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Multi-Objective Optimization of Building Energy Consumption: A Case Study of Temporary Buildings on Construction Sites

Xiaohui Guo [1], Yuanfeng Wang [1,*], Yinshan Liu [2], Lei Fan [3], Shaoqin Xue [1], Chengcheng Shi [4], Lei Pan [1], Boqun Zhang [1], Liping Wang [1] and Xinlei Chang [1]

[1] School of Civil Engineering, Beijing Jiaotong University, Beijing 100091, China; 19115017@bjtu.edu.cn (X.G.); 23111314@bjtu.edu.cn (S.X.); 19115037@bjtu.edu.cn (L.P.); 20115039@bjtu.edu.cn (B.Z.); 21115042@bjtu.edu.cn (L.W.); 24110317@bjtu.edu.cn (X.C.)
[2] Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China; liuyinshan@casisd.cn
[3] School of Economics and Management & Office of International Affairs, Beijing Jiaotong University, Beijing 100044, China; lfan1@bjtu.edu.cn
[4] School of Management, Tianjin University of Commerce, Tianjin 300134, China; shicc1124@163.com
* Correspondence: cyfwang@bjtu.edu.cn

Abstract: Building energy consumption management significantly impacts energy efficiency, environmental effects, and economic benefits throughout a building's life cycle. Optimizing building energy consumption has become a great challenge in the field of green buildings. This paper proposes an automated simulation method that integrates the EnergyPlus energy consumption simulation tool with Python scripting. This approach efficiently generates large volumes of energy consumption data and supports the development of machine learning surrogate models, thereby enhancing simulation efficiency and reducing computational costs. Based on this foundation, the multi-objective optimization algorithm NSGA-III is introduced to achieve a balanced optimization of three primary objectives: building energy consumption, photovoltaic electricity generation, and thermal comfort. Through a systematic analysis of a case study involving an office building and dormitory at a construction site in China, the effects of building envelope, air conditioning systems, and occupant behavior on energy consumption are examined. The optimization results indicate that energy consumption is reduced by 41% for the office building and 38% for the dormitory. Additionally, photovoltaic electricity generation increases by 176% and 169% compared to the baseline model, while thermal comfort improves by 19% and 6%, respectively. These improvements significantly enhance energy self-sufficiency and residential comfort.

Keywords: building energy consumption; photovoltaics; thermal comfort; surrogate models; multi-objective optimization; building design

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1. Instruction

As attention to green building and sustainable development intensifies, the effective control and optimization of building energy consumption has become a critical research topic in the field of buildings. Building energy consumption encompasses not only the energy used during the production of building materials and the construction phase but also the daily energy use after the building is completed. This multifaceted nature of energy consumption necessitates a comprehensive consideration of the building's overall energy efficiency during the design phase to achieve long-term economic benefits and environmental sustainability [1]. However, despite significant strides in this area, there

remain critical gaps in the existing research, particularly in terms of energy consumption simulation efficiency, real-time optimization, and the application of these techniques to temporary structures in construction environments.

Architectural design must strike a reasonable balance between energy efficiency and residential comfort. By selecting high-performance insulation materials, optimizing window designs, and incorporating natural daylight, it is possible to significantly reduce the heating and cooling demands of buildings [2]. Additionally, modern buildings increasingly utilize intelligent energy management systems that monitor and adjust internal energy usage in real time, ensuring energy efficiency while maintaining occupant comfort [3]. However, traditional methods, while effective in static buildings, often fail to address the complexities and dynamic nature of energy consumption in temporary structures at construction sites.

Energy consumption simulation tools play an irreplaceable role in energy management and optimization. These tools allow for precise predictions of a building's energy consumption under various strategies during the design phase, providing a scientific basis for energy optimization. Commonly used simulation tools include EnergyPlus and DeST, which offer detailed energy consumption analyses across multiple scenarios and parameters [4,5]. However, traditional energy simulation methods are increasingly revealing issues related to complexity, high computational load, and inefficiency, particularly in scenarios requiring repeated simulations and optimizations. These challenges drive researchers to seek more efficient solutions that enhance computational efficiency while maintaining accuracy [6]. Moreover, while the integration of artificial intelligence and machine learning has shown promise in improving simulation performance, its practical application in real-time energy optimization remains limited, especially in the context of temporary or construction-site-based buildings.

EnergyPlus is a widely recognized tool for building energy consumption simulation, offering high accuracy and flexibility. However, its traditional use requires manual input modifications, repeated execution for parameter changes, and separate result processing, which are time-consuming and error-prone, especially for large-scale studies.

To overcome these limitations, this study proposes a Python-based automation framework integrated with EnergyPlus. Key motivations include:

Efficiency: Automation eliminates repetitive tasks, significantly reducing simulation time.

Scalability: The framework enables large-scale data generation, essential for surrogate model training and optimization.

Enhanced Analysis: Python libraries allow advanced data processing, statistical analysis, and machine learning integration.

Flexibility: Dynamic parameter adjustments and streamlined execution make the tool adaptable to diverse scenarios.

This framework enhances EnergyPlus's usability and efficiency, supporting more comprehensive and practical building energy optimization applications.

The introduction of artificial intelligence and surrogate models has revolutionized building energy consumption simulation. Energy consumption simulation methods that incorporate machine learning algorithms significantly enhance computational efficiency and simulation accuracy while reducing costs [7,8]. Additionally, the application of multi-objective optimization algorithms allows for greater flexibility in energy efficiency optimization within complex building environments, facilitating the achievement of an optimal balance among multiple objectives such as energy efficiency, electricity generation, and occupant comfort [9]. For instance, the multi-objective optimization algorithm, NSGA-II (Non-dominated Sorting Genetic Algorithms II), demonstrates good adaptability and ef-

ficiency in balancing building energy consumption [10]. However, the use of AI-driven multi-objective optimization in dynamic, temporary building environments has not been fully explored, and this paper seeks to address this gap.

This research introduces a fully automated simulation framework that integrates Python scripting with EnergyPlus, significantly enhancing the efficiency of energy data generation. Unlike conventional methods that rely on manual simulation adjustments, the proposed approach automates the entire workflow, from parameter generation to simulation execution, creating a large-scale database for surrogate model training with minimal human intervention.

Furthermore, this study advances current knowledge by systematically combining surrogate modeling and the NSGA-III algorithm for multi-objective optimization. While previous research has explored these components separately, their integrated application in optimizing temporary building energy consumption, photovoltaic generation, and thermal comfort is novel. This integration allows for a holistic and efficient exploration of trade-offs between conflicting objectives, setting a benchmark for similar studies.

2. Method

2.1. Building Energy Modelling

In the field of building energy consumption simulation, simulation engines are essential tools for performing design specifications, parameter analysis, and optimization simulations for one or more building energy systems. Commonly used simulation engines include EnergyPlus, DOE-2, TRNSYS, DeST, and ESP-r [11]. Each of these tools has unique features, catering to various types of building energy consumption simulation needs.

Historically, DOE-2 and EnergyPlus have been widely used, particularly in the United States, where EnergyPlus was regarded as the most advanced comprehensive building energy modeling tool [12]. TRNSYS, developed by the University of Wisconsin, has been primarily utilized for modeling passive and active solar energy systems in buildings [13]. ESP-r, initially developed by researchers at University of Strathclyde, focuses on the thermal and acoustic performance modeling of building spaces [14]. DeST, developed by Tsinghua University, has been mainly used in China and integrated with AutoCAD to provide hourly building data reports [15]. It caters specifically to the needs of building energy consumption simulation in China. DeST excels in building load calculations, Heating, Ventilation and Air Conditioning (HVAC) system simulation, and energy efficiency evaluation, making it suitable for analyzing energy consumption in large public buildings and complex building systems.

EnergyPlus is currently the most widely used simulation engine for Building Energy Management System (BEMS) tasks related to design and control-oriented optimization [16]. It includes three built-in GUIs (Graphical User Interfaces): IDF-Editor, EP-Launch, and EP-Compare, along with OpenStudio, a specialized graphical user interface developed for EnergyPlus. This study employs SketchUp, OpenStudio, and EnergyPlus to conduct building energy consumption simulations. SketchUp is used for creating the physical model, OpenStudio identifies thermal zones, and EnergyPlus is used for setting model boundary parameters and performing thermal calculations.

2.2. Artificial Intelligence Agent Models

Traditional energy consumption simulation methods, while capable of providing precise results, are often complex to operate and computationally intensive, especially in scenarios requiring extensive simulations and optimizations. To address this issue, surrogate models create approximations of the original simulation model, enabling rapid response and significantly enhancing computational efficiency. These surrogate models are

typically generated through training with machine learning algorithms, which effectively reduce reliance on the original simulation model.

In this study, Python scripts are used to automate large-scale simulations in EnergyPlus, generating substantial data to train surrogate models. The Eppy library is employed to control EnergyPlus input files, enabling quick simulations by adjusting various design variables and producing a large volume of energy consumption data. This process provides robust data support for subsequent surrogate model training. This process involves three primary steps: (1) random generation of input parameters within predefined ranges, (2) automated modification of the IDF files through Python scripts, and (3) iterative simulation and data collection. By automating these tasks, the program significantly reduces manual effort and ensures consistent database generation.

Surrogate models hold significant application value in the field of building energy consumption prediction, as they can effectively simulate and predict a building's energy consumption behavior. A review study by Amasyali et al. [17] demonstrates the widespread use of machine learning algorithms in building energy consumption prediction. Artificial Neural Networks (ANNs) are used in 47% of the studies, while Support Vector Machines (SVM) and Decision Tree (DT) algorithms accounted for 25% and 4%, respectively. Additionally, 24% of the studies utilized other statistical methods, such as multiple linear regression, ordinary least squares, and autoregressive moving average models.

Regarding the comparative performance of different algorithms, existing research provides robust evidence. Zhao et al. [18] analyzed ANNs, Support Vector Regression (SVR), and traditional statistical models, finding that ANNs demonstrate notable advantages in both accuracy and computational speed. Furthermore, research by Wang et al. [19] highlighted the widespread application of ANNs in building energy consumption prediction, particularly in comparisons with regression and SVR models, where ANNs showed superior performance. Collectively, these studies indicate that ANN has become one of the most popular and efficient algorithms in the field of building energy consumption prediction [15].

The surrogate models were trained using the datasets generated by the automated process. Various machine learning algorithms in this study, including Linear Regression (LR), K-Nearest Neighbors (KNN), Random Forest (RF), and Artificial Neural Networks (ANNs), were tested for their predictive accuracy. Statistical metrics such as the coefficient of determination (R^2) and the Mean Absolute Percentage Error (MAPE) were employed to evaluate model performance.

2.3. Multi-Objective Optimization Algorithms

In multi-objective optimization research concerning building energy consumption, photovoltaic capacity, and thermal comfort, NSGA-III (Non-dominated Sorting Genetic Algorithm III) stands out as an advanced optimization tool capable of effectively managing multiple conflicting objectives. For example, the NSGA-III algorithm demonstrates higher iteration speed and optimization accuracy in joint planning of multi-objective distributed energy systems [20]. NSGA-III improves upon NSGA-II, specifically designed for complex optimization problems with three or more objectives. By introducing a reference point mechanism, it ensures diversity and uniform distribution of solutions in the optimization process.

The core principle of NSGA-III is to find an optimal trade-off set, or Pareto front, among objective functions through the evolutionary mechanism of genetic algorithms. Its main steps include population and reference point initialization, non-dominated sorting, reference point assignment, genetic operations (selection, crossover, and mutation), and the merging of offspring with parent populations to ultimately output Pareto-optimal solutions.

Compared to NSGA-II, NSGA-III demonstrates greater adaptability and global search capability in handling high-dimensional multi-objective problems, making it especially suitable for complex system optimization where multiple interdependent objectives must be balanced [21,22].

Overall, NSGA-III has become an effective tool for addressing multi-objective challenges in energy management and building optimization, due to its superior performance in multi-objective optimization tasks [23].

To provide a unified representation of the workflow and enhance clarity, we have included a flowchart summarizing the methodology used in this study. The flowchart highlights the key steps involved, including the modeling of temporary buildings, consideration of meteorological and material parameters, integration of occupant behavior and photovoltaic retrofitting, the use of Python calls to EnergyPlus for generating energy consumption databases, the development of artificial intelligence models, and the final NSGA-III genetic algorithm optimization process. The Figure 1 aims to offer readers a clear and structured understanding of the methodological flow.

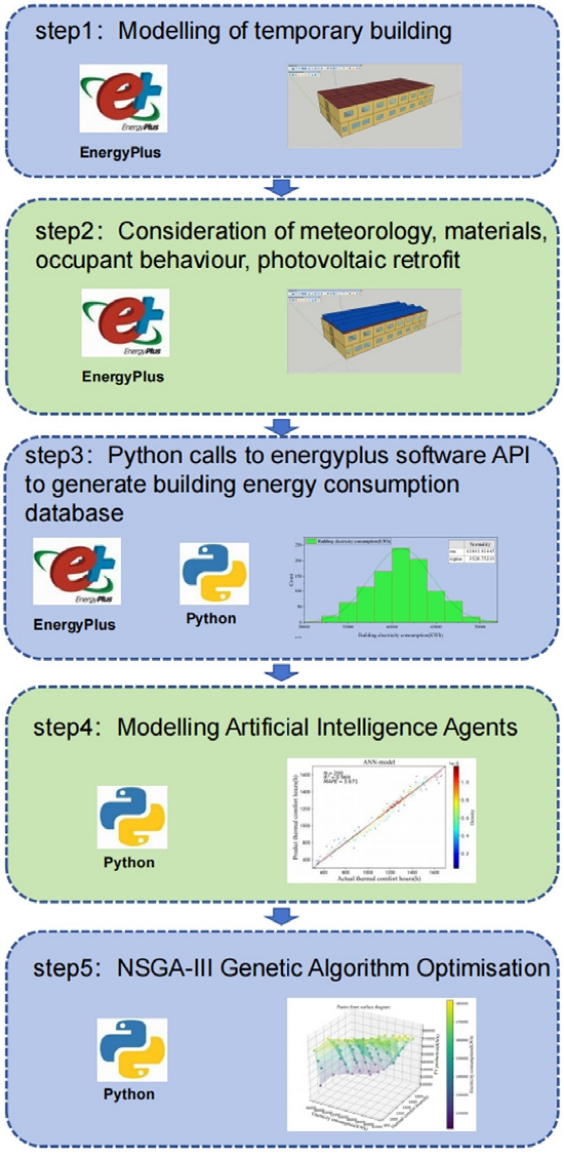


Figure 1. Flowchart.

3. Case Studies

3.1. Modelling Energy Consumption in Office Areas

In this study, a temporary office building at a construction site in Tianjin, China, was selected as the research subject. A 3D model of the office building was constructed using SketchUp, with thermal properties processed in OpenStudio, and detailed energy consumption simulations conducted in EnergyPlus. The office building model includes multiple functional areas such as a video room, offices, and meeting rooms. Comprehensive energy consumption analysis was performed, taking into account the usage of the air conditioning system, as well as lighting, equipment, and other loads.

Figure 2 presents the office building model, and Table 1 lists the room configurations and dimensions of this office building.

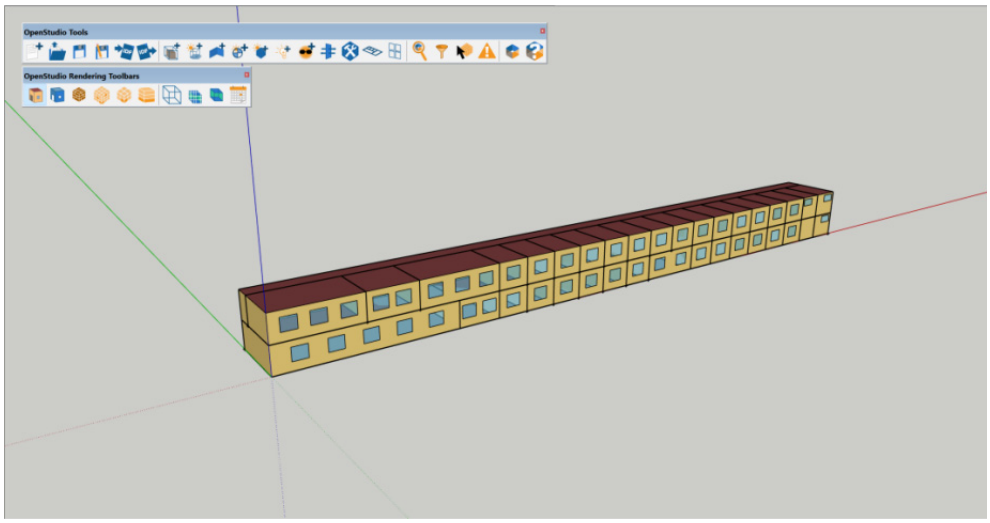


Figure 2. Office building model.

Table 1. Office building room configuration and dimensions.

First Floor Room Configuration	Room Name	Size (m)	Remarks
1	Video Room	5150 × 5700	1 room
2	Office	3800 × 5700	11 rooms
3	Meeting Room	20,750 × 7700	1 room
4	Men's Toilet	3725 × 5700	1 room
5	Women's Toilet	3275 × 5700	1 room
Second-Floor Room Configuration	**Room Name**	**Size (m)**	**Remarks**
1	Innovation Studio	10,000 × 5700	1 room
2	Party Activity Room	6000 × 5700	1 room
3	Reception Room	9900 × 5700	1 room
4	Office	3800 × 5700	13 rooms
5	Men's Toilet	3725 × 5700	1 room
6	Women's Toilet	3275 × 5700	1 room

With EnergyPlus, detailed configurations were set for the building's envelope, lighting, equipment, and air conditioning systems to simulate energy consumption under various conditions. During the simulation, operational schedules and modes for various equipment were adjusted based on actual usage patterns to ensure the realism and accuracy of the results. Table 2 summarizes the thermal performance of the materials used in the building's envelope. Additionally, the building was equipped with standard 174 mm × 95 mm sliding

plastic steel windows, with a U-value of 2 W/(m^2·K) and a solar heat gain coefficient (g-value) of 0.4.

Table 2. Summary of thermal properties of materials for office building envelopes.

Maintenance Type	Name	Thickness (mm)	Thermal Conductivity (W/(m·K))	Density (kg/m^3)	Specific Heat Capacity (J/(kg·K))	R-Value ((m^2·K)/W)
External Walls	Colour steel plate Rock wool board Colour steel plate	0.4 75 0.4	50 0.04 50	7850 120 7850	500 800 500	1.875
Internal Walls	Colour steel plate Rock wool board Colour steel plate	0.35 50 0.35	50 0.04 50	7850 120 7850	500 800 500	1.250
Floor	Colour steel plate Rock wool board Colour steel plate	0.4 75 0.4	50 0.04 50	7850 120 7850	500 800 500	1.875
Roof	Colour steel plate Rock wool board Colour steel plate	0.4 75 0.4	50 0.04 50	7850 120 7850	500 800 500	1.875

To conduct building energy consumption simulation, setting thermal disturbances for rooms is a critical step, as it significantly impacts the accuracy and reliability of simulation results. Previous studies have shown that occupant behavior is one of the key factors influencing building energy consumption [24]. Discrepancies between actual and simulated energy consumption may arise from inaccuracies in estimating occupancy rates [25]. In energy simulations of buildings, clearly defining schedules for lighting and occupant-generated heat disturbances is essential for accurately assessing energy consumption, thermal comfort, and energy management. This not only aids in optimizing building system design but also supports the development of effective energy management strategies, leading to more accurate simulation outcomes. Table 3 provides an overview of lighting, equipment, and occupancy schedules across different rooms in the office building.

Table 3. Thermal disturbances in indoor environments of office buildings.

Room Type	Thermal Disturbance	Unit	Power Density	Occupancy Time	Simultaneous Use Factor
Office	Lighting Equipment Body Heat Gain Personnel Density	W/m^2 W/person W/person m^2/person	15 15 130 4	 Workdays 8:00–18:00 	0.9 0.9 1 1
Meeting Room	Lighting Equipment Body Heat Gain Personnel Density	W/m^2 W/person W/person m^2/person	10 20 130 2	 Workdays 8:00–18:00 	0.9 0.7 0.7 0.7
Reception Room	Lighting Equipment Body Heat Gain Personnel Density	W/m^2 W/person W/person m^2/person	10 10 130 5	 Workdays 8:00–18:00 	0.8 0.6 0.6 0.6
Video Surveillance Room	Lighting Equipment Body Heat Gain Personnel Density	W/m^2 W/person W/person m^2/person	15 30 130 4	 Everyday 0:00–24:00 	0.9 1 1 1
Party Activity Room	Lighting Equipment Body Heat Gain Personnel Density	W/m^2 W/person W/person m^2/person	12 10 130 3	 Workdays 8:00–18:00 	0.9 0.7 0.7 0.7

Table 3. *Cont.*

Room Type	Thermal Disturbance	Unit	Power Density	Occupancy Time	Simultaneous Use Factor
Innovation Studio	Lighting	W/m^2	15	Workdays 8:00–18:00	0.9
	Body Heat Gain	W/person	130		0.7
	Personnel Density	m^2/person	3		0.7
Toilet	Lighting	W/m^2	7	Everyday 7:00–24:00	0.5
	Body Heat Gain	W/person	130		0.3
	Personnel density	m^2/person	10		0.3

The heating and cooling demands in office areas are primarily met by an air conditioning system. The Packaged Terminal Heat Pump (PTHP) system integrates heat pump and air conditioning functions, offering users an indoor environment solution characterized by integrated cooling and heating, independent control, and high energy efficiency. In this study, the PTHP system was used to simulate the operational conditions of split air conditioning units, with specific usage details provided in Table 4. To ensure indoor air quality, mechanical ventilation was activated on non-air-conditioned days to maintain an air exchange rate of 1 air change per hour.

Table 4. Summary of the use of air-conditioning systems in office buildings.

Heating and Cooling Requirements	Regional	Indoor Air Temperature (°C)	Air-Conditioning System Switch-on Time	COP (Coefficient of Performance)	Simultaneous Use Factor
Heating	Office	20	Workdays 8:00–18:00	3	0.8
	Meeting Room	20	Workdays 8:00–18:00	3	0.7
	Reception Room	20	Workdays 8:00–18:00	3	0.6
	Video surveillance room	20	Everyday 0:00–24:00	3	0.9
	Party Activity Room	20	Workdays 8:00–18:00	3	0.8
	Innovation Studio	20	Workdays 8:00–18:00	3	0.7
Cooling	Office	26	Workdays 8:00–18:00	3	0.8
	Meeting Room	26	Workdays 8:00–18:00	3	0.7
	Reception Room	26	Workdays 8:00–18:00	3	0.6
	Video Surveillance Room	26	Everyday 0:00–24:00	3	0.9
	Party Activity Room	26	Workdays 8:00–18:00	3	0.8
	Innovation Studio	26	Workdays 8:00–18:00	3	0.7

Thermal comfort refers to the state in which an individual feels satisfied with the surrounding thermal environment. This concept is particularly crucial in building environments, as it directly impacts occupants' well-being and productivity. Thermal comfort is influenced by various factors, including air temperature, humidity, air velocity, mean radiant temperature, metabolic rate, and clothing level. These elements collectively determine how comfortable individuals feel in a given space, emphasizing the importance of precise thermal regulation in building design and management [26].

In this study, the Predicted Mean Vote (PMV) method was primarily used to calculate thermal comfort indicators. The PMV method is an evaluation approach based on extensive experimental data analysis. It considers factors such as metabolic rate, clothing insulation, ambient temperature, relative humidity, air velocity, and mean radiant temperature to predict the average thermal sensation experienced by individuals in a given environment [27]. Specifically, in this study, the number of hours during which the PMV value falls within the range of -0.5 to 0.5 was calculated, using this as the primary metric for assessing thermal comfort. A PMV range of -0.5 to 0.5 indicates that most people feel comfortable in the environment, so the hours within this range effectively reflect the thermal comfort level of the building environment [28,29].

This study also explored the application of zero-emission renewable energy technologies, with a particular focus on the potential for rooftop photovoltaic (PV) panels. To accurately assess photovoltaic generation capacity, a full-coverage PV layout across the building's rooftop was implemented (see Figure 3).

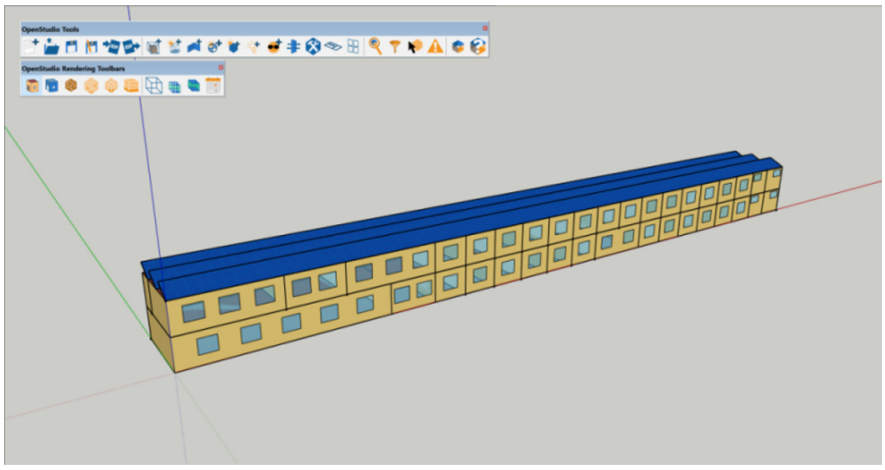


Figure 3. Office building roof full of photovoltaic panels model.

The study site is located in Tianjin, China (longitude 117°12′ E, latitude 39°58′ N). Based on calculations and analysis, the optimal installation angle for the PV panels was determined to be 35°. This angle was selected by taking into account the geographical and climatic characteristics of Tianjin to ensure maximum energy collection efficiency for the PV panels [30]. In addition to the installation angle, this study also considered other variables that may impact PV generation efficiency, including the conversion efficiency of the PV cells and the performance of the inverter. Table 5 provides detailed baseline model parameters, offering robust support for the accuracy and reliability of this study.

Table 5. Parameter values for rooftop photovoltaic panels.

Photovoltaic Panel Parameters	Value
Surface Area Ratio of Active Solar Cells	0.6
Photovoltaic Cell Efficiency	0.15
Inverter Efficiency	0.95

3.2. Modelling of Energy Consumption in Living Areas

The staff living area at the construction site is another significant source of building energy consumption, with building structures and equipment usage patterns differing from those in the office area. Similarly, a model was developed for the dormitory building in the living area, which includes configurations for functional zones such as the dormitory kitchen, dining hall, and sleeping quarters, along with thermal property settings. The application of a photovoltaic system was also considered for the dormitory building. Through an analysis of the dormitory's annual energy consumption, opportunities for improving energy efficiency and potential optimization strategies were identified.

Figure 4 shows the dormitory building model, and Table 6 lists the room configurations and dimensions for the dormitory building in the living area.

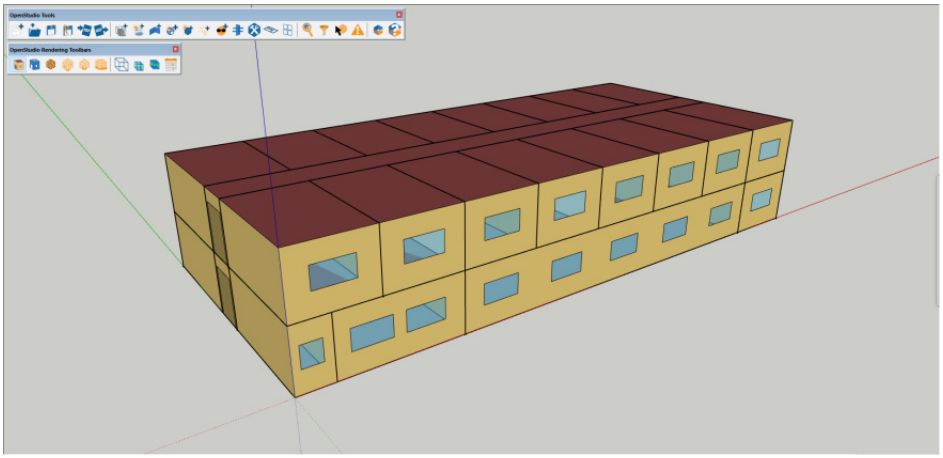


Figure 4. Dormitory building model.

Table 6. Room configurations and dimensions of dormitory buildings.

First Floor Room Configuration	Room Name	Size (m)	Remarks
1	Kitchen Workshop	5600 × 5700	1 room
2	Kitchen Warehouse	1600 × 5700	1 room
3	Large Dining Room	18,000 × 5700	1 room
4	Dishwashing Room	3600 × 5700	1 room
5	Dormitory	3600 × 5700	6 rooms
6	Men's Toilet	3600 × 5700	1 room
7	Women's Toilet	3600 × 5700	1 room
Second-Floor Room Configuration	**Room Name**	**Size (m)**	**Remarks**
1	Dormitory	3600 × 5700	14 rooms
2	Men's Toilet	3600 × 5700	1 room
3	Women's Toilet	3600 × 5700	1 room

Setting material properties for the external envelope of the dormitory building is a crucial step in conducting building energy consumption analysis. Table 7 provides a summary of the thermal performance of materials used in the dormitory's envelope.

Table 7. Summary of thermal properties of materials for the dormitory envelope.

Maintenance Type	Name	Thickness (mm)	Thermal Conductivity (W/(m·K))	Density (kg/m^3)	Specific Heat Capacity (J/(kg·K))	R-Value ((m^2·K)/W)
External Walls	Colour steel plate	0.4	50	7850	500	1.875
	Rock wool board	75	0.04	120	800	
	Colour steel plate	0.4	50	7850	500	
Internal Walls	Colour steel plate	0.35	50	7850	500	1.250
	Rock wool board	50	0.04	120	800	
	Colour steel plate	0.35	50	7850	500	
Floor	Colour steel plate	0.4	50	7850	500	1.875
	Rock wool board	75	0.04	120	800	
	Colour steel plate	0.4	50	7850	500	
Roof	Colour steel plate	0.4	50	7850	500	1.875
	Rock wool board	75	0.04	120	800	
	Colour steel plate	0.4	50	7850	500	

Table 8 presents the indoor thermal disturbances for the dormitory building. Unlike the office building, the dormitory's dining hall primarily operates during breakfast, lunch, and dinner hours, while the kitchen and dishwashing areas are mainly active during the daytime. Dormitory occupancy occurs predominantly at night, resulting in different heat transfer dynamics and thermal comfort considerations for occupants. Table 9 outlines the air conditioning system usage schedule for the dormitory, which operates from 18:00 to 7:00 the following day, ensuring optimal thermal comfort during rest hours for the occupants.

Table 8. Indoor heat disturbance in dormitory buildings.

Room Type	Thermal Disturbance	Unit	Power Density	Occupancy Time	Simultaneous Use Factor
Dormitory	Lighting	W/m^2	10	Everyday	0.9
	Equipment	W/person	10	18:00–23:00	0.7
	Body Heat Gain	W/person	130	Everyday	1
	Personnel Density	m^2/person	4	18:00–07:00 (+1)	1
Dining Room	Lighting	W/m^2	15	Everyday	0.9
	Equipment	W/person	20	7:00–9:00,	0.7
	Body Heat Gain	W/person	130	11:00–13:00,	1
	Personnel Density	m^2/person	2	17:00–19:00	1
Kitchen Workshop	Lighting	W/m^2	10		0.8
	Equipment	W/person	300	Everyday	0.7
	Body Heat Gain	W/person	130	6:00–20:00	1
	Personnel Density	m^2/person	5		0.8
Dishwashing Room	Lighting	W/m^2	10		0.8
	Equipment	W/person	20	Everyday	0.7
	Body Heat Gain	W/person	130	6:00–20:00	1
	Personnel Density	m^2/person	5		0.8
Toilet	Lighting	W/m^2	7	Everyday	0.5
	Body Heat Gain	W/person	130	0:00–24:00	1
	Personnel Density	m^2/person	10		0.3

Table 9. Summary of the use of air-conditioning systems in dormitory buildings in living areas.

Heating and Cooling Requirements	Regional	Indoor Air Temperature (°C)	Air-Conditioning System Switch-on Time	COP	Simultaneous Use Factor
Heating	Dormitory	20	Everyday 18:00–07:00 (+1)	3	1
	Dining room	20	Everyday 7:00–9:00, 11:00–13:00, 17:00–19:00	3	1
	Kitchen Workshop	20	Everyday 6:00–20:00	3	0.8
	Dishwashing Room	20	Everyday 6:00–20:00	3	0.8
Cooling	Dormitory	26	Everyday 18:00–07:00 (+1)	3	1
	Dining room	26	Everyday 7:00–9:00, 11:00–13:00, 17:00–19:00	3	1
	Kitchen Workshop	26	Everyday 6:00–20:00	3	0.8
	Dishwashing Room	26	Everyday 6:00–20:00	3	0.8

To maximize solar energy utilization, a full-coverage PV panel layout was also implemented on the dormitory building rooftop (as shown in Figure 5). The parameter settings for the rooftop PV panels are consistent with those used for the office building.

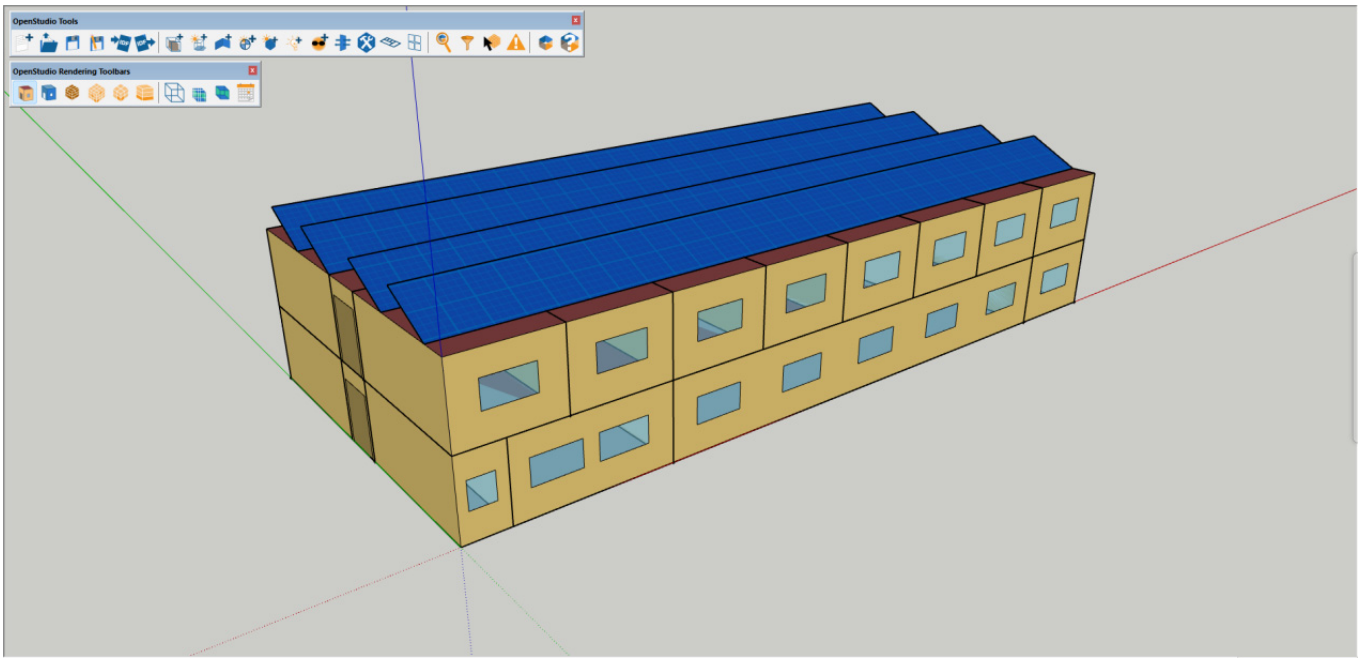


Figure 5. Full roof photovoltaic model for dormitory building.

4. Results and Discussion

4.1. Energy Consumption Simulation Results

To accurately predict a building's energy performance, simulations require detailed and precise meteorological data. Typical Meteorological Year (TMY) data are especially valuable as they synthesize weather data from multiple years to provide representative climate conditions, thus enhancing the reliability of simulation results. In this study, the TMY file used comes from the Chinese Standard Weather Data (CSWD) available on the EnergyPlus website. Provided by China's national meteorological observation stations, this dataset covers major climate regions across the country. The CSWD includes key parameters such as temperature, humidity, wind speed, and solar radiation and is specifically designed for building energy consumption simulation and environmental assessment.

Figure 6 presents the monthly temperature variations of outdoor, non-conditioned, and conditioned zones in the temporary office building under TMY conditions. Non-conditioned areas include corridors and stairwells, while conditioned zones refer to functional rooms such as offices and meeting rooms. The results show that the temperature in non-conditioned areas closely follows outdoor temperature trends, with significantly higher temperatures than outdoors in summer and slightly lower in winter. Conditioned areas, however, maintain a relatively stable temperature, around 20 °C year-round, demonstrating the regulatory effect of the air conditioning system.

The analysis indicates that non-conditioned areas are highly influenced by external environmental conditions, particularly in summer and winter. Therefore, thermal insulation and ventilation design should be prioritized for temporary buildings. The temperature control in conditioned areas proves to be highly effective, especially under extreme weather conditions, highlighting the importance of an efficient air conditioning system to enhance occupant comfort and productivity.

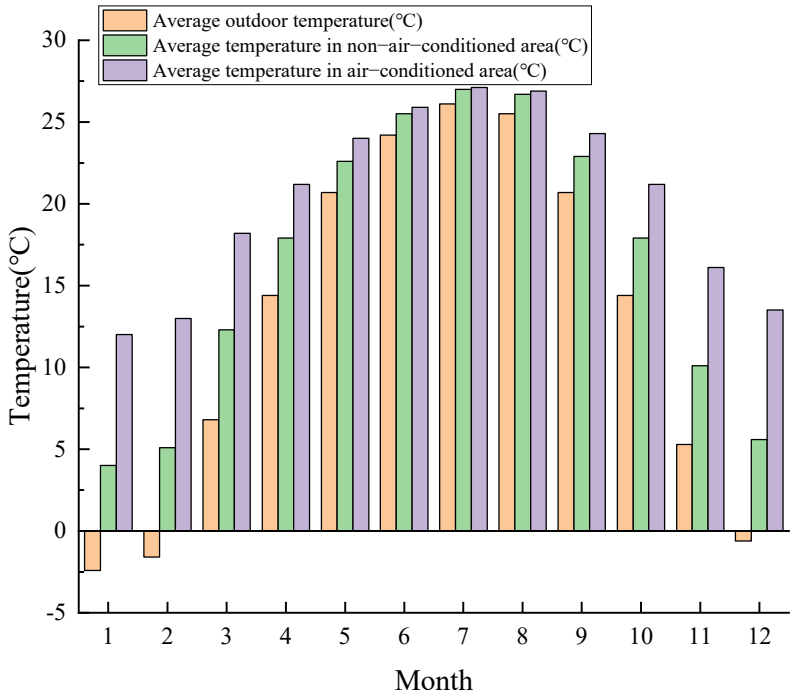


Figure 6. Changes in average monthly temperatures in temporary office buildings under TMY.

As shown in Figure 7, three different types of daily energy consumption are presented: heating load demand, cooling load demand, and total energy consumption. The figure reveals that total energy consumption and heating load demand fluctuate significantly throughout the year, with pronounced increases in summer and winter. This variation is directly related to temperature changes, as rising or falling temperatures lead to more frequent use of the air conditioning system. In contrast, cooling load demand remains relatively stable, indicating good thermal insulation performance in the building, with minimal impact from external temperature fluctuations.

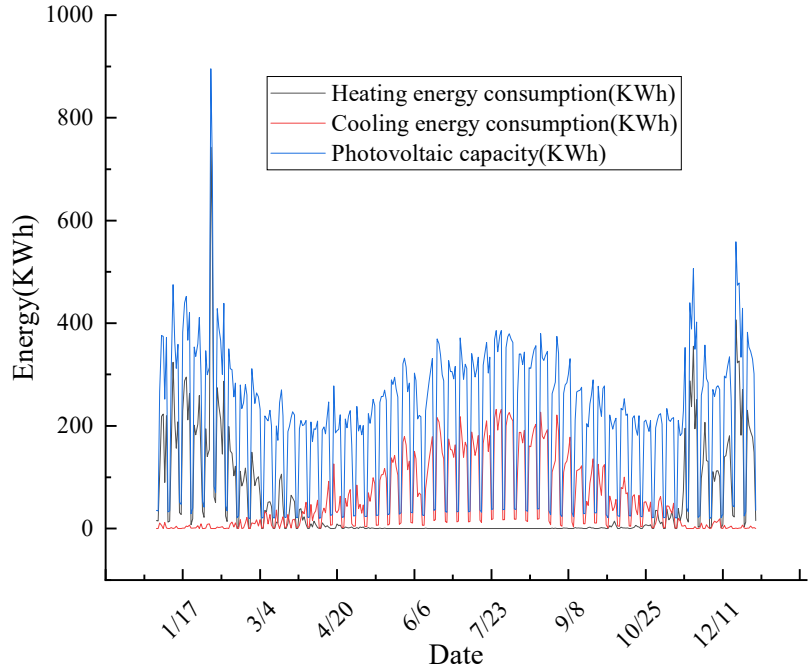


Figure 7. Average daily energy consumption of temporary office buildings under TMY.

The average daily thermal comfort PMV values for the office are shown in Figure 8, where the vertical axis represents the PMV value, and the horizontal axis represents the date. The red dashed lines indicate the thermal comfort range (−0.5 to +0.5), while the blue line shows the daily PMV values.

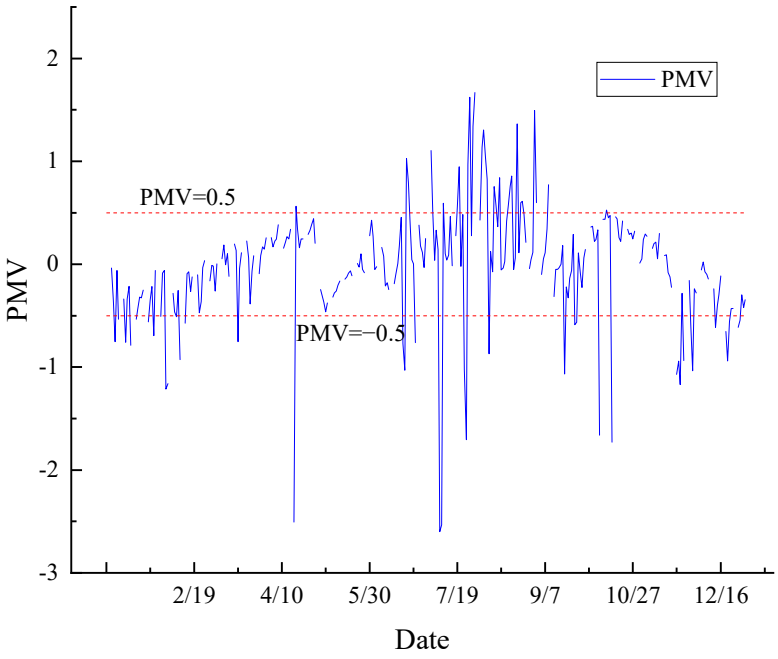


Figure 8. Average daily office thermal comfort PMV values.

Figure 8 illustrates that the PMV values remain within the comfort range (−0.5 to +0.5) most of the time, accounting for approximately 75.6% of the total time. During winter, the office environment is generally comfortable, but some fluctuations are observed. In certain instances, the PMV value drops below −0.5, potentially due to low indoor temperatures or excessive cooling by the air conditioning system, resulting in occupants feeling cold.

In summer, the PMV value occasionally exceeds +1.0 and at times reaches as high as +2.5, indicating that office temperatures are considerably high on these days. Potential causes include weather variations, direct sunlight, increased occupant activity, or improper adjustment of the air conditioning system. These high PMV values appear in several sharp peaks, suggesting significant temperature fluctuations that may impact employee comfort and productivity. Despite year-round operation of the air conditioning system, the office environment does not always maintain PMV values within the comfort range (−0.5 to +0.5), indicating that the system's regulation is suboptimal under certain conditions.

Similarly, temperature variations in the dormitory building within the living area under typical meteorological year conditions were analyzed. Figure 9 shows the monthly temperature variations in the dormitory. Non-conditioned areas exhibit a temperature trend consistent with outdoor temperatures, while the temperature in conditioned functional rooms and dormitory areas remains relatively stable. Throughout the year, dormitory temperatures are slightly higher than those in functional rooms. The analysis shows that seasonal changes in outdoor temperature significantly impact non-conditioned areas, although the building structure provides a buffering effect. The relatively stable temperatures in conditioned functional rooms and dormitories underscore the air conditioning system's critical role in maintaining a comfortable environment. The slightly higher temperatures in dormitories may be attributed to occupancy density and usage patterns.

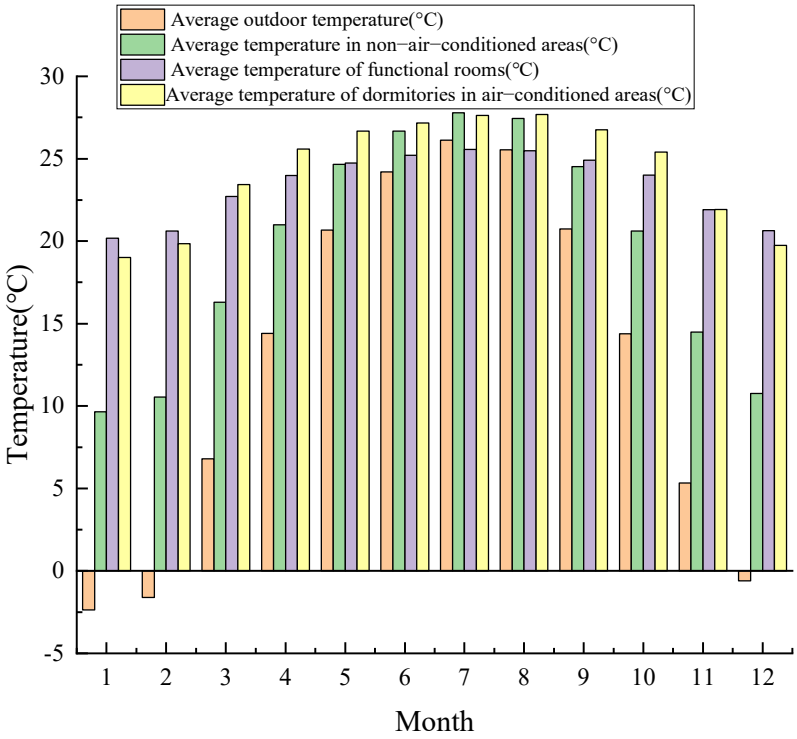


Figure 9. Monthly temperature changes in temporary structures of dormitory buildings under TMY.

Figure 10 illustrates the daily energy consumption variations for the dormitory building under typical meteorological year conditions. The black curve shows a distinct peak during the winter season, indicating a significant increase in energy consumption for the heating system when outdoor temperatures are lower. These peak values typically occur at the beginning and end of the year, closely tied to occupant activity and indoor temperature requirements.

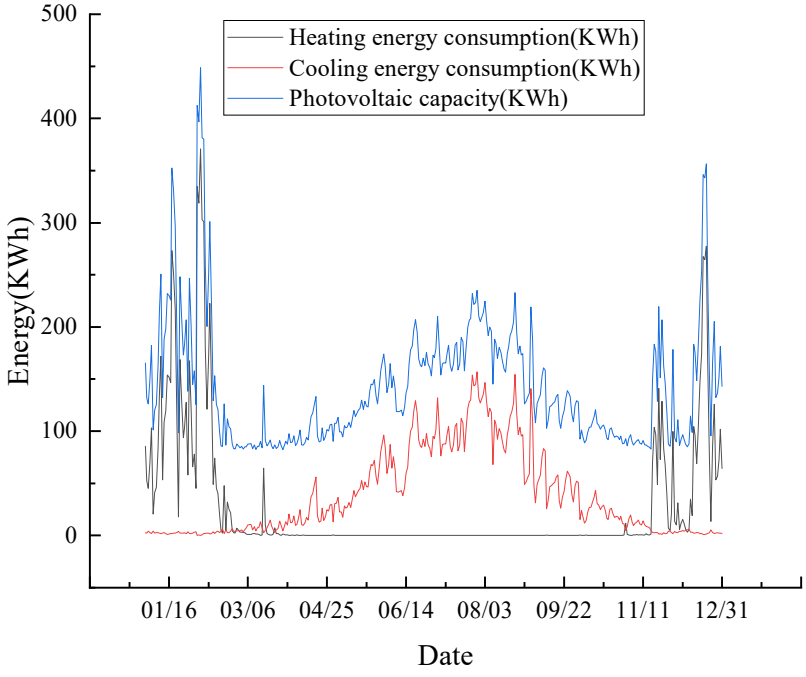


Figure 10. Changes in average daily energy consumption of temporary accommodation buildings under TMY.

The red curve peaks in summer, when outdoor temperatures are at their highest and demand for air conditioning and cooling is greatest. The blue curve, which combines heating and cooling energy consumption, reflects the overall energy consumption pattern for the temporary dormitory building. Total energy consumption is notably higher during the winter and summer peaks, with more stable levels observed during spring and autumn. This pattern highlights that the operation of the air conditioning system is the primary driver of energy consumption.

Figure 11 presents the annual variation in daily thermal comfort PMV values for the dormitory building under typical meteorological year conditions. The figure reveals significant fluctuations in the PMV values throughout the year, primarily reflecting the impact of indoor environmental adjustments in response to changing outdoor climatic conditions. Notably, the PMV values remain within the range of −0.5 to +0.5 for most of the year, indicating that the indoor environment in the dormitory building maintains a relatively comfortable range during the majority of the time.

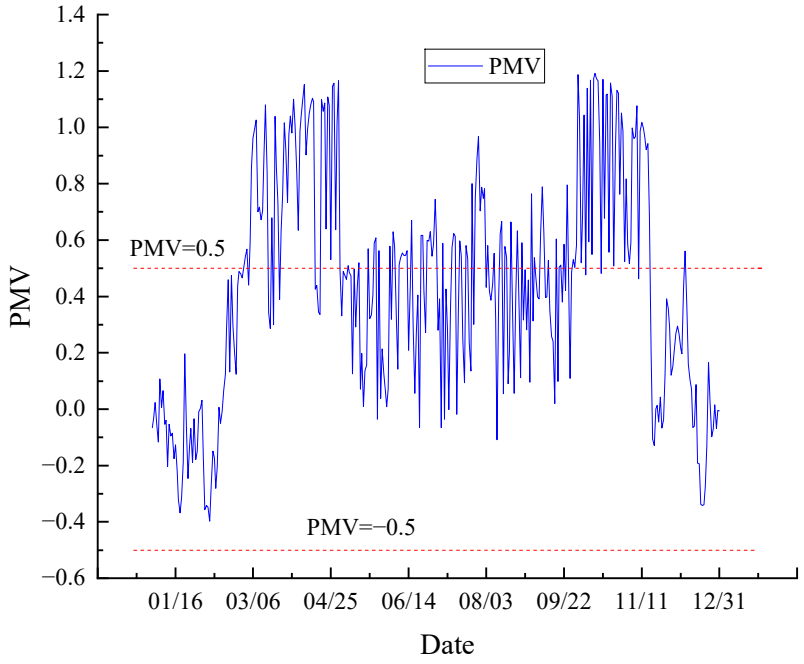


Figure 11. Average daily thermal comfort PMV of dormitory buildings.

In the hot summer months, the PMV values occasionally exceed the upper comfort limit of +0.5, indicating that the indoor environment may become too warm. During these times, the cooling function of the air conditioning system is particularly crucial. Effective use of air conditioning not only quickly reduces indoor temperatures but also adjusts humidity levels, significantly enhancing occupants' thermal comfort.

Conversely, in winter, the PMV values reflect lower readings, indicating a cooler indoor environment. Here, the heating function of the air conditioning system plays a vital role by providing the necessary warmth to improve thermal comfort. In cold weather, air conditioning systems not only offer heating but also help regulate indoor air circulation and humidity levels, further contributing to occupant comfort.

4.2. Artificial Intelligence Agent Modelling Results

To address the issue of insufficient data in building energy simulation, this study employed an automated simulation approach to rapidly generate training data, which supports the development of efficient surrogate models.

A Python-based automated simulation program was developed using the "Eppy" library to interface with the EnergyPlus software 22-1-0. By scripting, the program was able to automatically run multiple simulations under various combinations of design variables and collect energy consumption and performance data. This approach eliminates the cumbersome process of manual parameter adjustments, significantly increasing the speed of data generation.

Key design variables were selected based on critical factors in building energy simulation, including the building envelope, electrical equipment, usage behavior, and photovoltaic systems, resulting in a total of 16 parameters. Each variable was assigned a reasonable range from minimum to maximum values, ensuring that the simulations covered various scenarios encountered in actual building designs. The specific parameter ranges for both the office building and dormitory are detailed in Table 10.

Table 10. Range of values for office building design variable parameters.

Parameter Type	Designable Parameters	Abbreviation	Unit	Min	Max
Exterior enclosure	External R-value	ER	$(m^2 \cdot K)/W$	2	15
	Roof R-value	RR	$(m^2 \cdot K)/W$	2	15
	Glass U-value	GU	$W/m \cdot K$	1	2.5
	Glass SHGC value	GSHGC	-	0.2	0.6
Electrical Equipment	Lighting Power Density	LPD	W/m^2	8	15
	Equipment Power Density	EPD	W/person	10	20
	Heating Temperature	HT	°C	18	20
	Cooling Temperature	CT	°C	26	28
	Air-Conditioning Cooling COP	ACCOP	-	3	6
	Air-Conditioning Heating COP	AHCOP	-	3	6
Usage Behaviour	Air-Conditioning Usage Factor	AUF	-	0.7	0.9
	Lighting Usage Factor	LUF	-	0.8	0.9
	Equipment Usage Factor	EUF	-	0.7	0.9
Photovoltaic	Solar Active Battery Area Percentage	SABAP	%	0.6	0.9
	Battery Efficiency	BE	%	0.12	0.25
	Inverter Efficiency	IE	%	0.93	0.99

The automated simulation process consists of three main steps: First, the script randomly generates 1000 sets of input parameters based on the predefined variable ranges, with each set representing a distinct building design scenario. Next, the Eppy library modifies the relevant parameters in the IDF files and automatically initiates EnergyPlus for simulation. Finally, after the simulations are complete, the program automatically collects and stores key performance indicators, such as total energy consumption and photovoltaic output. This automated design significantly reduces manual intervention and enhances simulation efficiency.

Through this method, the study generated a substantial amount of data in a short period, reflecting the impact of different building design parameters on energy consumption. This data not only facilitates the training of high-precision surrogate models but also applies to predict and optimize building energy efficiency.

This study conducted 1000 energy consumption simulations for both the office building and dormitory, creating a comprehensive database for surrogate model training. Figure 12 illustrates the distribution of three sets of data for the office building simulations. The building's energy consumption shows a nearly normal, unimodal distribution, with a mean of 61,041 kWh and a standard deviation of 3520 kWh. In contrast, the PV energy production has a mean of 103,776 kWh and a standard deviation of 24,307 kWh, indicating a wider distribution that reflects the inherent variability in PV generation. The total hours of PMV

data demonstrate a skewed distribution, with a mean of 102.87 h and a standard deviation of 272.72 h, suggesting significant fluctuations in thermal comfort.

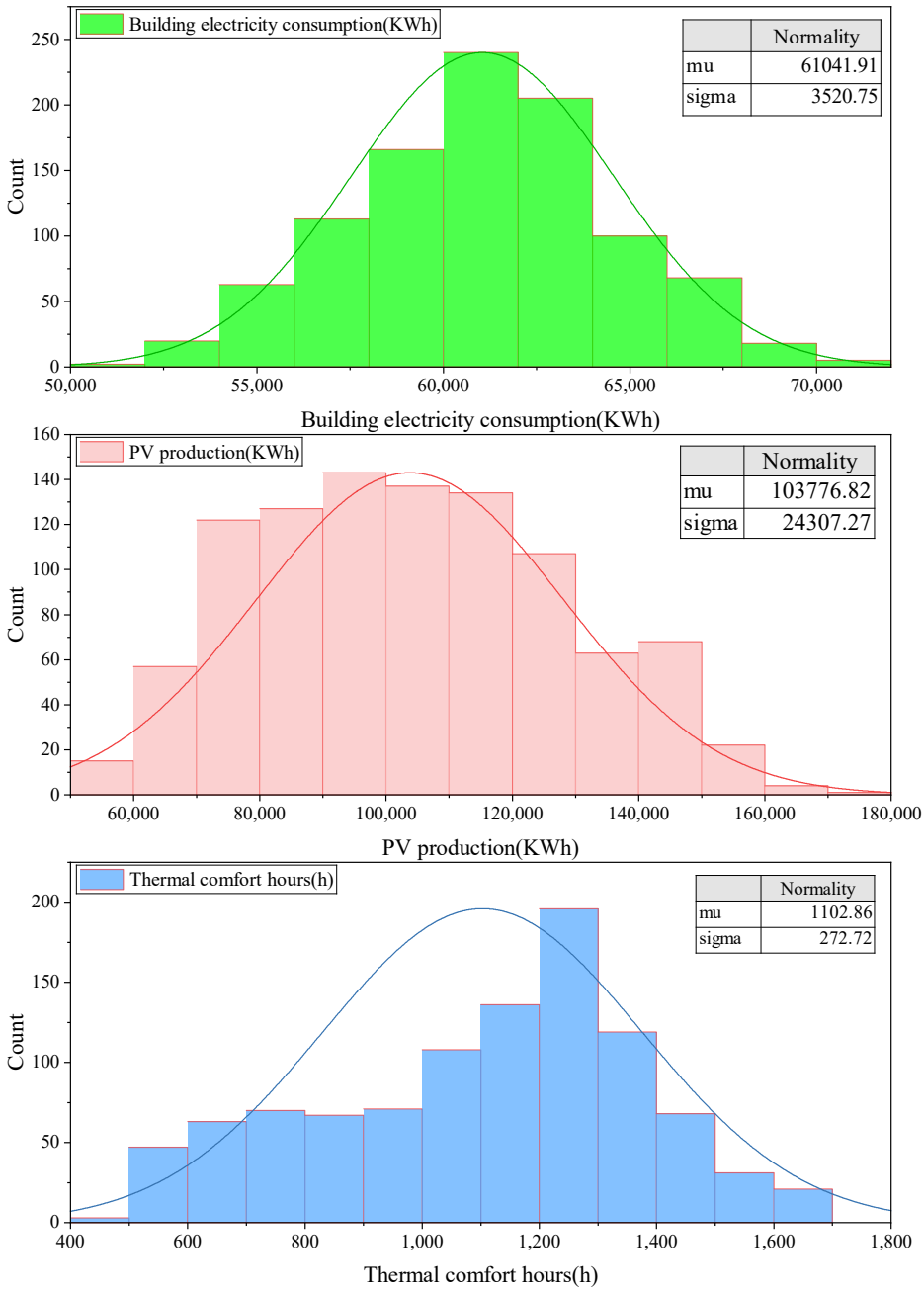


Figure 12. Distribution of data in the office building energy consumption database.

Figure 13 presents the energy consumption simulation results for the dormitory. Similar to the office building, the total energy consumption also exhibits a normal distribution, with a mean of 48,379 kWh and a standard deviation of 4312 kWh. The mean PV energy production stands at 45,924 kWh, with a standard deviation of 10,742 kWh, indicating considerable variability in energy output. The PMV hours data show a skewed distribution as well, with a mean of 580 h and a standard deviation of 183 h, highlighting uneven comfort levels and the presence of extreme cases.

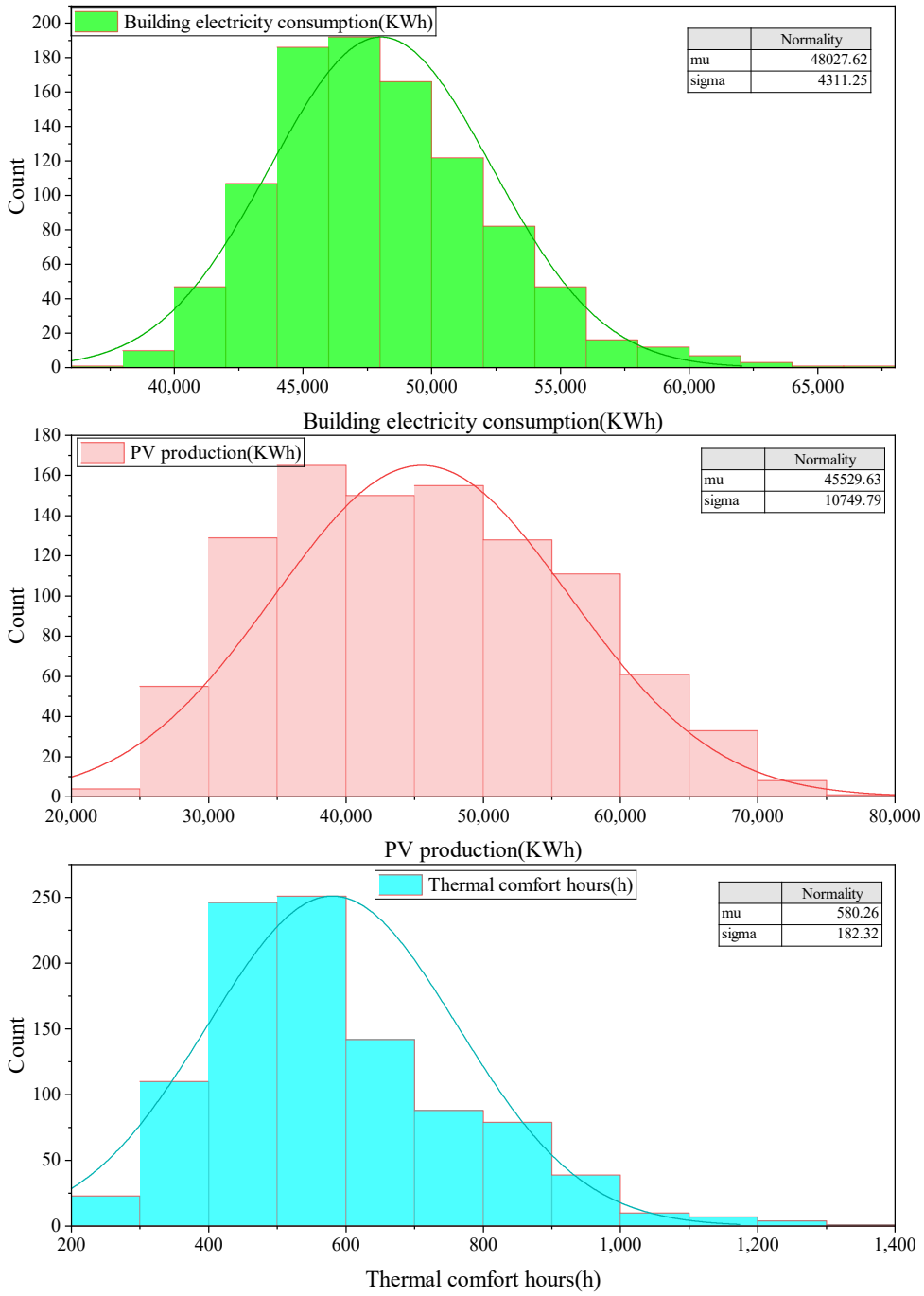


Figure 13. Distribution of energy consumption database data for dormitory buildings.

Overall, the findings reveal important insights into energy consumption patterns and thermal comfort in both building types, emphasizing the variability of PV output and the need for effective management strategies to enhance energy efficiency and occupant comfort.

This study compared the performance of four different machine learning models—Linear Regression (LR), K-Nearest Neighbors (KNN), Random Forest (RF), and Artificial Neural Networks (ANNs)—in predicting building electricity consumption, energy production, and thermal comfort hours. The accuracy and reliability of each model's predictions were evaluated using the coefficient of determination (R^2) and the Mean Absolute Percentage Error (MAPE).

Figure 14, Figure 15, and Figure 16 present a comparison of the algorithms for the electricity consumption, energy production, and thermal comfort hours of the office building, respectively. The results indicate that the LR model exhibits high accuracy and stability in predicting building electricity consumption, achieving R^2 values of 0.978 and 0.928, with corresponding MAPE values of 2.118 and 1.045. However, in other datasets, although the R^2 values remain high, the MAPE values are relatively large, suggesting a higher percentage of prediction error.

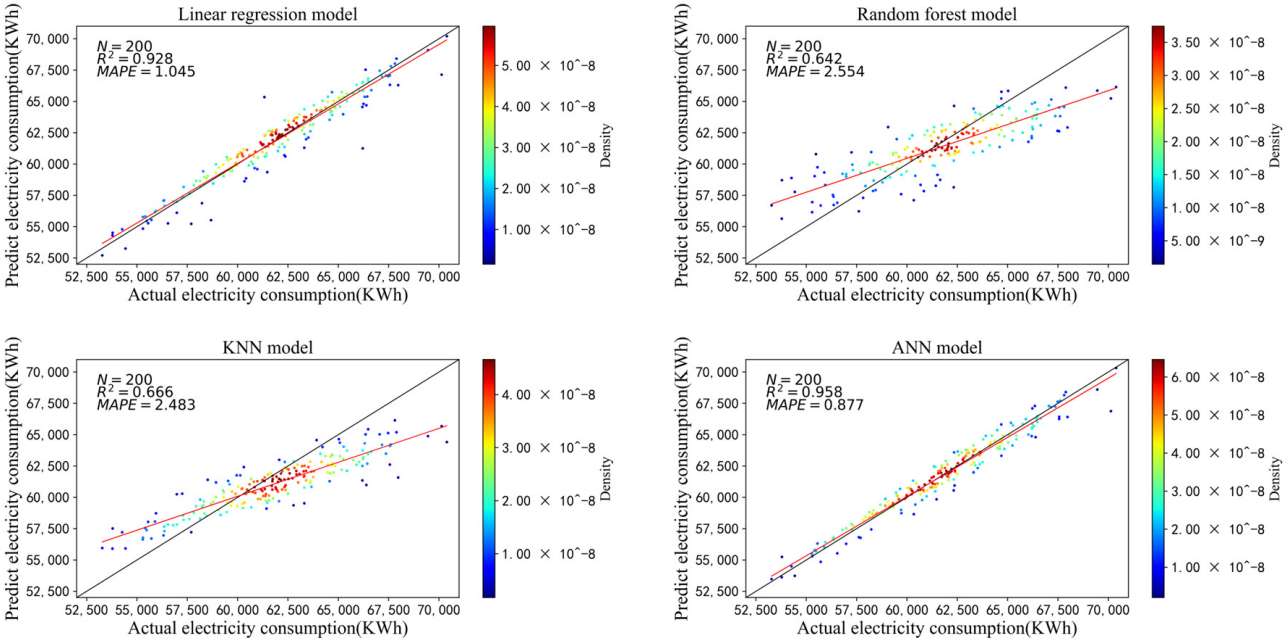


Figure 14. Comparison of the prediction accuracy of different algorithms for electricity consumption in office buildings.

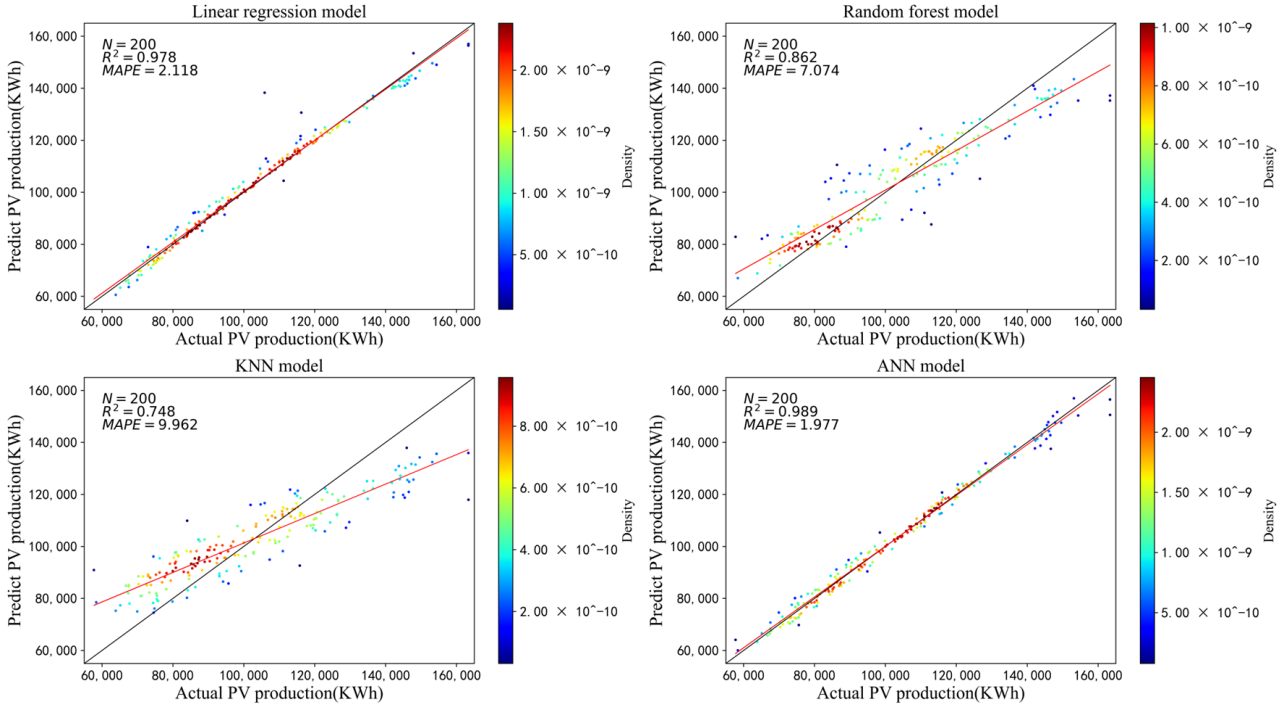


Figure 15. Comparison of the prediction accuracy of different algorithms for photovoltaic power production in office buildings.

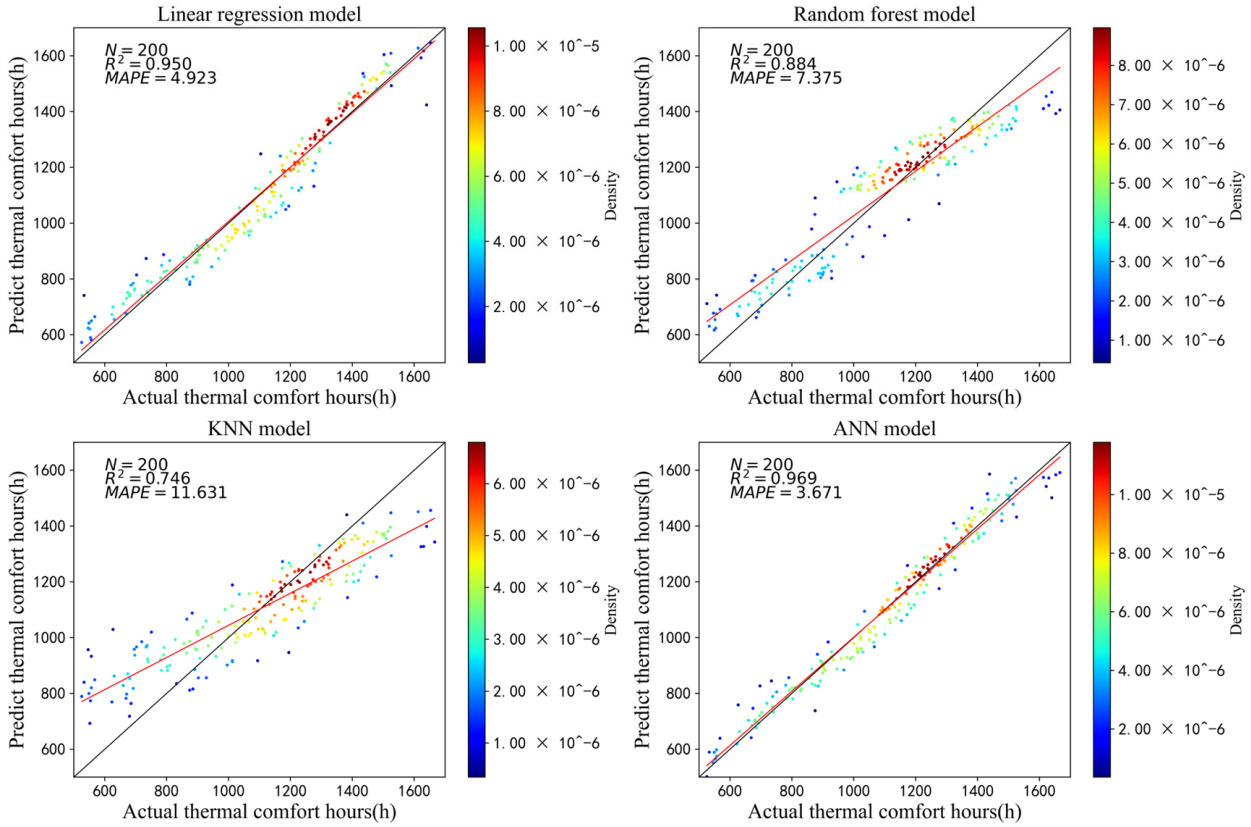


Figure 16. Comparison of prediction accuracy of different algorithms for office building comfort hours.

The performance of the KNN model is relatively poor, with R^2 values below 0.75 across all three datasets and generally high MAPE values. The RF model exhibits inconsistent performance across different datasets, with R^2 values showing significant fluctuations. For instance, in the building electricity consumption dataset, the R^2 values are 0.862 and 0.642, with corresponding MAPE values of 7.074 and 2.554, respectively. This suggests that while RF can provide reasonable predictions in certain cases, its inconsistency may limit its general applicability in practical scenarios.

In contrast, the ANN model demonstrates outstanding performance across all datasets. In predicting building electricity consumption and energy production, the ANN model achieves R^2 values of 0.989 and 0.958, respectively, while maintaining low MAPE values of 1.977 and 0.877, respectively. The ANN also excels in predicting thermal comfort hours, with an R^2 value of 0.969 and a MAPE of 3.671. These results indicate that the ANN model is effective in handling complex nonlinear relationships and providing highly accurate predictions.

The algorithmic prediction accuracy comparisons for the three components of the dormitory building are illustrated in Figures 17–19. For the prediction of building electricity consumption, the LR model exhibits a high goodness of fit, with R^2 values of 0.990 and 0.835, respectively. The KNN model performs poorly, yielding R^2 values of only 0.757 and 0.599, respectively. The RF model shows some improvement, with R^2 values reaching 0.907 and 0.688, respectively, indicating a moderate level of predictive capability. The ANN model outperforms all others, achieving R^2 values of 0.981 and 0.927, respectively, demonstrating a significant advantage in predicting building electricity consumption.

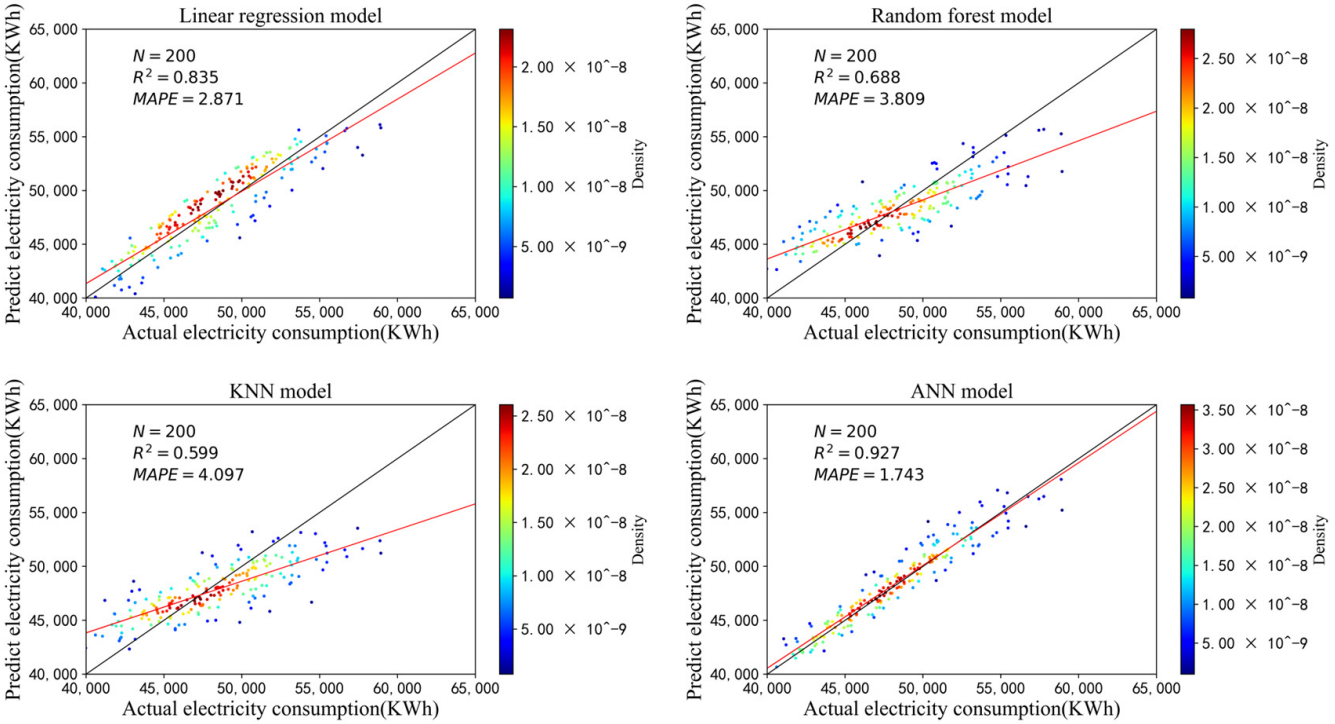


Figure 17. Comparison of prediction accuracy of different algorithms for dormitory building electricity consumption.

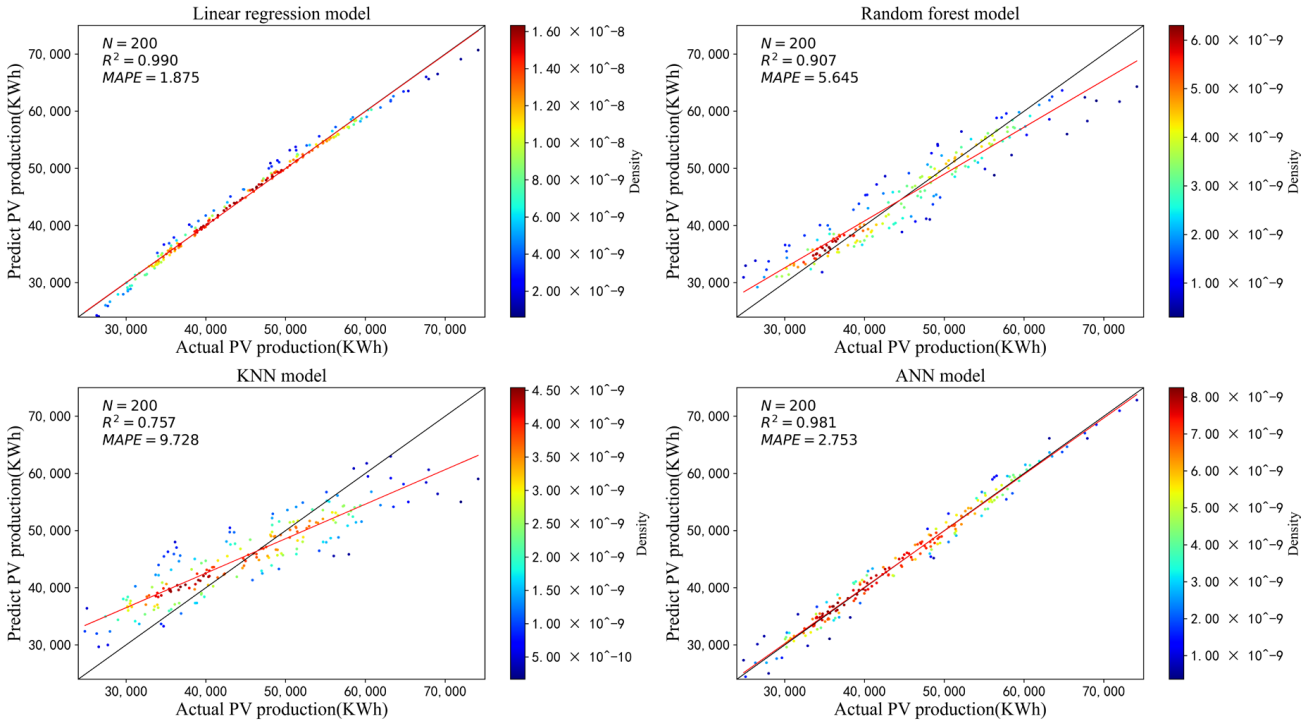


Figure 18. Comparison of the prediction accuracy of different algorithms for photovoltaic power production in dormitory buildings.

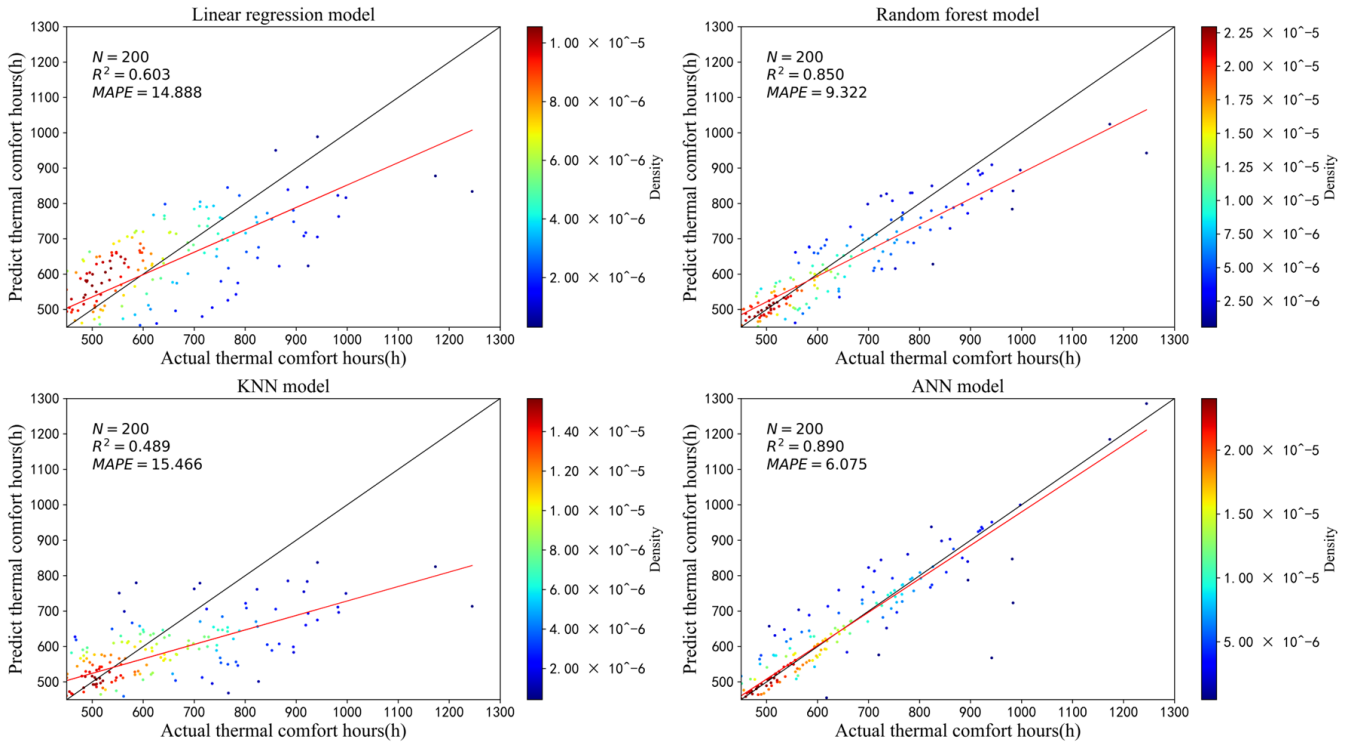


Figure 19. Comparison of prediction accuracy of different algorithms for comfort hours in dormitory buildings.

In the prediction of energy production, the LR model shows slightly lower performance, with an R^2 value of 0.835. The KNN model also underperforms, with an R^2 value of 0.599. The RF model also fell short, achieving an R^2 value of 0.688. In contrast, the ANN once again demonstrated exceptional performance, achieving an R^2 value of 0.927, thus confirming its efficiency and accuracy in handling such data.

For the prediction of comfort hours, the ANN model demonstrated the best performance, achieving an R^2 value of 0.890 and a MAPE of 6.075, respectively. These results indicate a high level of predictive accuracy and a low error rate.

4.3. Multi-Objective Optimization Results

This study employed the NSGA-III algorithm to address the multi-objective optimization problem of building energy consumption, energy generation, and comfort hours. Three optimization objectives are defined: minimizing energy consumption, maximizing energy generation, and maximizing comfort hours, which reflect the building's energy efficiency, energy self-sufficiency, and occupant comfort.

The NSGA-III algorithm's hyperparameters were tuned through a systematic grid search method to enhance its optimization performance. The parameters were tuned and their tested ranges included (see Table 11):

Population Size: Candidate solutions in each generation [50, 100, 200].

Number of Generations: Total iterations [100, 200, 300].

Crossover Probability: Likelihood of crossover between solutions [0.7, 0.9].

Crossover Index: Distribution index controlling the crossover extent [10, 20, 30].

Mutation Probability: Likelihood of mutation in a solution [0.1, 0.2].

Mutation Index: Distribution index for mutation operations [20, 30, 40].

The grid search tested all possible combinations of these parameters, and the performance of each combination was evaluated using the hypervolume indicator. This indicator measures the diversity and quality of the Pareto front solutions, with higher values indicating better performance. Based on this evaluation, the optimal hyperparameter combinations for the office and dormitory buildings were identified.

Tables 12 and 13 summarize the selected hyperparameter combinations for the NSGA-III algorithm in optimizing the office and dormitory buildings. The optimal configurations were chosen based on their ability to generate diverse and well-distributed Pareto front solutions, effectively balancing energy consumption, photovoltaic generation, and thermal comfort.

Table 11. NSGA-III algorithm hyperparametric search space.

Variable	Value
Population Size	[50, 100, 200]
Number of Generations	[100, 200, 300]
Crossing Probability	[0.7, 0.9]
Crossover Index	[10, 20, 30]
Mutation Probability	[0.1, 0.2]
Mutation Index	[20, 30, 40]

Table 12. Office building energy consumption NSGA-III algorithm optimal hyperparameter combination.

Variable	Value
Population Size	200
Number of Generations	200
Crossing Probability	0.7
Crossover Index	10
Mutation Probability	0.1
Mutation Index	40

Table 13. Optimal hyperparameter combination of NSGA-III Algorithm for energy consumption in dormitory buildings.

Variable	Value
Population Size	200
Number of Generations	200
Crossing Probability	0.7
Crossover Index	20
Mutation Probability	0.3
Mutation Index	40

The optimized hyperparameter settings significantly improved the efficiency of the NSGA-III algorithm in solving the multi-objective optimization problem. The resulting Pareto fronts (Figures 20 and 21) illustrate the trade-offs between the three objectives, highlighting the effectiveness of the tuned configurations in achieving optimal energy efficiency and comfort levels.

For the office building, energy consumption varies from approximately 47,500 KWh to 62,500 KWh, with corresponding increases in energy generation. When energy consumption is around 50,000 KWh, energy generation ranges between 130,000 KWh and 160,000 KWh. For energy consumption exceeding 60,000 KWh, some data points indicate energy generation close to 180,000 KWh, suggesting that high energy-consuming equipment or strategies may lead to higher energy recovery efficiencies. Comfort hours range from 1000 to 1800 h, with higher values appearing in areas where energy consumption exceeds 55,000 KWh, indicating that enhanced comfort levels require additional energy input.

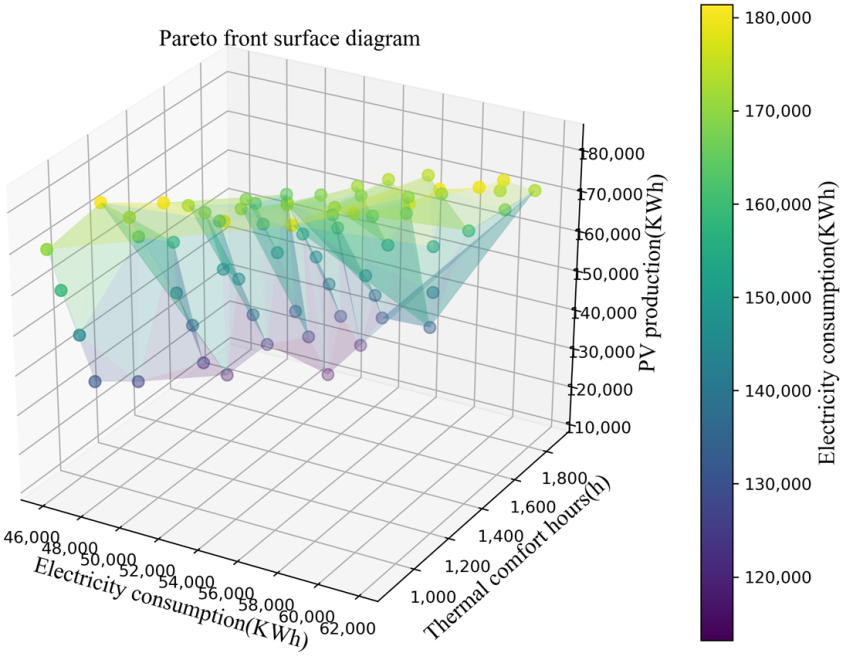


Figure 20. Multi-objective optimization of energy consumption in office buildings—Pareto frontier map.

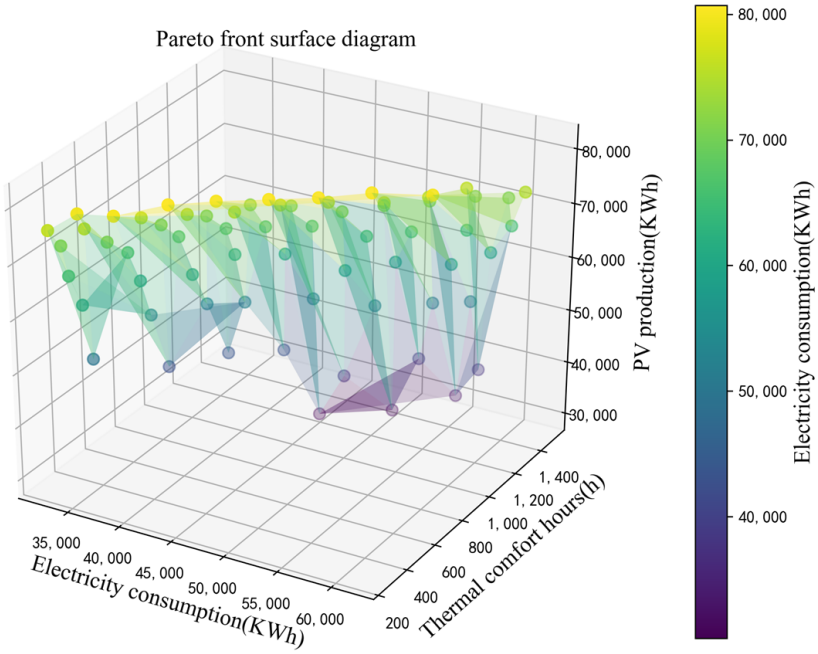


Figure 21. Multi-objective optimization of energy consumption in dormitory buildings—Pareto frontier diagrams.

Similarly, the dormitory building's energy consumption ranges from 47,500 KWh to 62,500 KWh, with energy generation increasing correspondingly. When energy consumption surpasses 60,000 KWh, energy generation may exceed 180,000 KWh. The range for comfort hours is approximately 1000 to 1800 h, with higher values associated with increased energy consumption. The data points in the figures reveal how efficient energy generation can be achieved while maintaining high energy consumption and elevated comfort levels.

Table 14 compares the performance of the office and dormitory buildings before and after optimization. After optimization, the office building's energy consumption is reduced by 41%, while the dormitory building has a 38% decrease in energy usage, resulting in significant energy cost savings and a reduced burden on the electrical grid. Additionally, energy generation increases by 176% for the office building and by 169% for the dormitory, enhancing energy self-sufficiency and lowering the carbon footprint. The comfort hours in the office building rose by 19%, while the dormitory's comfort hours increased by 6%, thereby improving indoor environmental quality.

Table 14. Comparison between the optimal solution with objective value and the initial working condition.

Building Type	Target Value	Unit	Baseline Model	Optimised Model	Degree of Optimization (%)
Office Building	Building Electricity Consumption	KWh	77,924	46,041	40.92
	Photovoltaic Output	KWh	65,971	181,953	175.81
	Comfort Hours	h	1576	1874	18.91
Dormitory Building	Building Electricity Consumption	KWh	52,230	32,575	37.63
	Photovoltaic Output	KWh	29,459	79,341	169.33
	Comfort Hours	h	1424	1511	6.11

When conducting a comprehensive analysis of building energy efficiency, it is essential to consider multiple key factors, including the envelope structure, air conditioning system, equipment power, occupant behavior, and photovoltaic systems. Figures 22–24 illustrate the optimal parameter distributions for energy consumption, photovoltaic generation, and thermal comfort in the office building.

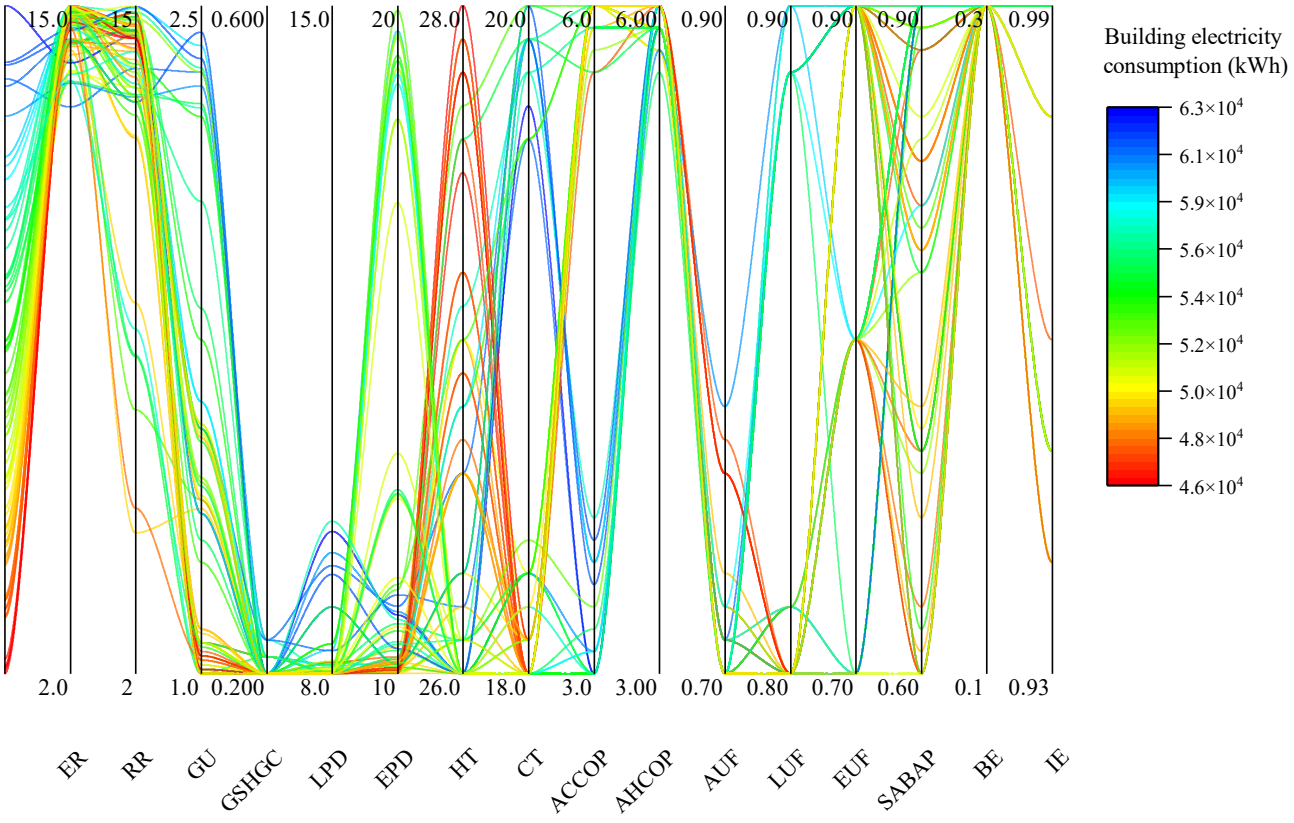


Figure 22. Distribution of optimal parameters for electricity consumption in office buildings.

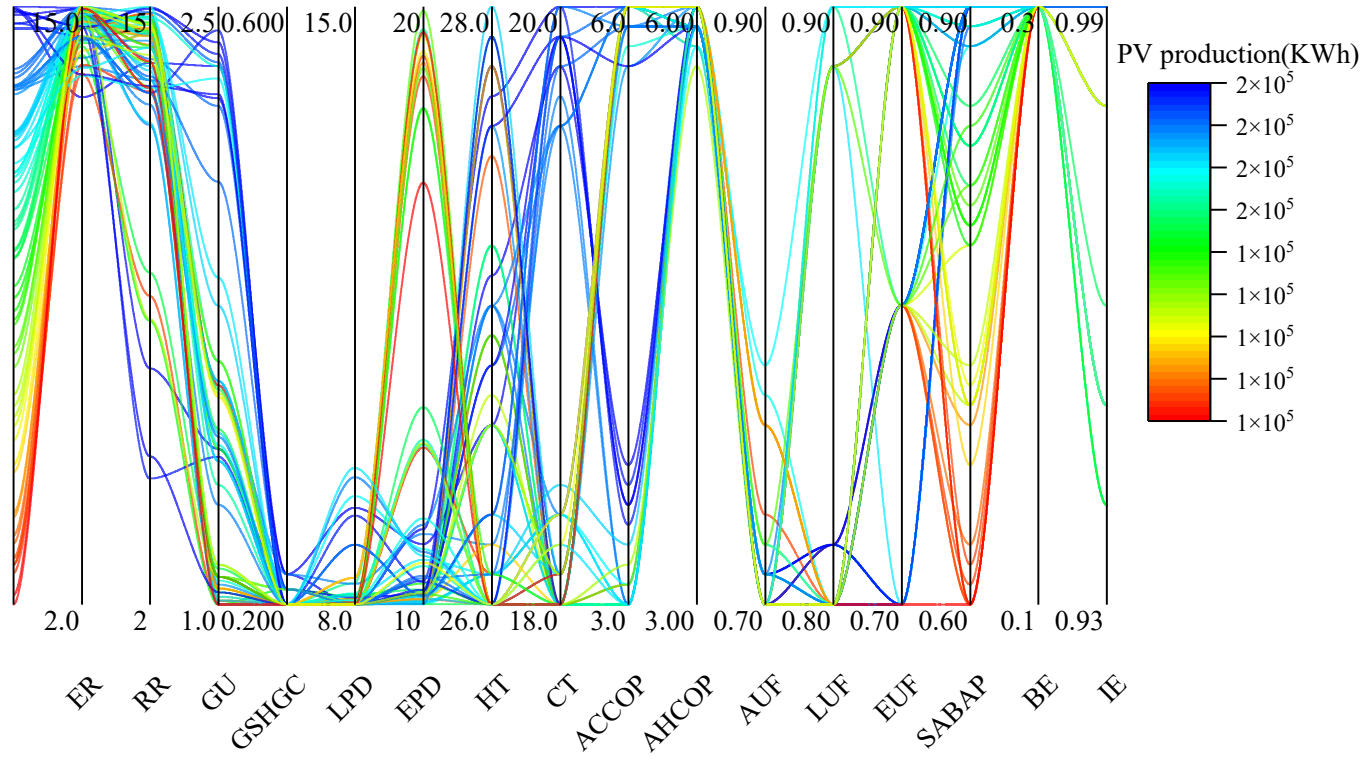


Figure 23. Optimal parameter distribution of photovoltaic power production in office buildings.

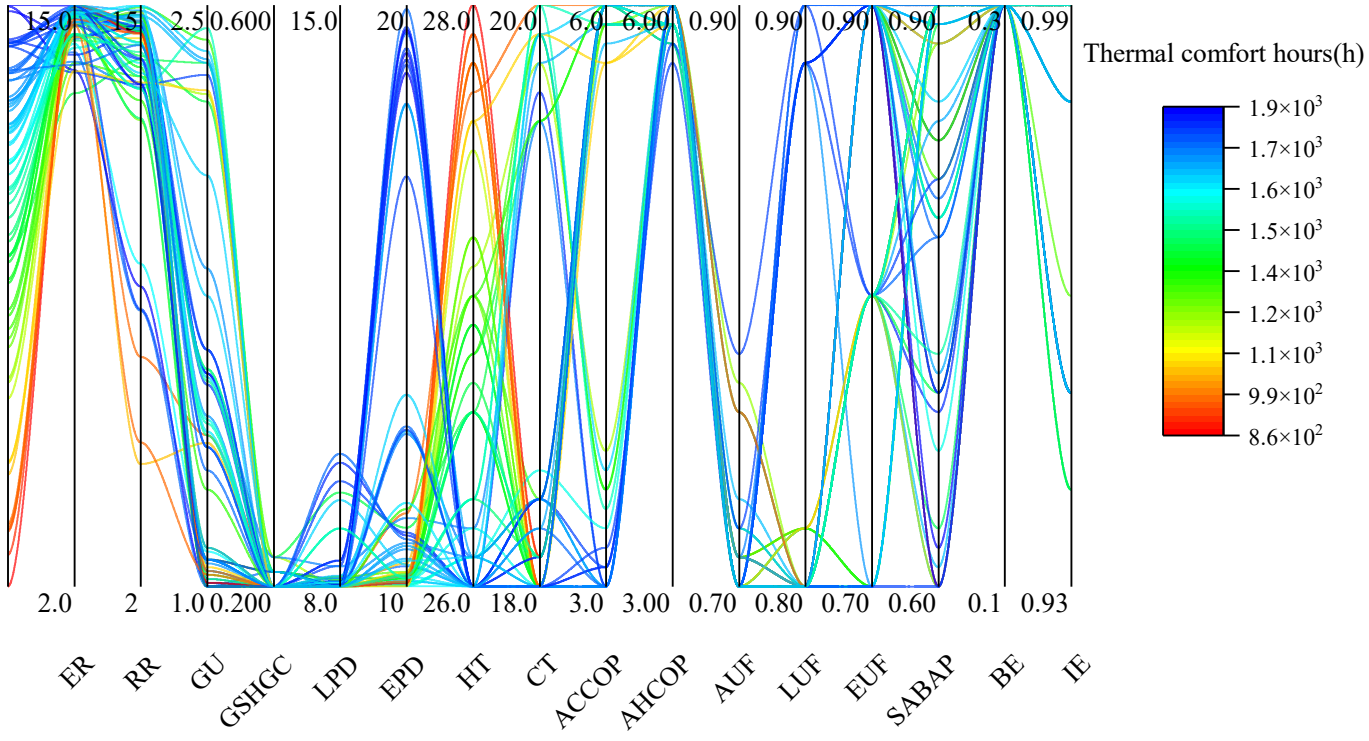


Figure 24. Distribution of optimal parameters for thermal comfort in office buildings.

Optimizing the envelope structure primarily involves the thermal performance of walls, roofs, and windows. Selecting high-thermal resistance materials (e.g., with an R-value close to 15) helps reduce heat loss and decrease air conditioning energy consumption. The optimization of window thermal transmittance (U-value) and solar heat gain coefficient (SHGC) is also crucial; lower U-values (e.g., 0.5) and moderate SHGCs (e.g., 0.5) effectively control heat flow, further reducing air conditioning loads.

The design of the air conditioning system and the power of equipment directly impact energy consumption and thermal comfort. Utilizing high-efficiency air conditioning systems (e.g., with a COP greater than 4.5) can provide necessary heating and cooling functions with lower energy consumption, minimizing energy waste. Setting reasonable temperature parameters (e.g., cooling at 28 °C and heating at 20 °C) reduces equipment operating time, lowers energy consumption, and maintains a comfortable indoor environment.

Occupant behavior significantly impacts building energy consumption. Frequent temperature adjustments or maintaining non-optimal setpoints can increase the frequency of air conditioning activation and overall energy use. Promoting energy-saving awareness and encouraging efficient habits (such as timely adjustments of curtains and windows) can substantially reduce unnecessary energy consumption.

The area ratio of PV systems and the efficiency of the components determine electricity generation. Increasing the proportion of high-efficiency PV panel installations (e.g., expanding coverage from 0.6 to 0.8) can significantly boost energy output, reduce reliance on external power, and even enable power feedback to the grid.

Figures 25–27 illustrate the optimal parameter distributions for energy consumption, photovoltaic generation, and thermal comfort in the dormitory building, which largely resemble those of the office building. However, the office may require more focus on sunlight management, incorporating more efficient shading and insulation technologies, while the air conditioning system design should prioritize peak period energy efficiency management. The dormitory, on the other hand, should consider around-the-clock temperature regulation, favoring high-efficiency systems with better temperature control, and optimize energy consumption through building automation. Both types of buildings should maximize rooftop area utilization to increase the proportion of photovoltaic coverage and enhance energy self-sufficiency.

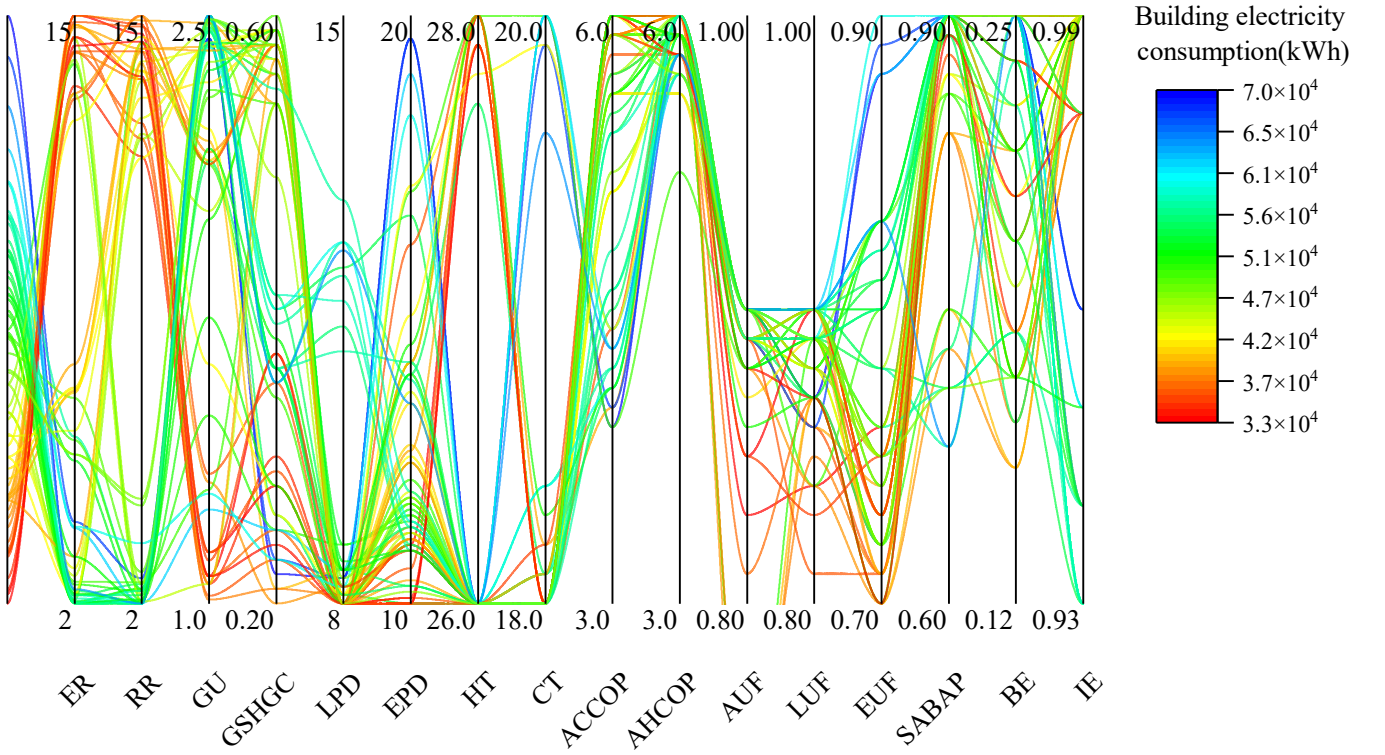


Figure 25. Distribution of optimal parameters of electricity consumption in dormitory building construction.

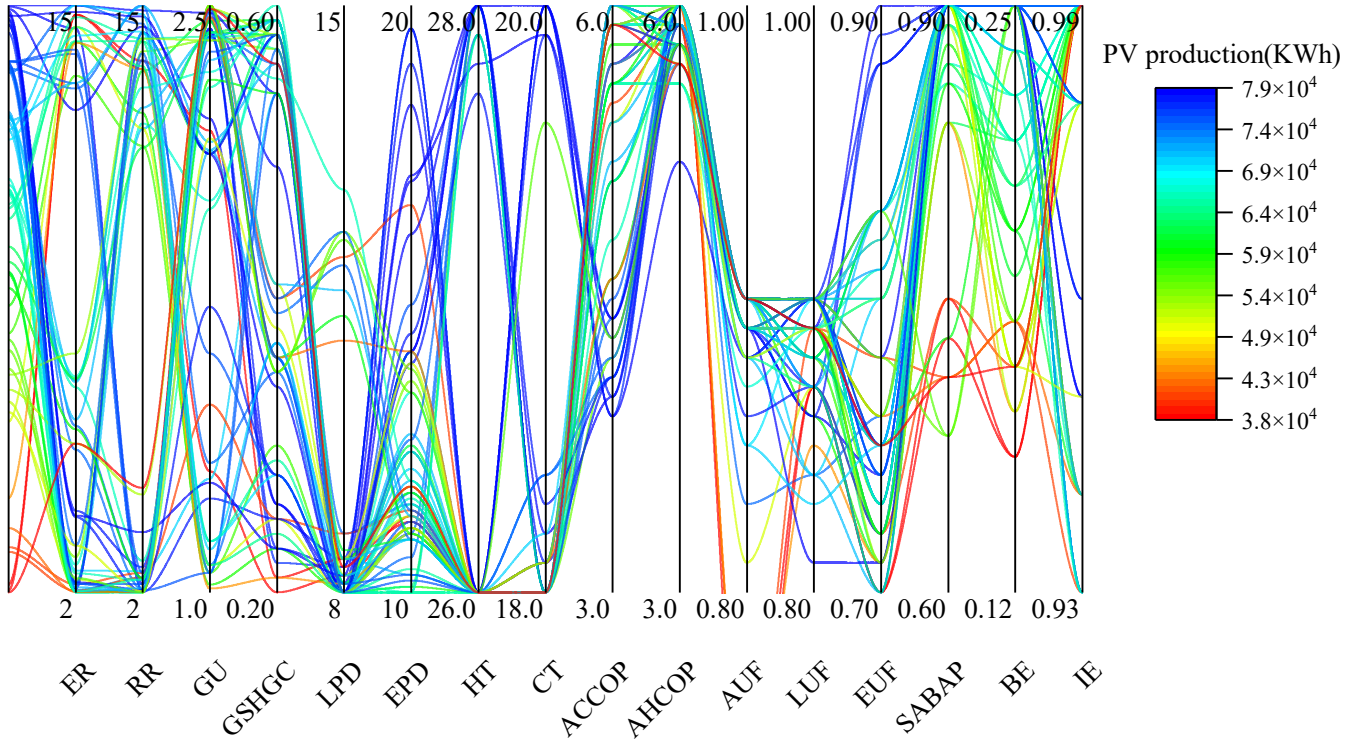


Figure 26. Optimal parameter distribution of photovoltaic power production in dormitory buildings.

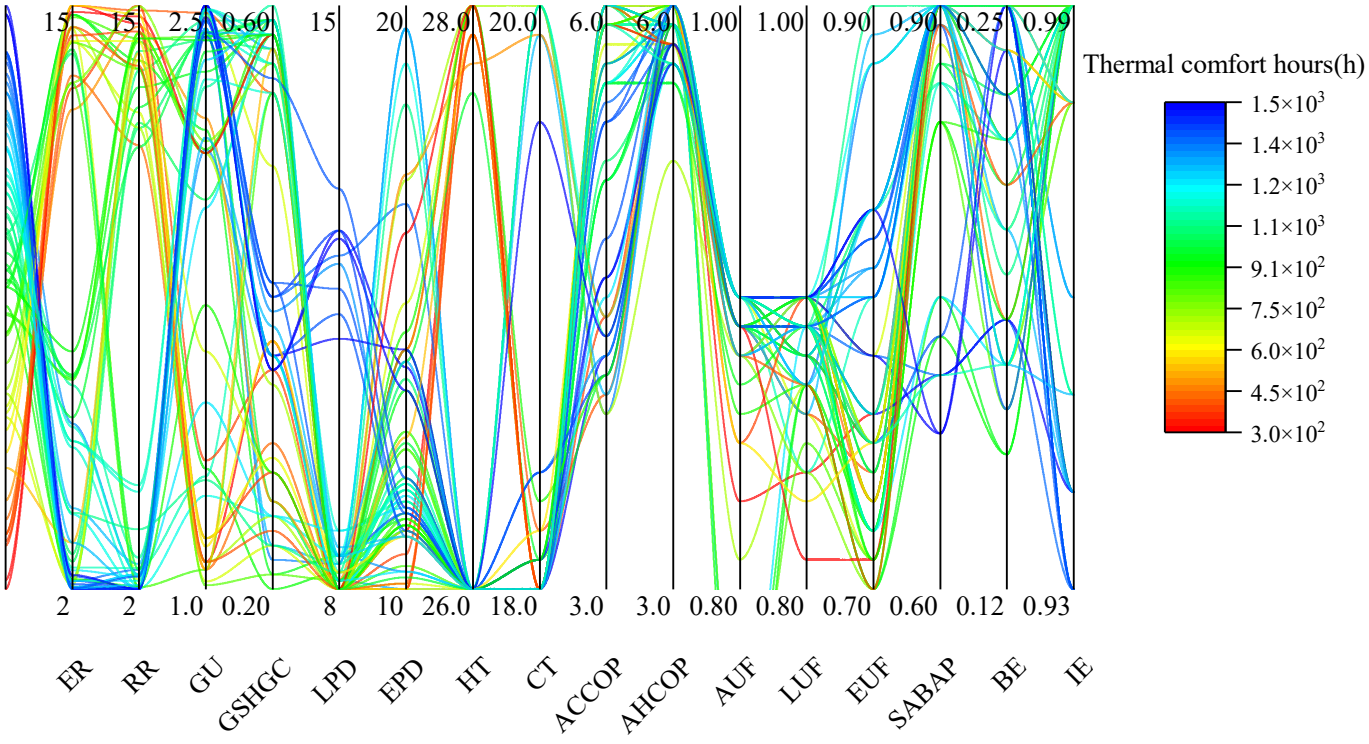


Figure 27. Distribution of optimal parameters for thermal comfort in dormitory building construction.

4.4. Discuss

While this study focuses on a case in China, the proposed Python-based automation framework is designed to be universally applicable. Its ability to dynamically modify EnergyPlus input files, execute simulations, and analyze results makes it adaptable to any geographical region, provided the necessary local data is available. The key considerations for global application include:

Climate Data: The framework can integrate regional climate data, such as Typical Meteorological Year (TMY) files, enabling accurate simulations tailored to local weather conditions.

Building Standards: The tool supports parameter adjustments to align with local building codes, material properties, and energy efficiency standards, ensuring compliance and relevance to regional practices.

Energy Systems and Usage Patterns: By allowing customization of system configurations and operational schedules, the framework can model diverse energy systems and occupant behaviors unique to different countries.

Surrogate Models and Optimization: The training and optimization processes are data-driven and adaptable to input–output relationships for buildings in varying contexts, ensuring robust results globally.

The software's reliance on EnergyPlus, a widely validated tool for building energy simulation, further ensures accuracy and consistency across different geographical settings. However, users must provide accurate and representative local data for optimal results. This adaptability underscores the potential of the proposed framework to support energy optimization and sustainability efforts worldwide.

It is worth mentioning that this study does not directly compare the simulation results with prototype buildings' real-time data, several measures have been implemented to ensure the accuracy of the predictions:

EnergyPlus Validation: EnergyPlus, the underlying simulation engine used in this framework, has been extensively validated in prior research through comparisons with experimental data and real-world building performance. By leveraging this robust tool, the accuracy of the simulations is inherently supported.

Surrogate Model Validation: The surrogate models developed in this study were validated using rigorous statistical metrics, including the coefficient of determination (R^2) and the Mean Absolute Percentage Error (MAPE). These metrics confirm the models' predictive accuracy within the dataset used for training and testing.

Input Data Quality: The accuracy of any simulation depends on the quality of input data. This study utilized detailed and representative data for building configurations, materials, and operational conditions, ensuring the validity of the simulated scenarios.

Comparative Analysis: The study outcomes, including energy consumption reductions and improvements in photovoltaic generation, align well with findings from similar studies in the literature. This consistency further supports the credibility of the results.

While direct validation with real-time data was beyond the scope of this study, future research will incorporate on-site monitoring of prototype buildings to strengthen the connection between simulated and actual performance. This planned effort will further enhance the reliability and applicability of the proposed framework.

5. Conclusions

This study systematically analyzed the factors influencing energy consumption in temporary buildings at construction sites, developed an energy consumption model, and employed artificial intelligence optimization methods to enhance energy efficiency. The results demonstrate that using surrogate models and multi-objective optimization algorithms can significantly improve the efficiency and accuracy of building energy consumption analysis, providing a novel solution for enhancing building energy efficiency.

The main conclusions of this study are as follows:

1. Through the construction and analysis of a refined energy consumption model, this research reveals the energy consumption patterns and influencing factors of different functional buildings at construction sites. External climate, building structure, and equipment usage behavior significantly affect energy consumption.
2. The introduction of a Python-based surrogate model markedly enhances the efficiency of energy consumption simulations, enabling the rapid generation of large volumes of simulation data to support efficient energy analysis and optimization.
3. The NSGA-III optimization algorithm was employed to achieve a multi-objective balance optimization of building energy consumption, photovoltaic generation, and thermal comfort. The resulting Pareto optimal solution set provides theoretical support and practical guidance for achieving a balance between energy conservation and livability. Compared to the baseline model, multi-objective optimization reduce energy consumption by 41% and 38% for the office and dormitory buildings, respectively, while increasing photovoltaic generation by 176% and 169%, and improving comfort levels by 19% and 6%.

This study makes several novel contributions to the field of building energy optimization:

1. The development of a Python-based automated simulation framework eliminates the inefficiencies of traditional manual simulation processes. This innovation enables the rapid generation of high-quality datasets, which can be leveraged for advanced surrogate model training.
2. The integrated use of surrogate models and the NSGA-III algorithm provides a comprehensive and efficient approach to multi-objective optimization, balancing energy efficiency, photovoltaic electricity generation, and thermal comfort. This integrated methodology represents a significant advancement over existing studies that typically focus on a single objective or rely on less efficient optimization techniques.
3. The application of the proposed framework to temporary buildings, a relatively underexplored category, highlights its practical applicability and scalability. The findings demonstrate how the framework can be adapted to unique building types and operational scenarios, contributing to sustainable construction practices.

By addressing the inefficiencies of traditional simulation techniques and advancing multi-objective optimization methods, this study offers a robust framework that significantly enhances both the theoretical and practical understanding of building energy efficiency.

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