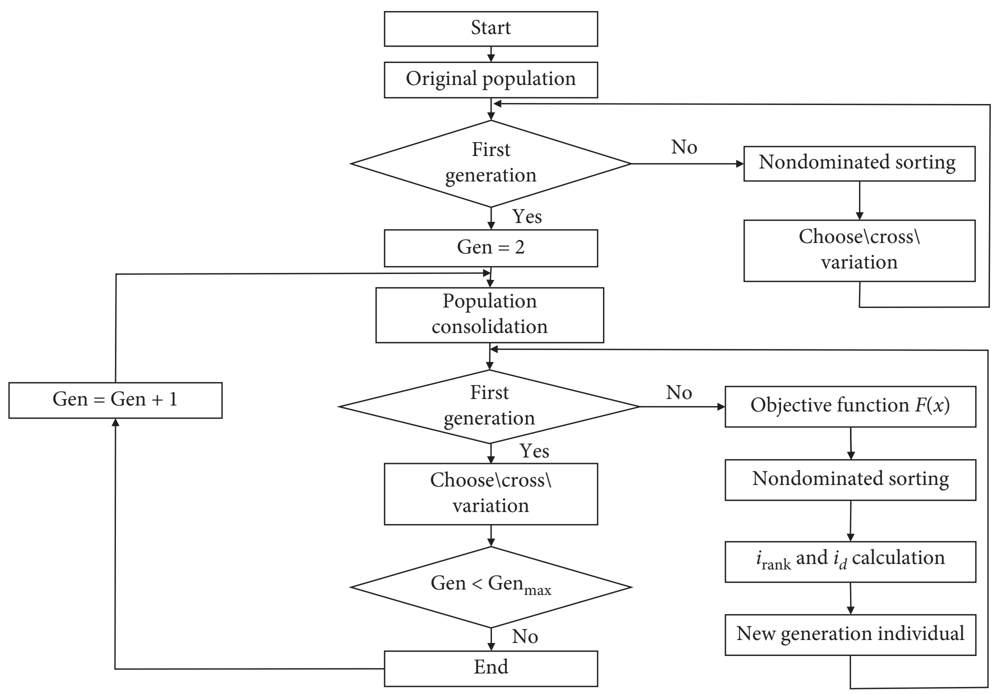


FIGURE 4: NSGA-II optimization algorithm concept and process.

(i) Determine the number $N$ of individuals to be selected each time (binary tournament selection means selecting two individuals).

(ii) Randomly select $N$ individuals from the population (each individual is selected with the same probability), and select the individual with the best fitness value among them to enter the next generation population.

(iii) Use crossover and mutation methods to produce two offspring each time and repeat the crossover and mutation process until a new population $Q_t$ with the same size as $N$ is generated.

*(4) Population Merge.*

(i) Combine the parent population $P_t$ and the offspring population $O_t$ into a new population $H_t$ with a size of $2N$.

(ii) Sort the population $H_t$ by nondominated ranks and calculate the crowding distance and produce the new population $P_{t+1}$.

(iii) Remove identical chromosomes in the new population, sort them by nondominated ranks and calculate the crowding distance, and select the top $N$ individuals with higher fitness to form the new population $P_{t+1}$.

The NSGA-II optimization algorithm concept and process are shown in Figure 4.

It is worth to note that NSGA-II suffers from drawbacks such as the inhomogeneity of the distribution of the Pareto optimal solution set, it does not guarantee that the nondominated solution set covers the entire Pareto front. To improve the NSGA-II algorithm, the concept of dynamic crowding degree is introduced. On the one hand, the idea of constrained nondominated ordering of NSGA-II for solving nonlinear multiobjective optimization problems is considered, while the dynamic crowding degree strategy is introduced to optimize the population distribution during the nondominated ordering process to obtain the Pareto frontiers that are closer to the true values. On the other hand, it can effectively avoid the shortcomings of traditional

Table 1: Green building evaluation standards of China and BIM technology applications.

| Evaluation standard of green building in China | Content | Parameter | Series of BIM software |
|---|---|---|---|
| Land saving | Building area, floor area ratio, green land ratio, etc. | Area statistics | Revit |
| | Architectural lighting | Lighting analysis | Ecotect |
| | Outdoor environment noise | Noise analysis | Sound |
| | Natural ventilation | Ventilation analysis | Fluent |
| | Natural landform | Landform analysis | Revit, Glodon |
| Energy saving | Energy consumption calculation | Energy consumption intensity | Revit, Glodon,Thsware |
| | Energy consumption of renewable energy equipment | Energy consumption intensity | |
| | Building shape, orientation parameters analysis | Window–wall ratio, visible light transmission ratio, etc. | |
| | Thermal performance of structure | Material parameter calculation | |
| | Energy consumption monitoring | Energy consumption intensity analysis, energy consumption optimization | Energy Plus |
| | Energy consumption of electromechanical equipment | Ventilation, heating, air-conditioning, elevator, etc. | |
| Water saving | Water metering device | Water consumption calculation | Revit, Glodon, Thsware |
| | Water-saving measures | Water-saving analysis | |
| Material saving | Building structure | Structural analysis | PKPM |
| | Architectural design | Building model | Revit |
| | Material consumption statistics | Material consumption analysis | Revit |
| Indoor environmental quality | Indoor environment noise | Noise analysis | Sound |
| | Natural ventilation | Ventilation analysis | Fluent |
| | Natural lighting | Lighting analysis | Dali, Radiance |
| | Building space | Optimize indoor space | Revit, Glodon, Thsware |

selection methods that rely too much on experience, so that the optimal design can be upgraded from empirical design to theoretical design. The calculation of dynamic congestion is shown in Formula (5):

$$\mathrm{DCD}_i = \frac{\mathrm{CD}_i}{\log\left(1/V_i\right)}. \tag{5}$$

*3.1.3. Building Energy Analysis Method Based on BIM Technology.* When using BIM models created in Revit for green building performance analysis, the current mainstream software includes Ecotect Analysis and EnergyPlus. Model conversion and data exchange between software are usually done using gbXML or DXF formats. In the building design stage, the BIM model is constructed and relevant parameters for green building special analysis are applied using the software, as shown in Table 1.

The core content of green building evaluation in China includes sun shading analysis, thermal analysis, energy analysis, ventilation analysis, etc. Traditional analysis methods focus on data calculation but lack the connection between different professions. BIM technology provides the basis for integrated design, allowing the calculation of different parameters from different professions to be integrated and providing visualization functions. Chinese software development companies such as Glodon and SWE have built collaborative design platforms to provide comprehensive energy-saving analysis reports for designers and provide a systematic reference for optimizing the design of green buildings.

*3.2. Model Establishment.* The paper describes a research focused on energy optimization in green building design for a residential construction project. The study uses the whole-process energy consumption as the performance evaluation indicator and follows the evaluation criteria specified in the "Green Building Evaluation Standard" (GB/T50378-2019) to establish the green building assessment level. Genetic algorithm and energy consumption software are employed to optimize the building integrated design for multiple variables including building orientation (BO), roof structure, selection of transparent insulation materials, and building spacing. The objective function is defined as Formula (6):

$$\min F(x) = \begin{cases} \min f_1(x) \\ \max f_2(x) \end{cases}, \tag{6}$$

where $f_1(x)$ is the annual average value of the project's energy consumption over its entire life cycle, considering the total energy consumption of multiple stages such as material production, construction, operation, and dismantling, and calculated

Table 2: Genetic algorithm code settings for green building influencing factors indicators.

| No. | Object | Index | Code |
|---|---|---|---|
| 1 | Total life cycle energy consumption | Material production energy consumption | 0000 |
| 2 | | Construction energy consumption | 0001 |
| 3 | | Operating energy consumption | 0010 |
| 4 | | Demolition energy consumption | 0011 |
| 5 | Green evaluation evaluation value | Building orientation | 0100 |
| 6 | | Roof material | 0101 |
| 7 | | Glass selection | 0110 |
| 8 | | Ventilation area ratio | 0111 |
| 9 | | Window–wall ratio | 1000 |
| 10 | | Exterior rall material | 1001 |

based on a 50-year service life for public buildings. $f_2(x)$ is the green building evaluation value, evaluated based on multiple projects according to the current "Green Building Evaluation Standard" (GB/T 50378-2019), and the objective function is the maximum evaluation value, as represented by Formula (7):

$$\max f_2(x) = f_{i1}(x) + f_{i2}(x) + \cdots + f_{it}(x). \tag{7}$$

The indicator system established in this study considers two aspects of energy consumption. First, the energy consumption levels at various stages of the building's lifecycle are considered, and the lowest energy consumption is set as the objective function for optimization. Therefore, the energy consumption indicators for the four stages of material production energy consumption, construction energy consumption, operating energy consumption, and demolition energy consumption are set as optimization factor indicators. The calculation of these indicators relies on China's green building standards, adjusted according to regional climate characteristics, and measured in electric energy consumption (kW·hr/m$^2$) and converted into a comprehensive calculation of carbon emissions based on a carbon emission factor of 0.5810, determined according to IPCC guidelines and China's latest standards.

Second, the energy consumption indicators for the parameters related to green building design are considered as optimization factor indicators, including six factors such as BO, roof material (RM), glass selection (GS), ventilation area ratio (VAR), window–wall ratio, and exterior wall material (EWM). In conducting multiobjective optimization design of the building, it is necessary to first analyze and organize the influencing factors of the building design. Based on the parameters observed in the BIM software series and relevant literature support, the specific factors and genetic code settings are shown in Table 2.

*3.3. Data Simulation.* Based on the indicator system in Table 2, the parameter ranges or combinations were further clarified to determine the constraints of the multiobjective optimization function. In the energy consumption target of the whole life cycle, the energy consumption level of the four stages is a continuous variable. According to the hot summer in Southwest China, reasonable building layout can effectively guide the flow of natural wind between building blocks to strengthen indoor natural ventilation and improve indoor comfort in summer and transition season. The parameters related to green low-carbon buildings that reduce energy consumption such as air conditioning energy consumption require the variable range to be determined, and the annual carbon emissions per unit building area are converted according to the carbon emission factor.

With the rapid development of China's urbanization construction, the theory and practice of green building have gradually moved toward systematization, and China's green building standard system has been established. However, at the same time, a large number of green building designs often rely too much on equipment technology, ignore the regional natural environment, pay less attention to climate, region, and the lifestyle of users, and lack in-depth research on traditional regional design and construction systems. Therefore, in the process of model building, this paper not only carries out optimization analysis from the perspective of multiple objectives but also makes targeted selection by fully considering the natural environment and human characteristics of different regions in the process of screening specific indicators.

Optimizing BO maximizes the use of natural light and heat, which will reduce indoor energy demand. Good roof construction provides effective insulation, thus reducing the impact of high summer temperatures on the interior of the building and the frequency of air conditioning use [58]. The right type of glazing balances thermal insulation with natural light to avoid energy consumption and improve comfort. Reasonable increase of effective ventilation area ratio can improve indoor air quality, contributing to occupant health and comfort. A moderate window-to-wall ratio can provide good natural lighting and ventilation, reducing indoor artificial lighting and energy use [59]. The choice of façade materials is not only about energy efficiency but also affects the aesthetics and long-term stability of the building, providing effective thermal insulation and reducing heat transfer and energy loss [60].

Therefore, in the green building design evaluation target of this study, six indicators have been chosen: BO, RM, GS, VAR, window–wall ratio (WR), and EWM. Among them, BO, VAR, and WR are continuous variables, while RM, GS, and EWM are discrete variables. The specific parameters and selections are shown in Table 3.

Table 3: Types and parameters of energy consumption impact factors in green building.

| No. | Object | Index | Type | Code | Parameter |
|---|---|---|---|---|---|
| 1 | Total life cycle energy consumption | Material production energy consumption | Continuous | 0000 | (65, 90) (Carbon emission: kg·m$^2$/y) |
| 2 | | Construction energy consumption | | 0001 | (40, 70) (Carbon emission: kg·m$^2$/y) |
| 3 | | Operating energy consumption | | 0010 | (75, 100) (Carbon emission: kg·m$^2$/y) |
| 4 | | Demolition energy consumption | | 0011 | (20, 45) (Carbon emission: kg·m$^2$/y) |
| 5 | Green building evaluation value | Building orientation | Continuous | 0100 | (175°, 345°) |
| 6 | | Roof material | Discrete | 0101 | R1: 50 mm lightweight aggregate concrete + 6 mm waterproof + 10 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R2: 50 mm lightweight aggregate concrete + 6 mm waterproof + 20 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R3: 50 mm lightweight aggregate concrete + 6 mm waterproof + 30 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R4: 50 mm lightweight aggregate concrete + 6 mm waterproof + 40 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R5: 50 mm lightweight aggregate concrete + 6 mm waterproof + 50 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R6: 50 mm lightweight aggregate concrete + 6 mm waterproof + 60 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R7: 50 mm lightweight aggregate concrete + 6 mm waterproof + 70 mm EPS board + 150 mm concrete + 400 mm furred ceiling<br>R8: 50 mm lightweight aggregate concrete + 6 mm waterproof + 80 mm EPS board + 150 mm concrete + 400 mm furred ceiling |
| 7 | | Glass selection | Discrete | 0110 | G1:Sgl-Clr<br>G2:Sgl-LoEClr<br>G3:Dbl-Clr<br>G4:Dbl-LoEClr |
| 8 | | Ventilation area ratio | Continuous | 0111 | (10%, 30%) |
| 9 | | Window–wall ratio | Continuous | 1000 | (10%, 90%) |
| 10 | | Exterior wall material | Discrete | 1001 | W1: 10 mm tile + 10 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W2 : 10 mm tile + 20 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W3 : 10 mm tile + 30 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W4 : 10 mm tile + 40 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W5 : 10 mm tile + 50 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W6 : 10 mm tile + 60 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W7 : 10 mm tile + 70 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W8 : 10 mm tile + 80 mm EPS board + 200 mm concrete block brick + gypsum plaster<br>W9 : 10 mm tile + 90 mm EPS board + 200 mm concrete block brick + gypsum plaster |

The optimization algorithm used in this study is the MOGA, which is implemented by calling the GA function in MATLAB 2016b through partial programing. In the parameter settings, the crossover probability and mutation probability have a crucial impact on the behavior and performance of the GA algorithm and also affect the convergence speed and effect. A higher crossover probability leads to a faster generation of new individuals but may destroy the genetic patterns and result in the loss of individuals with high fitness. Conversely, a lower crossover probability may slow

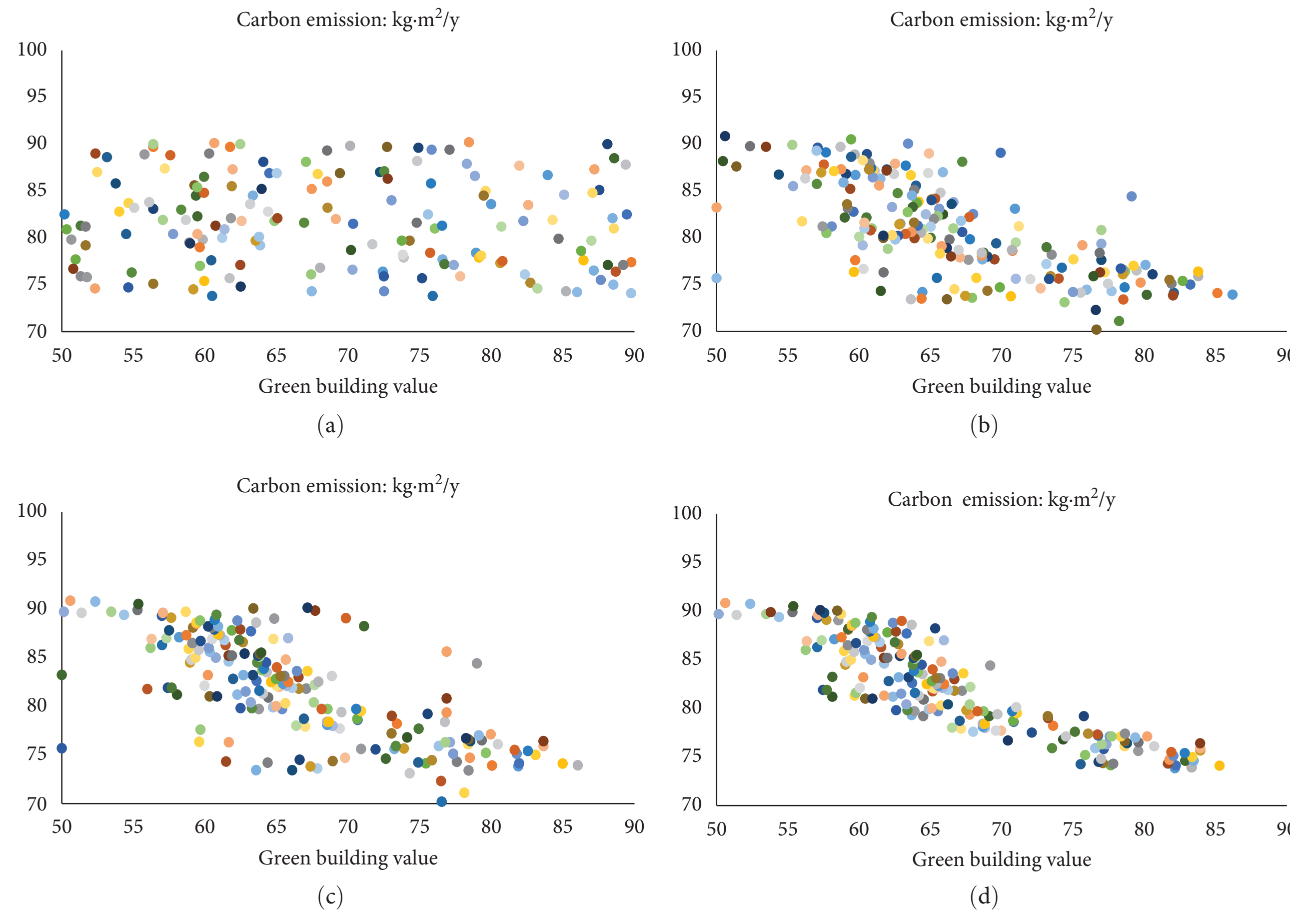


Figure 5: Convergence of Pareto solutions based on objective functions: (a) iteration once, (b) iteration 25 times, (c) iteration 50 times, and (d) iteration 100 times.

down or even stall the optimization process. Generally, the crossover probability is recommended to be set between 0.9 and 0.97. The mutation probability is usually set between 0.001 and 0.1, and a smaller value makes it difficult to generate new individuals while a larger value may lead to a completely random trend. In this optimization calculation, refer to the calculation conditions in Wang et al.'s [61] and Li et al.'s [62, 63] studies, and further determine the parameters set as crossover probability = 0.9, the mutation probability = 0.02, the maximum number of iterations is set to 100, and the population size is set to 200. One, 25, 50, and 100 iterations were selected for observation to summarize the convergence pattern and extract the Pareto optimal solution, as shown in Figure 5.

The hypervolume measurement is the area (or hypervolume, HV) of the area enclosed by several hypercubes. For a population set, the hypervolume measurement is equal to the area of the shadow region. In general, if a population has a larger hypervolume measurement value, it is considered that the quality of the population is better. Fleischer [64] proved in literature that the set is Pareto optimal when its hypervolume index reaches the maximum. However, it should be noted that the time complexity of the algorithm usually used to calculate the hypervolume index increases exponentially with the increase in the number of targets [65, 66]. Therefore, it takes a long time for traditional computational methods to optimize problems with many subobjectives. Therefore, this study is based on the method in Basak et al.'s [67] study, that is, the contribution of an individual to the hypervolume index of the population can be reflected by the hypervolume index of the independent dominated area of the individual, and directly calculating the hypervolume index of the independent dominated area of the individual will reduce the time cost to a certain extent.

The HV calculation formula is shown in Formula (8):

$$\mathrm{HV} = \lambda\left(U_{i=1}^{|s|} v_i\right), \tag{8}$$

where $S$ is the set of target vectors obtained by the algorithm, $\lambda$ is the measure, and $v_i$ is the region dominated by each individual and reference point. The hypervolume indicator area obtained for Pareto optimization is shown in Figure 6.

As shown in Figures 5 and 6, after iterating the multi-objective function constructed by 10 factors using genetic algorithm, ideal convergence effect is obtained with the increase of iteration times. The HV indicator area reaches maximum stability in iterative optimization. And the convergence trend is from bottom to top and from left to right, indicating that the energy consumption level of the target

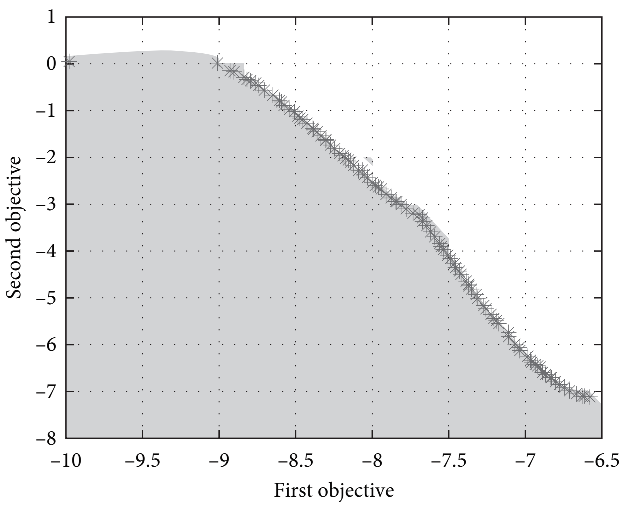


Figure 6: Hypervolume indicator region of the Pareto solution set.

Figure 7: Renderings of the case project.

building gradually tends to be stable, and the median of the optimized green building evaluation value moves to the right, and the overall evaluation level is improved.

## 4. Case Study

*4.1. Project Overview.* Based on the aforementioned research conditions, in order to further verify the feasibility of using genetic algorithm for energy-efficient design optimization of green buildings, this study selected the data of an office building project in the digital cultural and creative industry park of a southwestern province in China as a case study. The project has a total building area of 29,940 $m^2$, six floors above ground, and a building height of 30.2 m. The main structure is a frame structure, with a total cost of about 40.85 million yuan. The project's building exterior is designed with green building concepts, with a building curtain wall as the enclosure structure and equipped with LED intelligent lighting system. The shape is simple, avoiding a large number of decorative components. Compared with general wall structures, it has the advantages of strong lighting, moisture resistance, light weight, easy disassembly, easy maintenance, and long service life. The unique accordion-style corner curtain wall can reduce unnecessary heat and achieve the unity of low carbon and aesthetics, meeting the requirements of green buildings, as shown in Figure 7.

The project was modeled in BIM using Revit software, including structural, architectural, and MEP models, which were then integrated (as shown in Figure 8), providing the basis for further energy analysis.

During the collision detection process of the optimized structural model, the location of collisions can be accurately determined through collision detection, which can timely solve design blind spots that are not easy to find, and effectively improve the design quality and the work efficiency of designers. In this project, Revit collaboration function was used to perform collision detection for each specialty, and more than 500 collisions were found and adjusted in the pipeline layout. Fuzor software was used for net height analysis of the project, and after multiple rounds of modifications and docking, the average compression of the pipeline height was 10 cm, and the interfloor net height was increased by 2.5%, as shown in Figure 9.

### *4.2. Scheme Optimization and Sensitivity Analysis*

*4.2.1. Scheme Optimization.* The original design scheme of the case project, which was obtained through collision inspection, was used as the initial scheme. Based on the optimization in Sections 3.2 and 3.3, of this article, and all Pareto values and their corresponding parameter values are arranged in ascending order of $CO_2$ emission values from low to high, as shown in Table 4.

It can be seen in Figure 10 that after multiobjective optimization, the Pareto frontier of the project is formed based on the two dimensions of carbon emission and green building evaluation value, indicating that the optimization of the project has significant convergence and satisfactory optimization results have been obtained.

*4.2.2. Sensitivity Analysis.* Sensitivity analysis is a descriptive tool for quantitative models. Sensitivity analysis on the parameters could help further validate the robustness of the obtained optimal solutions. Sensitivity analysis can be divided into single factor sensitivity analysis and multifactor sensitivity analysis. Considering that the calculation process of multifactor sensitivity analysis is complicated and there may be interaction among various related factors, single factor sensitivity analysis is more common. The sensitivity analysis tool adopted in this paper is single factor sensitivity analysis.

In the specific calculation process, assuming that other factors remain unchanged, let a factor increase by 1%, so as to obtain the sensitivity coefficient of the factor. The sensitivity coefficient is calculated, as shown Tables 5 and 6.

The concept of sensitivity factors points out that the factors with large changes do not mean that they have a large impact on the valuation results, and only the factors with large absolute values of sensitivity coefficients are the most important factors for the valuation results. Therefore, it can be found that OEC has the greatest impact on carbon emission in the whole life cycle, followed by CEC, MPEC, and OEC. In the index of green evaluation value, VAR has a significant impact on carbon emission. From the perspective of the evaluation value of green buildings, OEC has the greatest impact on carbon emission in the whole life cycle, followed by CEC, MPEC, and OEC. VAR and WR among the

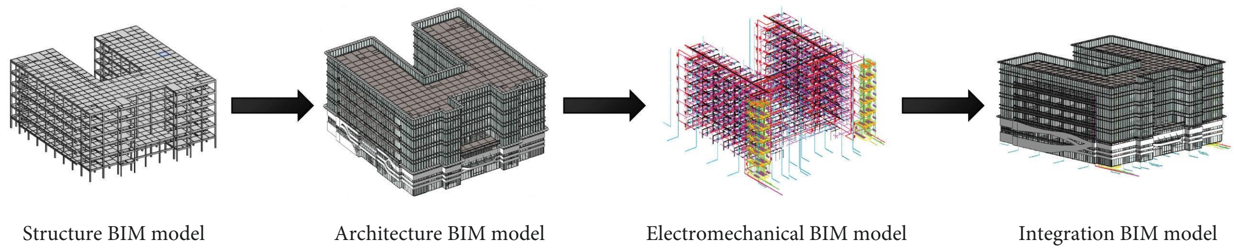


FIGURE 8: Multidisciplinary BIM model integration.

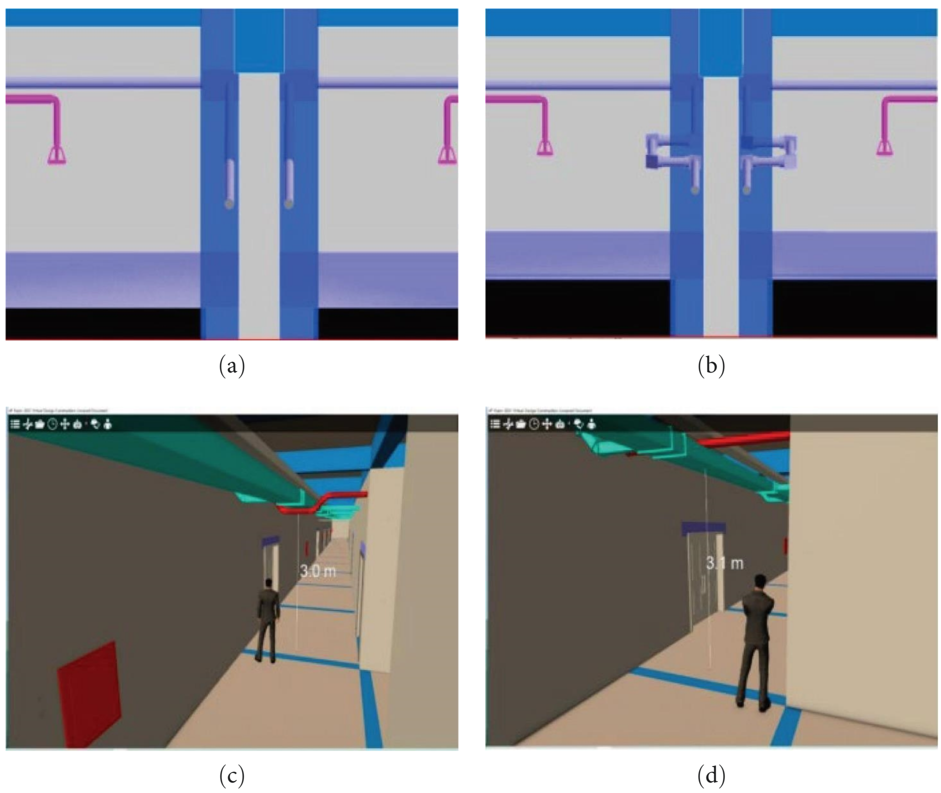


FIGURE 9: Navisworks is used for BIM model collision detection. (a) Part of the pipeline before optimized design, (b) part of the pipeline after optimized design, (c) building storey height before optimized, and (d) building storey height after optimized.

index of green evaluation value have a more significant impact on the evaluation value of green buildings. Through the above 20 Pareto values and their corresponding parameter values, it is found that the selected index system has relative stability, which enhances the reliability of the optimization results.

*4.3. Effect Evaluation of Optimization.* After obtaining the parameter value combinations corresponding to the Pareto optimal solutions in Table 4, three data sets were established to evaluate the overall optimization effect of the parameter value combinations obtained through genetic algorithm. The first parameter to be calculated is the maximum energy-saving rate, which represents the maximum energy-saving space of the optimized scheme and is calculated as Formula (9):

$$U_{\max} = (E_{\max} - E_0)/E_0. \tag{9}$$

The second is the average energy-saving rate, which is calculated using Formula (10) and represents the average energy-saving space of all optimized solutions:

$$\overline{U} = \sum_{t=1}^{T} (E_t - E_0)/nE_0. \tag{10}$$

The calculation formula for the increment of green building rating score is shown in Formula (11):

$$V_{\max} = (V_{\max} - V_0)/V_0, \tag{11}$$

where $E_0$ is the annual energy consumption of the original building design, measured in kW·hr, $E_{\max}$ is the maximum annual energy consumption value among all the optimized solutions in the Pareto solution set, also measured in kW·hr,

Table 4: The parameter values of the Pareto solution set.

| No. | Index of total life cycle energy consumption | | | | Index of green evaluation value | | | | | | $CO_2$ (kg) | Green evaluation value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MPEC | CEC | OEC | DEC | BO | RM | GS | VAR | WR | EWM | | |
| 1 | 78 | 50 | 77 | 24 | 200.91 | R3 | G1 | 17.11 | 62.04 | W6 | 74.35 | 81.64 |
| 2 | 82 | 54 | 75 | 43 | 199.59 | R7 | G3 | 10.38 | 74.17 | W9 | 75.05 | 80.98 |
| 3 | 90 | 60 | 75 | 34 | 203.86 | R4 | G2 | 19.89 | 64.18 | W5 | 75.61 | 79.75 |
| 4 | 78 | 52 | 79 | 20 | 200.54 | R2 | G1 | 25.18 | 46.45 | W7 | 75.65 | 78.96 |
| 5 | 70 | 70 | 81 | 31 | 202.29 | R8 | G4 | 27.28 | 47.33 | W8 | 76.31 | 78.53 |
| 6 | 66 | 58 | 83 | 31 | 200.96 | R1 | G2 | 14.14 | 66.76 | W5 | 77.22 | 74.09 |
| 7 | 81 | 67 | 80 | 35 | 205.78 | R4 | G4 | 20.61 | 39.24 | W5 | 78.39 | 69.74 |
| 8 | 65 | 61 | 86 | 33 | 208.08 | R2 | G3 | 27.51 | 76.23 | W3 | 79.35 | 67.55 |
| 9 | 84 | 43 | 84 | 35 | 195.93 | R3 | G2 | 13.16 | 54.79 | W8 | 80.21 | 67.14 |
| 10 | 69 | 63 | 88 | 36 | 193.46 | R8 | G2 | 26.87 | 85.90 | W4 | 80.75 | 66.79 |
| 11 | 82 | 49 | 87 | 26 | 193.85 | R5 | G3 | 27.97 | 87.91 | W5 | 81.56 | 65.37 |
| 12 | 90 | 60 | 85 | 37 | 206.37 | R4 | G1 | 13.12 | 73.62 | W6 | 82.23 | 64.09 |
| 13 | 88 | 57 | 86 | 45 | 192.81 | R7 | G4 | 24.80 | 41.37 | W3 | 83.54 | 63.78 |
| 14 | 73 | 54 | 91 | 35 | 192.30 | R4 | G2 | 12.88 | 69.79 | W2 | 84.33 | 62.02 |
| 15 | 80 | 55 | 91 | 33 | 202.22 | R6 | G3 | 25.04 | 80.67 | W4 | 85.61 | 61.92 |
| 16 | 73 | 47 | 97 | 23 | 201.67 | R8 | G2 | 16.21 | 38.33 | W4 | 87.24 | 60.57 |
| 17 | 79 | 52 | 96 | 32 | 199.72 | R2 | G1 | 29.83 | 66.10 | W2 | 88.36 | 59.41 |
| 18 | 84 | 70 | 95 | 34 | 208.00 | R3 | G1 | 27.56 | 82.60 | W3 | 89.33 | 58.53 |
| 19 | 90 | 61 | 94 | 38 | 199.13 | R2 | G4 | 29.71 | 80.04 | W1 | 90.05 | 58.02 |
| 20 | 87 | 52 | 95 | 41 | 193.21 | R8 | G3 | 18.55 | 45.83 | W2 | 90.47 | 57.84 |

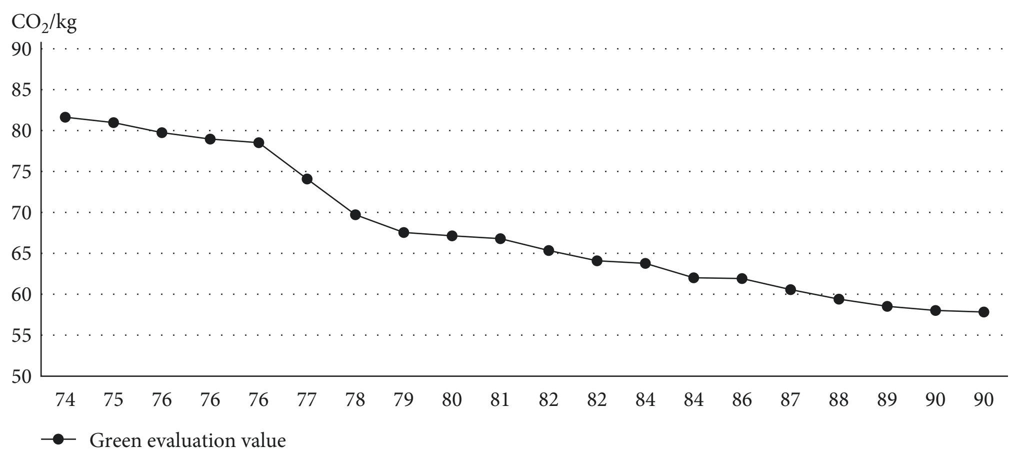


Figure 10: Optimized Pareto front surface.

$E_t$ is the annual energy consumption value of the $t$-th optimized solution, measured in kW·hr, $U_{\max}$ is the maximum energy savings rate, $\overline{U}$ stands for average energy-saving rate, $V_{\max}$ is the maximum value of the green building rating among all the solution sets, while $V_0$ is the green building rating value of the original building design.

After calculation, $U_{\max}$ is 0.081, $V_{\max}$ is 0.181, $\overline{U}$ is 0.0702. This means that through reasonable optimized design in the design stage, the green building evaluation score of 18.1% can be improved by reducing its energy consumption by 8.1%. The average energy-saving rate of 7.02% indicates that the average effect of the optimized solutions is significant, and the average energy-saving rate of all the optimized solutions has reached the expected level.

Based on the optimization results of the parameter values corresponding to the Pareto solution set in Table 4, and in combination with the two indicators of life-cycle energy consumption and green building evaluation, the analysis yields Figure 11.

It can be observed in Figure 10 that after optimization using genetic algorithms, the range of the life cycle energy consumption values in the Pareto solution set fluctuates

Table 5: Factor sensitivity coefficient of carbon emission.

| No. | Index of total life cycle energy consumption | | | | Index of green evaluation value | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | MPEC | CEC | OEC | DEC | BO | RM | GS | VAR | WR | EWM |
| 1 | 4.993 | 2.458 | 7.971 | 0.701 | 0.578 | 0.428 | 0.235 | 1.467 | 0.626 | 0.145 |
| 2 | 4.339 | 2.165 | 2.169 | 0.325 | 0.612 | 0.368 | 0.107 | 1.109 | 0.496 | 0.358 |
| 3 | 2.156 | 1.402 | 1.953 | 0.39 | 0.972 | 0.395 | 0.198 | 1.466 | 0.709 | 0.193 |
| 4 | 4.721 | 1.196 | 3.053 | 0.456 | 0.712 | 0.336 | 0.139 | 1.293 | 0.46 | 0.222 |
| 5 | 3.279 | 1.765 | 6.948 | 0.361 | 0.599 | 0.394 | 0.177 | 1.01 | 0.398 | 0.129 |
| 6 | 2.665 | 2.724 | 6.657 | 0.313 | 0.728 | 0.393 | 0.121 | 1.138 | 0.541 | 0.302 |
| 7 | 3.988 | 5.586 | 6.576 | 0.585 | 0.568 | 0.367 | 0.213 | 1.358 | 0.446 | 0.388 |
| 8 | 3.285 | 6.111 | 6.061 | 0.758 | 0.819 | 0.374 | 0.249 | 1.133 | 0.663 | 0.143 |
| 9 | 2.688 | 5.438 | 6.015 | 0.733 | 0.764 | 0.397 | 0.174 | 1.319 | 0.916 | 0.231 |
| 10 | 1.099 | 3.155 | 2.464 | 0.741 | 0.984 | 0.394 | 0.2 | 1.056 | 0.606 | 0.12 |
| 11 | 4.25 | 2.291 | 6.207 | 0.415 | 0.618 | 0.321 | 0.128 | 1.454 | 0.8 | 0.187 |
| 12 | 1.782 | 4.11 | 6.249 | 0.946 | 0.615 | 0.437 | 0.125 | 1.395 | 0.96 | 0.29 |
| 13 | 2.851 | 5.622 | 5.398 | 0.143 | 0.842 | 0.464 | 0.104 | 1.388 | 0.93 | 0.23 |
| 14 | 1.928 | 5.139 | 1.279 | 0.4 | 0.801 | 0.363 | 0.192 | 1.136 | 0.462 | 0.346 |
| 15 | 1.049 | 5.986 | 3.342 | 0.535 | 0.682 | 0.471 | 0.121 | 1.397 | 0.358 | 0.148 |
| 16 | 0.915 | 2.306 | 3.542 | 0.755 | 0.727 | 0.493 | 0.133 | 1.216 | 0.443 | 0.328 |
| 17 | 4.409 | 6.404 | 8.399 | 0.773 | 0.784 | 0.442 | 0.251 | 1.373 | 0.5 | 0.167 |
| 18 | 2.618 | 1.6 | 8.62 | 0.989 | 0.726 | 0.487 | 0.169 | 1.128 | 0.475 | 0.276 |
| 19 | 3.317 | 3.454 | 8.452 | 0.375 | 0.979 | 0.445 | 0.282 | 1.332 | 0.799 | 0.33 |
| 20 | 4.183 | 2.633 | 1.485 | 0.614 | 0.965 | 0.42 | 0.279 | 1.07 | 0.478 | 0.189 |
| Max | 4.993 | 6.404 | 8.62 | 0.989 | 0.984 | 0.493 | 0.282 | 1.467 | 0.96 | 0.388 |
| Min | 0.915 | 1.196 | 1.279 | 0.143 | 0.568 | 0.321 | 0.104 | 1.01 | 0.358 | 0.12 |
| Difference ratio | 0.82 | 0.81 | 0.85 | 0.86 | 0.42 | 0.35 | 0.63 | 0.31 | 0.63 | 0.69 |

between 74.35 and 90.47. With the increase of energy consumption in the whole life cycle in this range, the green building evaluation value decreases gradually.

## 5. Discussion and Conclusions

*5.1. Discussion.* Based on the previous modeling and the calculation of the project case, the following discussion is carried out in this paper:

(1) Figure 10 shows the calculation of the Pareto optimal solution by NSGA-II for the indicator types and parameters of the green building energy consumption influencing factors set in Table 3. After the solution set is arranged according to the ascending order of energy consumption in the whole life cycle, it is found that the green building evaluation value of the case projects shows a gradual decline rule.

(2) The optimal solution of BO is distributed in the range of 192.3–208.08, which is slightly different from the suitable orientation recommended in the Energy-Saving Design Standard for Low-Energy Residential Buildings (DB42/T 559-2013, EDSLRB). The recommended suitable orientation is mainly calculated based on the simulation of light demand and solar radiation. Furthermore, the optimized results obtained from the consideration of the building's energy consumption are more straightforward. There are differences in the appropriate orientation of different building sizes, and the range of the differences is concentrated around the optimal value. The optimization results in this paper provide practical guidance for subsequent site-specific design of green buildings. For this project, on the premise of meeting the recommended design standards of EDSLRB (DB42/T 559-2013), the orientation angle can be appropriately increased to improve the energy saving and consumption reduction level of buildings.

(3) The design standards in different regions of China are strictly controlled for window–wall ratio, while the optimization results in Table 3 show that the values of the window-to-wall ratios are more discrete, indicating that there is not a single reduction of window-to-wall ratios to achieve building energy efficiency. The window-to-wall ratio indicator is also associated with sunlight conditions. The energy consumption of office buildings in Southwest China is characterized by high energy consumption of air conditioning and low energy consumption of heating, and energy saving design emphasizes shading and ventilation, which is different from the emphasis on insulation and air tightness in the north. Too large window–wall ratio has higher requirements for thermal parameters of glass, which directly leads to an increase in cost, and

Table 6: Factor sensitivity coefficient of green evaluation value.

| No. | Index of total life cycle energy consumption | | | | Index of green evaluation value | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | MPEC | CEC | OEC | DEC | BO | RM | GS | VAR | WR | EWM |
| 1 | 6.476 | 4.883 | 5.012 | 2.583 | 1.15 | 1.637 | 0.75 | 3.928 | 1.711 | 0.798 |
| 2 | 7.481 | 7.395 | 8.095 | 2.758 | 1.104 | 1.782 | 0.997 | 3.434 | 2.753 | 0.696 |
| 3 | 3.86 | 3.725 | 5.037 | 1.106 | 1.301 | 1.519 | 0.967 | 3.252 | 1.746 | 0.929 |
| 4 | 5.355 | 4.916 | 6.979 | 1.465 | 1.363 | 1.714 | 0.851 | 3.4 | 1.636 | 0.73 |
| 5 | 5.999 | 1.54 | 7.644 | 2.145 | 1.213 | 1.268 | 0.746 | 2.37 | 1.667 | 0.847 |
| 6 | 4.603 | 8.545 | 6.502 | 1.136 | 1.464 | 1.347 | 0.55 | 2.919 | 1.454 | 0.758 |
| 7 | 5.033 | 2.603 | 5.592 | 2.036 | 1.162 | 1.6 | 0.763 | 2.027 | 2.328 | 0.924 |
| 8 | 4.447 | 6.455 | 5.788 | 1.315 | 1.795 | 1.316 | 0.778 | 2.092 | 2.838 | 0.855 |
| 9 | 5.93 | 4.645 | 5.318 | 2.807 | 1.178 | 1.997 | 0.974 | 3.357 | 2.429 | 0.851 |
| 10 | 3.7 | 5.687 | 7.547 | 2.217 | 1.648 | 1.856 | 0.573 | 2.607 | 1.713 | 0.923 |
| 11 | 6.769 | 3.343 | 6.86 | 1.004 | 1.765 | 1.441 | 0.826 | 3.252 | 1.472 | 0.832 |
| 12 | 6.8 | 6.269 | 8.376 | 1.426 | 1.169 | 1.228 | 0.912 | 2.396 | 1.119 | 0.869 |
| 13 | 7.994 | 1.381 | 8.878 | 2.554 | 1.367 | 1.758 | 0.841 | 3.857 | 2.741 | 0.835 |
| 14 | 3.544 | 4.957 | 8.829 | 1.852 | 1.722 | 1.816 | 0.87 | 3.88 | 1.965 | 0.728 |
| 15 | 7.829 | 4.454 | 5.186 | 1.662 | 1.957 | 1.695 | 0.913 | 3.83 | 2.125 | 0.815 |
| 16 | 6.558 | 2.573 | 6.456 | 2.416 | 1.578 | 1.335 | 0.609 | 3.991 | 2.505 | 0.731 |
| 17 | 5.22 | 5.495 | 6.469 | 2.245 | 1.821 | 2.016 | 0.918 | 2.158 | 1.994 | 0.701 |
| 18 | 3.079 | 5.59 | 7.526 | 1.881 | 1.833 | 1.384 | 0.643 | 2.336 | 1.82 | 0.872 |
| 19 | 7.884 | 3.865 | 8.37 | 2.506 | 1.781 | 1.762 | 0.501 | 3.68 | 2.747 | 0.925 |
| 20 | 5.176 | 1.945 | 8.044 | 1.664 | 1.444 | 1.242 | 0.51 | 2.441 | 1.074 | 0.937 |
| Max | 7.994 | 8.545 | 8.878 | 2.807 | 1.957 | 2.016 | 0.997 | 3.991 | 2.838 | 0.937 |
| Min | 3.079 | 1.381 | 5.012 | 1.004 | 1.104 | 1.228 | 0.501 | 2.027 | 1.074 | 0.696 |
| Difference ratio | 0.61 | 0.84 | 0.44 | 0.64 | 0.44 | 0.39 | 0.50 | 0.49 | 0.62 | 0.26 |

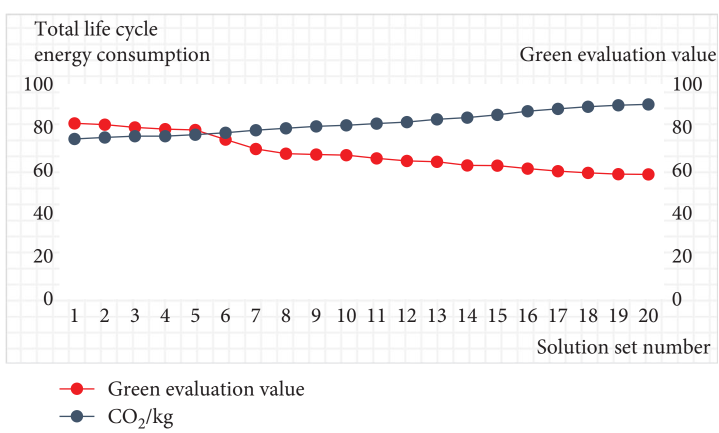


Figure 11: Comparison of whole life cycle energy consumption and green building design evaluation data.

too low window wall ratio also affects the lighting and ventilation of the project. Therefore, in the design of this project, the window–wall ratio can be appropriately improved by adopting low radiation double glazing and appropriately increasing shading design, etc., so as to meet the demand of energy saving and consumption reduction of office buildings in Southwest China.

*5.2. Conclusions.* In this paper, a multiobjective function is constructed based on the two important dimensions of building whole life cycle carbon emission and green building evaluation. The NSGA-II algorithm in genetic algorithm is applied to optimize the calculation of 10 indicators in these two objectives. In order to achieve this research objective, an office building project in Southwest China was selected for BIM modeling, while energy consumption analysis and evaluation were conducted based on the project's multidisciplinary model, which in turn revealed the relationship between the whole life cycle carbon emissions of the building and the green building evaluation value. The main contributions of this paper are as follows:

(1) The NSGA-II method in genetic algorithm can provide scientific and predictive support for the multiobjective

optimization of construction projects. It can quickly search the Pareto optimal solution set through multiple iterations, improve the efficiency and quality of optimization analysis, and provide important reference for the analysis of full life cycle energy consumption of green buildings and scheme optimization in the design stage.

(2) The optimization simulation calculation of typical cases shows that the full life cycle energy consumption and the green building evaluation level have a nonlinear relationship. In the small energy consumption value range, there is a larger space for the improvement of the green building evaluation level. This means that it is necessary to control the full life cycle energy consumption of construction projects in a lower range to have a greater significance in improving the green building evaluation level.

(3) Combining the genetic algorithm with the building simulation software to construct a green building optimal design model can provide the building designer with multiple sets of optimal design solutions under the constraints of the lowest energy consumption and the highest green evaluation value, which greatly enhances the space of available solutions. Referring to the current building energy-saving design standards, there is still a huge energy-saving potential with reasonable optimal design.

(4) This paper summarizes the effect of BIM technology on energy saving and carbon reduction of green buildings in the whole life cycle and provides information model and data basis for the optimization algorithm. Through energy consumption analysis based on BIM model, it is found that the ratio of window-to-wall is correlated with the heat transfer coefficient of the roof and the structure of the external wall. In terms of building natural lighting, orientation, window–wall ratio, and GS are related, so in the architectural design stage, it is necessary to focus on the setting of physical parameters of the perimeter structure.

Future research can be further in-depth from the following three aspects: first, considering the economic benefits of construction projects in the planning of objective functions, further exploration and establishment of cost functions to achieve multidimensional economic optimization of green buildings; second, expand other evaluation dimensions, including resource utilization efficiency, social impact, and indoor environmental quality indicators, so as to evaluate the comprehensive benefits of green buildings more comprehensively; third, expand different types of building projects, case studies in different regional environments, and a wider range of green building implementation, increase the universality and applicability of research, and provide more useful references and suggestions for the practice of green building.

## Data Availability

All data generated or analyzed during this study are included in this published article.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Authors' Contributions

All the authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Ting Ouyang, Fengtao Liu, Bingzhang Huang, and Jiehong Zhao. The first draft of the manuscript was written by Ting Ouyang, and all authors commented on the previous versions of the manuscript. All the authors read and approved the final manuscript.

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