Article

Multi-Objective Optimization of Building Energy Saving Based on the Randomness of Energy-Related Occupant Behavior

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Abstract: Given the escalating global energy demand driven by building energy consumption, this study is dedicated to meticulously investigating efficient energy-saving strategies in buildings, with a keen focus on the impact of occupant behavior’s randomness on energy efficiency and multi-objective optimization. The methodology encompassed a thorough analysis of various energy consumption factors, including building envelope and architectural form. We employed Latin Hypercube Sampling for in-depth sampling studies across each factor’s reasonable range. Utilizing Sobol sensitivity analysis, we pinpointed variables of high sensitivity and embarked on multi-objective optimization targeting two primary indicators: energy consumption and thermal comfort. Leveraging the NSGA-II algorithm, we adeptly identified optimal solutions, culminating in the proposition of building energy-saving strategies anchored on the Pareto frontier. Through stochastic modeling simulations of occupant behavior in window opening and air conditioning usage, a comparison was made with models that do not consider occupant behavior. It was found that incorporating occupant behavior into energy-saving designs can reduce energy consumption by up to 20.20%, while ensuring thermal comfort. This approach can achieve improved energy efficiency and indoor comfort.

Keywords: occupant behavior; multi-objective optimization; sensitivity analysis; pareto front

1. Introduction

According to statistics, the energy consumption and CO₂ emissions of buildings in developed countries account for 40% of the total energy consumption and CO₂ emissions in society. The energy consumption of residential and commercial buildings, including public buildings, has increased, reaching 20–40% of the global total energy usage. Half of this building energy consumption is used for heating, ventilation, and air conditioning systems for people [1]. Due to the accelerating urbanization and increasing living standards of residents, the energy demand in the building sector is expected to continue growing. The building envelope plays a crucial role in the early stages of design [2]. It affects not only the energy efficiency of buildings but also directly relates to the total cost and overall performance of the building [3–5]. This compels architects to precisely simulate a building’s energy performance during the design process, ensuring a clear understanding of key structural parameters such as exterior walls [6], roofs [7], external windows, and shading devices [8]. This ensures a more accurate estimate of the building’s energy consumption. Therefore, the accuracy of simulation is an indispensable part of building energy conservation.

Analyzing from the perspective of the building itself, to reduce energy consumption and maintain indoor thermal comfort, it’s essential to enhance the building’s climatic regulation capacity. Hence, low-energy building design plays a pivotal role. Secondly, key design parameters are challenging to grasp. Energy-saving concepts and characteristics should be reflected in building layout, orientation, shape coefficient, and functional use, with an emphasis on adaptability to the climate. By using technologies such as non-transparent envelopes with higher thermal insulation performance, external windows with...
better thermal insulation, and designs and constructions without thermal bridges, the overall performance of the building is enhanced.

Architectural design, due to the complexity of building variables, design phases, and architectural artistic features, often lacks clear trade-off criteria in many aspects. Therefore, computer-aided design has been developed and applied in many aspects of architectural design [9]. By introducing architectural performance simulation software, the physical environment performance of design schemes is realized. Differing from traditional architectural design processes, architects no longer base designs on varied standards, energy-saving guidelines, and years of accumulated experience. During the preliminary design stages of a building, sustainable architecture is achieved based on its parameterized conception. While enhancing the inherent performance of the building, it ensures the accuracy and scientific validity of the architectural design scheme [10–12]. For example, optimizing energy consumption in architecture can lead to a 40% enhancement in energy-saving efficiency during the initial design stages. Although there are various methods to analyze the thermal and daylighting performance of buildings, including detailed simulation software, many of these methods yield evaluative results rather than actual outcomes experienced by users. Many of these methods yield evaluative results rather than actual outcomes experienced by users. Therefore, it’s essential for architecture to undergo objective optimization problem-solving. Generally, the goal of architectural design is to obtain a Pareto solution set, considering both the objective function and constraints, essentially seeking a balanced solution between conflicting objectives. Different optimization algorithms can be combined with architectural simulation tools to help designers identify the best design solutions for high-performance buildings. Although there are various methods and tools available for building energy optimization, the application of optimization algorithms, despite its use in expansive solution spaces, has certain constraints and is time-intensive. They exhibit randomness, and the optimization outcomes aren’t guaranteed to be consistent each time, necessitating algorithms to be robust for such challenges.

While detailed building energy simulations can provide estimated values for energy consumption, the computational cost of these simulations becomes a concern in optimization. In architectural design, computer simulations can take anywhere from several minutes to multiple hours because it’s necessary to establish a physical performance model based on geometric models. During this modeling process, thermal and other parameters of the building need to be set, followed by thousands of iterations using the computational core, such as simulating the thermal environment inside the building with Fluent software, which could take several days to converge. In the optimization process, because every generation of the population needs to be simulated to obtain results, this further increases the time cost. In the actual design process, especially in the preliminary design phase, the constant replacement of design schemes amplifies the application of optimized design. Therefore, many studies have been trying to find a modeling method that reduces computational costs without compromising evaluation accuracy too much, still keeping it within acceptable engineering limits. For example, simplifying the model might be an approach, but it might also lead to reduced interpretability of the model. Therefore, the use of sensitivity analysis can avoid excessive simplification of the model, leading to a decrease in interpretability. By quantitatively analyzing the relevant decision variables of the building, design variables with high sensitivity coefficients can be screened out, as their cumulative importance can effectively control the model’s accuracy, allowing for the selective omission of less significant parameters. Another approach is the surrogate model, or metamodel, for building aerothermal performance. Machine learning primarily uses computers to simulate occupant learning behavior, acquiring new knowledge from existing information, and continually refining its methods and techniques. This method has been widely applied in the field of building energy consumption [13,14], primarily aiming to analyze the characteristics of energy consumption data and establish reliable energy prediction models based on the newly discovered knowledge or patterns [15].
amount of energy simulation calculations is often required, leading to excessive time spent on modeling and computation. Constructing a reliable machine learning predictive model with specific parameters can replace the actual energy model for computational analysis. It is formed from vast amounts of real data from actual monitored measurements, such as hourly indoor temperatures, hourly cooling and heating loads, or detailed building energy consumption simulation data, and then trained using various machine learning algorithms. These models can be used as substitutes for detailed building energy simulations during the optimization process. Traditional architectural design methods rely on the architect’s own experience or depend on architectural design standards, making it unclear on how design variables impact building performance. Architectural and energy-saving designs are subjective and lack scientific rigor, and the final design cannot guarantee energy-saving needs. Therefore, to enhance building energy-saving efficiency, it’s essential to combine local climate and environmental resources, study the influence of design variables on building performance, use parametric analysis methods to screen out major impact parameters, and then carry out efficient energy-saving designs. For instance, in this article, the set optimization stop condition is 60 generations, requiring a total of 2100 simulation calculations. If using the software alone, the optimization time cost is roughly 5 days. However, after obtaining the surrogate model using machine learning, the time cost can be reduced to 4 h.

From the era of informatization leaping to the age of big data, many technologies have emerged and driven changes in the way society produces and transforms, especially artificial intelligence and machine learning, which have seen tremendous growth and application in various aspects of society. In the architectural domain, there has been significant development and application, effectively predicting the design and operational energy consumption of new buildings, renovated buildings, and the hourly and annual operation of existing buildings. Numerous parameters influence building energy consumption. Identifying key design parameters from a vast array helps in optimizing design, validating the effectiveness of energy-saving design strategies, establishing a reasonable energy consumption prediction model, and enhancing energy analysis efficiency. Sensitivity analysis is a fundamental method to determine the degree of impact of each parameter and identify crucial ones [16–23]. Wang Chunlei took a large office building in a hot-summer and warm-winter region as an example, using an orthogonal experimental design combined with variance analysis to study the impact of parameters on energy consumption. The research found that lighting power density, air conditioning system type, indoor design parameters, office equipment power density, number of chiller units, personnel density, and chiller units are significant factors affecting energy consumption and should be emphasized when establishing energy prediction models [24]. Liang Zhen and colleagues took office buildings and shopping malls in Harbin as examples, selecting various parameters like building area, number of floors, orientation, building aspect ratio, and window-to-wall ratio. Using orthogonal experimental variance analysis, they identified the primary parameters affecting building energy consumption [25]. This article mainly employs the Sobol [26] sensitivity analysis method. Sobol evaluates parameter sensitivity by calculating the contribution of individual and multiple parameters to the variance of model output.

Al-Shehri, A. [27] proposed a user-based model, utilizing an ANN model to predict residential building energy consumption. The input of the prediction model consists of user characteristics and activities, while the output represents the energy consumption simulated by the building. Kalogirou, S.A. and Bojic, M [28] developed various models, including Extreme Gradient Boosting (XGBoost), Random Forest (RF), Artificial Neural Network (ANN), Gradient Boosted Decision Trees (GBDT), and Support Vector Regression (SVR) to predict thermal energy usage in a residential building in Tianjin, China. Kalogirou, S.A [29] and others focused on an existing passive solar residential building, constructing a BP neural network model to forecast building energy consumption in both winter and summer, based on data concerning the impact of building envelope thickness on energy consumption. The model’s coefficient of determination (R) reached an impressive 0.9985, indicating a very high prediction accuracy. Additionally, Beccali [30] demonstrated that
Artificial Neural Networks could be regarded as a valuable tool for updating a building’s energy consumption, presenting superior performance over other methods in estimating building energy consumption. Zhai [31] introduced a multi-objective optimization strategy combining NSGA-II with EnergyPlus (23.1.0), specifically targeting window design optimization; while Magnier and Haghighat [32] leveraged TRNSYS simulation, genetic algorithms, and artificial neural networks to holistically optimize building design. Jian. Yao found significant differences in the energy performance of different housing units when overall building energy efficiency was already high [33]. In various architectural design scenarios, several types of genetic algorithms [4,34–36] have been adopted. Pu [37] et al. used a BP neural network to predict future carbon emissions, avoiding errors caused by non-linear relationships between influencing factors and predicted values.

Occupants’ impact on buildings’ energy performance can be demonstrated via rational analyses and simulation studies [38,39]. Broday et al. [40] went through a literature review to validate how IoT can be used for building control (for energy conservation purposes) and to monitor IEQ conditions within buildings in order to provide a better environment for occupants in terms of health and comfort, and he found that machine learning methods are mainly used for energy conservation purposes, understanding the behavior of occupants within buildings, with a focus on thermal comfort. Asadi [41] shows that human behavior has a direct impact on building energy consumption. Simulation software and methods can predict IEQ factors and human behavior. Mahdavi [42] demonstrated that the occupant behavior as explained is not a supplement axis to study for the evaluation of the energy building performance, but a main and critical factor that should not be neglected.

This study is grounded on a foundational office model. Using architectural form, building envelope, and occupant behavior as variables, it employs the Sobol sensitivity analysis method to identify key parameters. With energy consumption and thermal comfort as optimization goals, once optimization is complete, it is compared with a model without occupant behavior considerations to analyze and summarize energy-saving strategies and methods. Points of innovation are as follows:

Most existing building energy consumption models focus primarily on fixed physical and technical parameters such as building materials, design, and equipment efficiency. However, occupant behavior is influenced by various factors, many of which are random and unpredictable. Owing to these random factors, the modeling of buildings becomes more intricate. This suggests that singular, linear strategies might not suffice in addressing such a complex model. Considering the randomness of energy consumption behavior, this presents an innovative approach. Integrating the unpredictability of user behaviors can lead to a more accurate prediction and optimization of a building’s actual energy consumption.

Latin hypercube sampling and sensitivity analysis were utilized, and multi-objective optimization was also incorporated. By integrating these methods, it ensures addressing occupant random behaviors from multiple perspectives and finding the optimal energy-saving strategy.

2. Methodology

This research comprehensively employed five key methodologies: models that consider various sensitivity factors, models of occupant behavior randomness, multidirectional impact analysis, sensitivity analysis, and the NSGA-II algorithm. This article delved into the specific enclosure structures of various buildings, the behavioral differences of different populations, and potential random influences. Based on these four methods, subsequent sensitivity analysis and NSGA-II further provide us with an in-depth analysis of the model results and multi-objective optimization strategies. Figure 1 illustrates the complete workflow of this research.
2.1. Latin Hypercube Model

Previous studies mostly considered the sensitivity analysis of individual factors on building energy consumption, without taking into account the combination of multiple factors for a comprehensive analysis. The model generates a series of sample points through the Latin Hypercube Sampling (LHS) method, representing various possible parameter combinations. LHS is a statistical method used to generate uniformly distributed samples, ensuring thorough exploration of the parameter space. Latin Hypercube Sampling (LHS) is a statistical method used for generating multivariate random samples, commonly used in computer simulations and modeling. The main advantage of LHS is its ability to effectively cover the parameter space, thereby improving the accuracy and robustness of the model. In this model, the primary modifications were made to building materials, including the thickness of wall insulation, roof insulation, window-to-wall ratio, window glass material, room airtightness, solar heat absorption coefficient for roofs and walls, personnel density, lighting density, and equipment density in nine major categories. Based on past research, the sample size chosen was 680 [43] to explore the combined influence of various factors on the energy consumption and its variation pattern in office rooms.

2.2. Occupant Behavior Random Model

Residents’ behavior towards air conditioning significantly influences building energy consumption. Current building simulations often assume residents operate air conditioning ideally based on fixed schedules or at fixed temperature setpoints, turning on the system once the temperature exceeds the set point. However, in reality, users’ behaviors towards air conditioning are not deterministic. Their actions vary randomly based on air conditioning schedules, temperature setpoints, and other factors. This means that predictions made using models with fixed schedules are often inaccurate, leading to energy-saving office designs that may not perform as intended.

To address this, our study employs a random air conditioning behavior model to predict energy consumption. This modeling method integrates measured data, statistical analysis, and logistic regression to derive a stochastic behavior model. The model provides probabilities concerning when occupants might turn on the air conditioner, at what temperature threshold they might do so, the potential temperature settings they might choose, and when they might turn it off.
The EnergyPlus simulation tool, invoked using the eppy package in Python, implements energy consumption simulations based on this model. The accuracy of the developed simulation model was then validated using on-site measurements.

2.3. Considering Factors of Different Orientations

Previous research on office energy-saving design has mainly focused on improving the overall energy performance of the office [44,45]. For instance, after adjusting the performance parameters of windows and exterior walls, they were directly applied to the entire external facade of the building, doing so has the advantage of directly improving energy-saving effects, and the specifications of the enclosure structures are largely consistent, which is convenient during the construction phase. However, since this study needs to consider a greater range of energy consumption differences affecting the room, this method obviously has significant limitations. Because for offices in different locations, the window-to-wall ratios of different facades, sunlight exposure duration, and solar radiation angles all vary, the energy performance of different offices naturally differs.

2.4. Sensitivity Analysis

In this study, considering sampling and model decomposition, the Sobol sensitivity analysis method was adopted. The Sobol method evaluates the sensitivity of parameters by calculating the contribution of individual and multiple parameters to the variance of model outputs. The objective function for sensitivity target analysis is the annual cooling and heating energy consumption. The Sobol method doesn’t have specific requirements concerning whether the model is linear, whether it’s a monotonic model, or the probability distribution characteristics of input parameters. However, it involves significant computational effort and requires each input parameter to be independent.

Since sensitivity analysis can explore the impact of changes in input parameters on model outputs, it’s widely used in the study of building parameters affecting building energy consumption, further guiding energy-saving designs and focusing on key energy-saving points. In building energy consumption analysis, using sensitivity analysis helps identify the parameters with the most significant impact on energy consumption, guiding architects or engineers towards effective energy-saving designs; it aids in filtering out parameters that are not sensitive to energy consumption and appropriately discarding them, simplifying the building model and enhancing design efficiency. Furthermore, it clarifies the correlation and mechanism of action between design parameters and energy consumption.

2.5. Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

In 1995, Srinivas and Deb [46] introduced the Non-Dominated Genetic Algorithm. The NSGA algorithm is based on the genetic algorithm and is derived from the concept of Pareto optimality. The main difference between NSGA and the basic genetic algorithm is that NSGA performs a fast, non-dominated sorting of individuals before the selection operation, increasing the probability that superior individuals are retained. The operations such as selection, crossover, and mutation are the same as in the basic genetic algorithm, hence, it performs better than traditional multi-objective optimization.

However, due to issues such as large computation volume and slow operation, Deb and others introduced the NSGA-II algorithm in 2002. Compared to the NSGA algorithm, the NSGA-II algorithm mainly improved in the following three aspects:

The NSGA-II algorithm uses a fast non-dominant sorting method, reducing the algorithm’s computational complexity from $O(mN^3)$ to $O(mN^2)$ and significantly reducing the calculation time.

An elitist strategy is adopted, where parent and offspring individuals are merged and then subjected to non-dominated sorting. This enlarges the search space. When generating the next generation of parents, individuals with higher priority are selected in order, and the crowding degree is used for selection among individuals of the same level, ensuring that superior individuals have a higher probability of being retained.
The method of crowding distance replaces the fitness sharing strategy that requires a designated sharing radius. It serves as the criterion for selecting exemplary individuals among the same tier, ensuring diversity within the population. This approach is conducive for entities to undergo selection, crossover, and mutation across the entire spectrum. The formula for calculating crowding distance is shown below as Equation (1):

\[
CD(i) = \sum_{m+1}^{M} \left( \frac{f_m(i + 1) - f_m(i - 1)}{f_m^{\text{max}} - f_m^{\text{min}}} \right)
\]

where \( CD(i) \) is the crowding distance of the \( i \)-th solution, \( f_m(i + 1) \) denotes the value of the \( (i + 1) \) objective function, \( f_m(i - 1) \) denotes the value of the \( (i - 1) \) objective function, \( f_m^{\text{max}} \) is the maximum value of the objective function, and \( f_m^{\text{min}} \) is its minimum value. The NSGA-II parameter configurations used in this study are presented in Table 1.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial population size</td>
<td>35</td>
</tr>
<tr>
<td>Maximum number of generations</td>
<td>60</td>
</tr>
<tr>
<td>Crossover</td>
<td>0.9</td>
</tr>
<tr>
<td>Mutation probability</td>
<td>1</td>
</tr>
</tbody>
</table>

To ensure convergence and a rich solution set in the optimization process, the population size is set to 40, approximately twice the number of decision variables used in the optimization. The crossover rate and mutation rate are conventionally set at 0.9 and 1, respectively. The convergence condition is based on occupant judgment, and the optimization process is terminated when it reaches a maximum of 60 evolutionary generations. The selection of variables is based on those with higher sensitivity rankings, targeting the aforementioned two objective functions for energy-saving design optimization. Less-sensitive variables are filtered out. This study selected the first 18 variables, namely: air tightness (five rooms), window-to-wall ratio (east, south, west, north), insulation layer thickness (south, west, north), glass solar absorption rate (east, south, west, north), and occupancy density (south, north).

3. Case Study

3.1. Description of the Building Model

This case focuses on a typical office building that consists of 5 rooms, of which four rooms have windows facing the four directions: east, west, south, and north. It is located in Ningbo, a city typically hot in summer and cold in winter. The total area of the building is 26.3 m². Figures 2 and 3 provide examples of the model in this study as illustrated in DesignBuilder. The architectural geometric model is established using the DesignBuilder (7.0.0.116) simulation software.
The envelope structure is designed using typical energy-saving building materials, meeting the energy efficiency design standards for residential buildings in hot summer and cold winter areas. The U-values for the outer walls and roof are set at 0.3–1.2 W/m²K and 0.2–0.8 W/m²K, respectively. Table 2 presents the detailed architectural enclosure information for this office.

Table 2. The detailed building information.

<table>
<thead>
<tr>
<th>Component</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exterior Walls</td>
<td>Extruded polybenzene board density = 35 kg/m³, 1100 mm thickness</td>
<td>U = 0.9 W/(m²·K)</td>
</tr>
<tr>
<td>Exterior Windows</td>
<td>LoE hollow glass with a 12 mm air layer</td>
<td>U = 3.2 W/(m²·K), SHGC = 0.6</td>
</tr>
<tr>
<td>Roofing</td>
<td>Glass Wool, density = 12 kg/m³, 1100 mm thickness</td>
<td>U = 0.5 W/(m²·K)</td>
</tr>
<tr>
<td>Ventilation</td>
<td>Natural ventilation 1.0 h⁻¹</td>
<td>—</td>
</tr>
<tr>
<td>Sunshade Components</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Air Conditioning system</td>
<td>Air conditioning cooling design temperature: cooling 26 °C</td>
<td>Cooling efficiency EER = 3.4</td>
</tr>
</tbody>
</table>

The air conditioning cooling temperature is set at 26 °C, and the heating temperature is 18 °C. The energy efficiency ratio (EER) of the air conditioning during cooling is 3.4, and the coefficient of performance (COP) during heating is 1.5. It operates throughout the year to meet indoor temperature settings. The ventilation rate is 2.0 times per hour. The total power density of other loads (including lighting systems and occupants) is 4.3 W/m². These settings are in accordance with energy-saving standards for buildings.

As this case study focuses on an office with five rooms, the influence of different orientations is considered. Therefore, during the design variable phase, each room facing different directions is sampled individually, accurately simulating real-world conditions.

3.2. Design Variables

The design, construction, and later operations of a building all involve occupant and environmental factors. A good architectural design should not only meet the users’ needs but also minimize its impact on the surrounding environment. To achieve this, numerous variables related to architectural design and system operation need consideration. The aim of this study is to assist architects or property owners in achieving energy-efficient, comfortable, and cost-effective preliminary design solutions.
3.2.1. Morphological Design and Building Envelope

This includes nine major categories: the insulation thickness of building exteriors, roof insulation thickness, window-to-wall ratio, window glass material, room air tightness, solar heat absorption coefficient of roofs, solar heat absorption coefficient of walls, population density, lighting density, and equipment density. Since the rooms are oriented in four directions: east, south, west, and north, each room’s sampling is independent and randomized, leading to 33 distinct factors. The sampling value range is based on the “Zhejiang Provincial Public Building Energy Conservation Design Standard (db33/1036-2021)” [47]. Some sampling points are discrete, so there will be repeated sampling for these values. The following Table 3 provides the sampling selection information:

Table 3. Latin Hypercube Sampling Selection Information.

<table>
<thead>
<tr>
<th>Type of Sampling</th>
<th>Value Range</th>
<th>Type of Selection Point</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall Insulation Material Thickness</td>
<td>0.022–0.158 m</td>
<td>Continuous</td>
</tr>
<tr>
<td>Roof Insulation Material Thickness</td>
<td>0.054–0.263 m</td>
<td>Continuous</td>
</tr>
<tr>
<td>Window-to-Wall Ratio</td>
<td>0.1–0.9</td>
<td>Continuous</td>
</tr>
<tr>
<td>Air Tightness</td>
<td>2–4</td>
<td>Continuous</td>
</tr>
<tr>
<td>Type of Window Glass Material</td>
<td>5 types</td>
<td>Discrete</td>
</tr>
<tr>
<td>Roof Solar Heat Absorption Coefficient</td>
<td>0.25–0.75</td>
<td>Continuous</td>
</tr>
<tr>
<td>Glass Solar Heat Absorption Coefficient</td>
<td>0.25–0.75</td>
<td>Continuous</td>
</tr>
<tr>
<td>Occupant Density</td>
<td>0.071–0.16667 people/m²</td>
<td>Continuous</td>
</tr>
<tr>
<td>Lighting Density</td>
<td>3–10 W/m²</td>
<td>Continuous</td>
</tr>
<tr>
<td>Other Equipment Density</td>
<td>10–20 W/m²</td>
<td>Continuous</td>
</tr>
</tbody>
</table>

3.2.2. Occupant Behavior Factors

The occupant behavior factors involved in this study are based on the random occupant behavior model described in Section 2. Mainly includes the air conditioning random model and the window opening regulation model. These models determine the most comfortable settings based on people’s actual behaviors, such as arrival and departure times and choices to open windows or use air conditioning. This not only provides us with a realistic simulation of occupant behavior but also achieves energy savings to a certain extent. This article uses Python to call the EnergyPlus API function and ensure it meets the requirements of the logistic regression model. For the logistic regression model, its core lies in calculating the handle value (P) based on the average temperature of a specific area. This value represents the likelihood of adjusting the cooling set point. When this probability exceeds a random value of a uniform distribution, the cooling set point will be adjusted accordingly. The foundational equation for this model (2) is:

\[
P(X = x) = \frac{e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}{1 + e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n)}}
\]  

where \( P(Y = 1 | X = x) \) represents the probability that an event will occur under the given conditions of \( X \), \( \beta_0, \beta_1, \ldots, \beta_n \) is the parameter of the model, which needs to be estimated using the maximum likelihood estimation method. \( x_1, x_2, \ldots, x_n \) is the independent variable. Its main feature is that it can estimate the probability of an event occurring.

Air Conditioning Random Model
According to J. Yao’s research [48], the cooling demand of a building is controlled by adjusting the cooling set point. Figure 4 shows a schematic diagram of the air conditioning model.

When the average air temperature in a certain area rises to 27.5 °C, the cooling set point of the air conditioner will be adjusted based on the current time, a normal distribution random number, and the logistic regression model. Turning on the air conditioner must meet the following conditions: Firstly, the current simulation time must be within the range determined by the normal distribution random number; secondly, the average temperature in the room must exceed 27.5 °C; and finally, it must meet the requirements of the logistic regression model. It is worth noting that since the seed of the random number of the normal distribution is determined by the number of seconds of the current simulation time, the simulation time range is not always the same each time. This provides a practical basis for simulating the uncertainty of occupant daily behaviors, such as arrival and departure times.

Window opening adjustment model

According to J. Yao’s research [48]. This model takes into account multiple influencing factors. By adjusting the ventilation design flow of the partition, this article controls the window opening requirements of the building. First, determine the occupancy of the room based on the days of the week and people’s daily routines. Combining the current time, normal distribution random number, and logistic regression model, adjust the window’s opening and closing status. Figure 5 shows the schematic diagram of the window opening model.
The opening and closing of windows are influenced by multiple factors:

a. Whether it meets the current simulation time defined by the normal distribution random number.

b. Whether it is Saturday or Sunday.

c. Whether the current date is a public holiday.

d. Whether it conforms to the standards of the logistic regression model.

If it’s a weekend (Saturday or Sunday), it’s assumed that there’s no one in the room by default. For public holidays, they have different judgment standards with the logistic regression model, as people’s probability of being in the office significantly decreases during holidays. Furthermore, people’s behavior of opening and closing windows varies according to different seasons. For instance, in winter, if the room is too cold, people might choose to close the windows to keep warm; while in summer, if the room is too hot, they might close the windows and turn on the air conditioner. However, this model takes into account various factors that might influence the opening and closing of windows, and each factor has a different corresponding weight. Ultimately, the model uses logistic regression to predict the likelihood of opening the window and decides whether to open it based on that.

4. Results Analysis

4.1. Sensitivity Analysis Results

Table 4 represents the display names of the variables in the figure. The following figure presents the sensitivity analysis results based on energy consumption using the Sobol method. The Sobol sensitivity analysis method most commonly uses two indicators: first-order coefficient and total order coefficient. The first-order coefficient refers to the sensitivity importance of a certain parameter. A larger coefficient indicates stronger sensitivity and a greater impact on the results. Since only a preliminary selection of data was done to determine which parameters have a larger impact and which can be ignored, calculating higher-order Sobol indices requires more model evaluations, which can be computationally intensive. In cases where resources or time are limited, prioritize calculating the first-order index.
Table 4. Symbols Representing Variable Names.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Variable x</th>
<th>Variable Name</th>
<th>Variable x</th>
</tr>
</thead>
<tbody>
<tr>
<td>Material Thickness South</td>
<td>x1</td>
<td>Glass Solar Absorptance North</td>
<td>x18</td>
</tr>
<tr>
<td>Material Thickness West</td>
<td>x2</td>
<td>Person Density South</td>
<td>x19</td>
</tr>
<tr>
<td>Material Thickness East</td>
<td>x3</td>
<td>Person Density West</td>
<td>x20</td>
</tr>
<tr>
<td>Material Thickness North</td>
<td>x4</td>
<td>Person Density East</td>
<td>x21</td>
</tr>
<tr>
<td>Material Thickness Roof</td>
<td>x5</td>
<td>Person Density Middle</td>
<td>x22</td>
</tr>
<tr>
<td>Window-to-Wall Ratio South</td>
<td>x6</td>
<td>Person Density North</td>
<td>x23</td>
</tr>
<tr>
<td>Window-to-Wall Ratio West</td>
<td>x7</td>
<td>Lighting Power Density South</td>
<td>x24</td>
</tr>
<tr>
<td>Window-to-Wall Ratio East</td>
<td>x8</td>
<td>Lighting Power Density West</td>
<td>x25</td>
</tr>
<tr>
<td>Window-to-Wall Ratio North</td>
<td>x9</td>
<td>Lighting Power Density East</td>
<td>x26</td>
</tr>
<tr>
<td>Air Tightness South</td>
<td>x10</td>
<td>Lighting Power Density Middle</td>
<td>x27</td>
</tr>
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<td>Air Tightness West</td>
<td>x11</td>
<td>Lighting Power Density North</td>
<td>x28</td>
</tr>
<tr>
<td>Air Tightness East</td>
<td>x12</td>
<td>Equipment Power Density South</td>
<td>x29</td>
</tr>
<tr>
<td>Air Tightness Middle</td>
<td>x13</td>
<td>Equipment Power Density West</td>
<td>x30</td>
</tr>
<tr>
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<td>x14</td>
<td>Equipment Power Density East</td>
<td>x31</td>
</tr>
<tr>
<td>Glass Solar Absorptance South</td>
<td>x15</td>
<td>Equipment Power Density Middle</td>
<td>x32</td>
</tr>
<tr>
<td>Glass Solar Absorptance West</td>
<td>x16</td>
<td>Equipment Power Density North</td>
<td>x33</td>
</tr>
<tr>
<td>Glass Solar Absorptance</td>
<td>x17</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figures 6 and 7 are the comparisons of sensitivity analysis without and with considering occupant behavior, respectively. The top ten in Figure 6 are: Eastward solar heat absorption, middle house air tightness, westward house air tightness, eastward house air tightness, westward solar absorptance, northward house air tightness, southward insulation material thickness, westward insulation material thickness, northward insulation material thickness, and southward person density. The top ten in Figure 7 are: Eastward solar heat absorption, middle house air tightness, northward house air tightness, westward house air tightness, westward solar absorptance, northward insulation material thickness, southward solar heat absorption, northward solar heat absorption, eastward house air tightness, and southward person density. By comparison, we can see some differences in the top ten factors: Regardless of whether occupant behavior is considered, eastward solar heat absorption is the most important factor, and air tightness is also important, but its direction of influence has changed. When considering occupant behavior, the air tightness of the northward house becomes more important, while the influence of the air tightness of the eastward and westward houses relatively decreases. The westward solar absorptance is an important factor in both figures. However, after considering occupant behavior, the southward and northward solar heat absorptions also enter the top ten. In general, after considering occupant behavior, the influence of some factors becomes more important, while the impact of other factors relatively decreases. This indicates that occupant behavior is a factor that cannot be ignored in building performance assessment.
Due to the small volume of office buildings, the window area and volume ratio are relatively large. This means that, relative to its total volume, a small building has more surface area for heat exchange with the external environment. Therefore, windows (as a
part of these surfaces) play a significant role in heat exchange. This is different from most previous studies.

4.2. Multi-Objective Optimization Result Analysis

The optimization strategy has a Pareto optimal solution distribution in the simulation of 2100 and 60 evolutionary generations. As shown in the figure below, there are a total of 35 Pareto optimal solutions. Occupant behavior is a key variable. To assess the impact of occupant behavior on building energy consumption, we conducted two sets of experiments: the experimental group considered occupant behavior, while the control group did not. The schedule for the control group is fixed, with no randomness. The following Figures 8 and 9 shows the distribution of the Pareto frontier.

**Figure 8.** Pareto frontier considering occupant behavior. (The red dot is the optimal solution, and the black dot is all the solutions).

**Figure 9.** Pareto frontier without considering occupant behavior. (The red dot is the optimal solution, and the black dot is all the solutions).

Without changing building parameters, the energy consumption of the building is 1542.68 kWh, and the number of uncomfortable hours is 2935. After calculation, in the model without considering occupant behavior, the average energy consumption of the building is 1245.61 kWh. The average number of uncomfortable hours is 2826.07. In the model considering occupant behavior, the average energy consumption of the building is 1230.93 kWh. The average number of uncomfortable hours is 2809.56. From the data, it can be seen that when occupant behavior is considered, the average energy consumption of the
building can save 20.20%, and the uncomfortable hours can decrease by 4.2%. Compared to the model without considering occupant behavior, considering occupant behavior can reduce energy consumption by 1.2%. This indicates that occupant behavior has a significant impact on both building energy consumption and thermal comfort. Figures 10–14 are box plots of 18 variables.

![Box plot of window-to-wall ratio.](image1)

**Figure 10.** Box plot of window-to-wall ratio.

![Box plot of solar heat absorption coefficient.](image2)

**Figure 11.** Box plot of solar heat absorption coefficient.
When combining and compare these five box plots, considering occupant behavior versus not considering it. The following observations and analyses can be conducted:

Window/Wall Ratio: In the eastward and southward directions, after considering occupant behavior, the median window/wall ratio has slightly increased, indicating a larger window/wall ratio in scenarios with occupant activity for these directions. The window/wall ratio in the westward direction has significantly increased after considering occupant behavior.

Insulation Thickness: The insulation thickness in the southward and westward directions has increased after considering occupant behavior. This might be because people prefer a warmer environment, leading to the choice of thicker insulation in these directions.

Glass Solar Absorption Rate: In all directions, after considering occupant behavior, the solar absorption rate of the glass has slightly decreased, especially in the southward and westward directions.
Airtightness: After considering occupant behavior, the airtightness has significantly increased in the southward, central, and westward directions, while it has slightly decreased in the eastward and northward directions.

Population Density: In the northward direction, the population density has decreased after considering occupant behavior, while it has increased in the westward direction.

From these five box diagrams, it can be observed that there are significant differences in multiple variables when considering passenger behavior. This indicates that occupant behavior has a significant impact on architectural design and functional choices. To design and optimize buildings better, considering these occupant behavior factors is crucial.

5. Discussion

This study revealed that considering occupant behavior can lead to a significant reduction in building energy consumption, averaging a 20.20% decrease. This aligns well with the findings presented in a comprehensive review, which suggested that educating occupants could result in an energy saving ranging from 4% to 30% [49]. This similarity indicates that our results fall within the expected range of energy savings when occupant behavior is taken into account.

Furthermore, this research highlights the positive impact of occupant behavior on both energy consumption and indoor comfort. This observation is consistent with the conclusions of comparative studies, which emphasize that the impact of occupants’ behavior is at least as significant as that of the quality of the building envelope or the efficiency of technology [50]. This underscores the pivotal role of occupant behavior in energy consumption and indoor environmental quality.

In addition, this findings on the reduction of discomfort hours reinforce the importance of considering occupant behavior. A comprehensive review focusing on the impact of occupant behavior in residential buildings, which account for 70% of the global building floor area, supports our observations [51]. This review highlights the crucial role of occupant behavior in bridging the gap in energy performance in residential buildings.

6. Conclusions

Energy consumption and indoor comfort often contradict each other as objectives. However, through a series of energy-saving strategies, it is possible to ensure indoor comfort while also reducing energy consumption.

Considering or disregarding occupant behavior can influence the outcomes of sensitivity analysis to some degree. Moreover, in multi-objective optimization, it can simultane-
ously reduce energy use and discomfort hours. Hence, occupant behavior plays a pivotal role in architectural design and assessment. Therefore, it’s imperative to factor in occupant behavior during the design and optimization stages of a building. Table 5 are the most common values of the decision variables, compared with the scenario without random occupant behavior.

Table 5. Comparison of decision variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Without People</th>
<th>With People</th>
</tr>
</thead>
<tbody>
<tr>
<td>WindowWallRatio_West</td>
<td>0.13</td>
<td>0.1</td>
</tr>
<tr>
<td>WindowWallRatio_North</td>
<td>0.33</td>
<td>0.15</td>
</tr>
<tr>
<td>WindowWallRatio_East</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>WindowWallRatio_South</td>
<td>0.46</td>
<td>0.49</td>
</tr>
<tr>
<td>GlassSolarAbsorption_North</td>
<td>0.45</td>
<td>0.53</td>
</tr>
<tr>
<td>PopulationDensity_North</td>
<td>7.62</td>
<td>13.03</td>
</tr>
<tr>
<td>AirTightness_East</td>
<td>2.07</td>
<td>2.76</td>
</tr>
<tr>
<td>AirTightness_Middle</td>
<td>2.03</td>
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<td>AirTightness_North</td>
<td>2.14</td>
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</tr>
<tr>
<td>AirTightness_South</td>
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</tr>
<tr>
<td>InsulationThickness_South</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>InsulationThickness_North</td>
<td>0.12</td>
<td>0.12</td>
</tr>
<tr>
<td>InsulationThickness_West</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>GlassSolarAbsorption_South</td>
<td>0.54</td>
<td>0.31</td>
</tr>
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<td>GlassSolarAbsorption_West</td>
<td>0.36</td>
<td>0.49</td>
</tr>
<tr>
<td>GlassSolarAbsorption_East</td>
<td>0.38</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Occupant behavior has a positive impact on both building energy consumption and discomfort hours, meaning they both decrease. This might suggest that occupant behavior, to some extent, helps improve energy efficiency and enhance indoor comfort. It further confirms the importance of occupant behavior in building energy consumption and indoor environments. Considering the behavior and habits of residents in architectural design and operation may lead to better energy efficiency and indoor comfort. Under multi-objective optimization, the average energy consumption of the building can be saved by 20.20%, and discomfort hours can be reduced by 4.2%.

There are certain limitations on this study. This model primarily focuses on summer air conditioning, overlooking the energy consumption associated with heating during winter. Future research should include an analysis of winter heating systems to comprehensively assess the annual energy efficiency of buildings.

The model may not fully capture the complexities of the real world, such as the long-term impacts of climate change, diversity in building structures (like varying building materials and designs), and changes in usage patterns. These factors could affect the accuracy and applicability of the model.

In this study, certain variables might demonstrate low sensitivity; however, this does not imply they are inconsequential in practical applications. These variables could produce unexpected effects when interacting with other factors, thereby influencing energy consumption and indoor environmental quality.

The assumptions regarding occupant behavior in this model may have limitations. For instance, the model might assume homogeneous and static occupant behavior, which in reality, can vary due to individual habits, cultural backgrounds, economic conditions, etc. Moreover, occupant behavior patterns might evolve over time, which may not be adequately accounted for in the model.
Author Contributions: Conceptualization, J.Y. and R.Z.; Methodology, J.Y.; Software, Z.Z. and J.Y.; Investigation, Z.Z. and J.Y.; Writing—original draft, Z.Z.; Writing—review & editing, J.Y. and R.Z.; Supervision, J.Y. and R.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Healthy & Intelligent Kitchen Engineering Research Center of Zhejiang Province, Ningbo 315211, China.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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