Journal of Engineering, Project, and Production Management
2026, 16(1), 2025-298

# Design of Integrated Energy Systems for Green Buildings and Analysis of Low-Carbon Benefits

Yang Yuan
Engineer, Jilin University of Architecture and Technology, Changchun 130114, Jilin, China, E-mail: 3315420@163.com

Project Management
Received December 2, 2025; revised January 27, 2026; accepted January 28, 2026
Available online January 28, 2026

---

**Abstract:** With the increasing demand for energy conservation and low-carbon development in green buildings, the optimization design of integrated energy systems for green buildings has become a research hotspot. This paper proposes a system optimization method based on the Multi-Objective Evolutionary Algorithm with Decomposition (MOEA/D) to simultaneously optimize economic efficiency, environmental performance, and energy utilization efficiency. The study first constructs an optimization model that incorporates three objectives: investment cost, carbon emissions, and the renewable energy utilization rate. Decision variables, such as equipment capacity, operational parameters, and energy allocation ratios, are defined. Based on this model, the MOEA/D algorithm is applied to optimize a typical building case, with comparisons against Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) algorithms. The study constructs a static simulation scenario based on typical meteorological year data, focusing on system performance under standard operating conditions, and does not currently account for uncertainties related to extreme weather or real-time price fluctuations. Results indicate that the proposed method achieves superior metrics compared to the comparison algorithms in terms of total system cost, carbon emissions, and energy utilization: The MOEA/D-optimized system achieves a total cost of $1.2\times10^6$ yuan, representing reductions of 14.3% and 20% compared to NSGA-II and MOPSO, respectively. Carbon emissions are reduced to 150 tons, a decrease of 17%–25% over the comparison methods. Renewable energy utilization reached 60%, representing a 10%–15% improvement over other algorithms. Additionally, MOEA/D demonstrated superior convergence speed and balanced Pareto solution distribution. The study concludes that this method effectively achieves low-carbon, high-efficiency operation of green building integrated energy systems, providing a feasible pathway and technical support for building energy conservation, emission reduction, and sustainable development.

**Keywords**: Multi-objective optimization algorithm, green building integrated energy system, low-carbon benefit analysis, decomposable multi-objective evolutionary algorithm.


DOI 10.32738/JEPPM-2025-298

---

## 1. Introduction

The continuous growth in global energy demand and increasingly severe environmental challenges have driven the building sector toward green, low-carbon development (Chadly et al., 2023). Green Building Comprehensive Energy Systems (GB-CES) integrate multiple energy forms to achieve efficient energy utilization and emission reduction, emerging as a key development in the building field (Fan et al., 2024). The design of GB-CES must not only ensure the reliability and economic viability of energy supply but also prioritize environmental sustainability (Gabbar and Ramadan, 2025). Designing these systems using multi-objective optimization algorithms enables comprehensive optimization of economic, environmental, and energy-efficiency metrics, providing robust support for green building development (Leu and Shi, 2024). Consequently, researching design methodologies for integrated energy systems in green buildings that incorporate low-carbon benefit analysis is of profound significance and provides essential support for advancing green buildings (Choi et al., 2024).

The design methodology for green building integrated energy systems primarily encompasses system architecture design, construction of optimization models, implementation of algorithms, and low-carbon benefit analysis (Gu et al., 2023). In recent years, the design and optimization of integrated energy systems for green buildings have become a hot research topic both domestically and internationally. Overseas scholars have conducted extensive research on system integration and the application of optimization algorithms (Sirin et al., 2023). Wang (2024) proposed an optimization method based on genetic algorithms for the integrated utilization of solar and wind energy. Zhang et al. (2025) investigated the coordinated optimization of heat pumps and energy storage devices to enhance the system's energy utilization efficiency. Domestic scholars, however, have focused more on the practical application and economic analysis of the systems. Lv (2025) conducted an economic assessment of an energy system in a green building; Akpan (2024) investigated the integrated optimization of solar photovoltaic and energy storage systems. Additionally, recent research has explored applying machine learning models to predict the electricity generation capacity of rooftop solar energy systems on buildings (Hoang Son and Duy, 2023).

However, existing research predominantly concentrates on single-objective optimization, lacking in-depth exploration of multi-objective optimization (Huener and Telli, 2023). Furthermore, analyses of low-carbon benefits remain incomplete due to the lack of long-term environmental impact assessments (Mersal, 2023). Regarding optimization algorithms, while genetic algorithms and particle swarm optimization are widely applied, these methods exhibit limitations when handling complex multi-objective optimization problems (Shum and Zhong, 2023; Brzozka, 2024).

Despite significant progress in research on integrated energy systems for green buildings, several shortcomings and challenges remain. First, optimization involves multiple conflicting objectives such as economic viability, environmental sustainability, and energy efficiency, making simultaneous optimization challenging (Pham and Tran, 2023). Second, existing studies on low-carbon benefits predominantly focus on carbon emission calculations, lacking comprehensive assessments of the system's long-term environmental benefits (Fu et al., 2025). Third, current multi-objective optimization algorithms exhibit slow convergence and insufficient solution diversity when applied to complex systems (Li, 2024).

To address these limitations, this paper proposes a design methodology for green building integrated energy systems based on the Multi-Objective Evolutionary Algorithm (MOEA/D) (Sui et al., 2025). To address the aforementioned challenges, this study investigates the following core questions: (1) How can a high-dimensional multi-objective optimization model be constructed to simultaneously balance economic costs, environmental impacts, and energy efficiency? (2) Does the MOEA/D algorithm possess significant advantages over traditional multi-objective algorithms when handling the complex nonlinear constraints of green building integrated energy systems? Based on these questions, this paper proposes a systematic optimization framework to resolve these conflicts. Key contributions include establishing a multi-objective optimization model for integrated energy systems in green buildings. This model comprehensively considers economic viability, environmental sustainability, and energy utilization efficiency. We also modified the MOEA/D algorithm to enhance its convergence speed and solution diversity, tailored to the characteristics of green building integrated energy systems. Finally, we validated the proposed method through practical case studies and conducted comparative analyses with other optimization approaches to demonstrate its advantages.

To systematically present the research content, this paper is structured as follows. Section 2 details the design methodology for green building integrated energy systems, including system architecture, optimization models, and low-carbon benefit analysis. Section 3 proposes the principles and implementation steps of the MOEA/D-based optimization algorithm. Section 4 conducts experimental validation using typical case studies and compares the results with algorithms such as NSGA-II and MOPSO. Finally, section 5 summarizes the research conclusions, identifies limitations, and proposes future research directions. Through this structure, the paper aims to comprehensively reveal the optimization pathways and the low-carbon value of integrated energy systems in green buildings, focusing on economic efficiency, environmental sustainability, and energy efficiency.

## 2. Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D)

### 2.1. Algorithm Principle

The Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) (Xue et al., 2025) is an efficient multi-objective optimization algorithm that has been widely applied in solving complex multi-objective optimization problems in recent years, as shown in Fig. 1. MOEA/D decomposes multi-objective optimization problems into multiple single-objective subproblems and utilizes neighborhood information for optimization. This approach effectively enhances the algorithm's convergence speed and solution diversity.

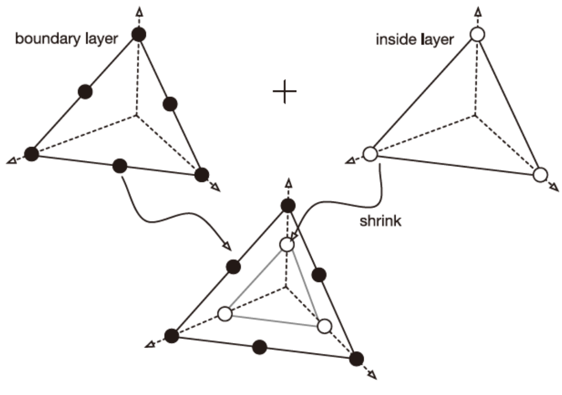


**Fig. 1.** MOEA/D algorithm

The core idea of MOEA/D is to decompose a multi-objective optimization problem into multiple single-objective subproblems and approximate the global optimum by optimizing these subproblems. The objective function for each subproblem is formed by combining multiple objective functions through weighting (Meng et al., 2024). By optimizing these weighted objective functions, the algorithm can simultaneously handle multiple objectives and generate a set of Pareto optimal solutions in the solution space.

In MOEA/D, the objective function for each subproblem can be expressed as a weighted sum, as shown in Eq. (1):

$$f_i(x) = \sum_{j=1}^{M} \lambda_{ij} \cdot g_j(x) \tag{1}$$

where: $f_i(x)$ denotes the objective function for the i-th subproblem; $M$ represents the number of objective functions in the original multi-objective optimization problem; $\lambda_{ij}$ indicates the weight coefficient, used to balance the contributions of different objective functions; $g_j(x)$ is the j-th objective function in the original multi-objective optimization problem.

The weight coefficient $\lambda_{ij}$ is typically distributed uniformly based on the subproblem number and the total number of objective functions. For a two-objective optimization problem, the weight coefficients can be generated as Eq. (2):

$$\lambda_{i1} = \frac{i-1}{N-1}, \lambda_{i2} = 1 - \frac{i-1}{N-1} \tag{2}$$

where $N$ denotes the total number of subproblems.

### 2.2. Algorithm Steps

Based on the principles of the MOEA/D algorithm, its algorithmic flow is illustrated in Fig. 2, with specific steps as follows:

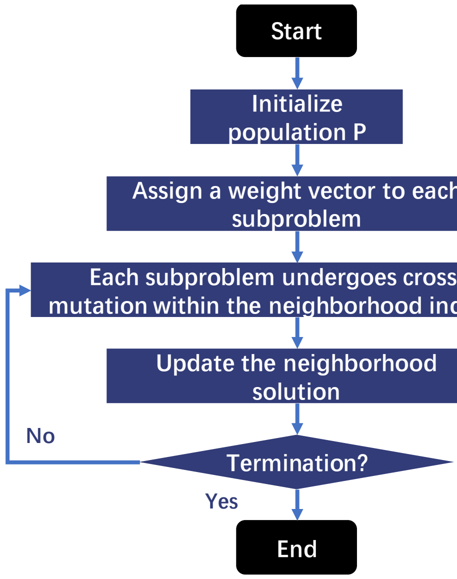


**Fig. 2.** Algorithm flowchart

Step 1: Initialize the population. Randomly generate the initial population P with size N; initialize the weight coefficient λ for each subproblem.

Step 2: Construct the neighborhood. For each subproblem, identify the T subproblems closest to it based on their weight coefficients as its neighborhood.

Step 3: Optimize subproblems. For each subproblem, select several individuals from its neighborhood to perform crossover and mutation operations, generating new solutions; compute the objective function values of new solutions and update solutions in the neighborhood.

Step 4: Update neighborhood solutions. If a new solution outperforms an existing solution in the neighborhood, replace the existing solution with the new one.

Step 5: Check termination conditions. If termination criteria (e.g., maximum iterations reached or convergence) are satisfied, halt the algorithm. Otherwise, return to Step 3.

Step 6: Output results. Output the optimal solutions for all subproblems, forming the Pareto front.

### 2.3. Application Analysis

Based on the principles and optimization process of the MOEA/D algorithm, it offers significant advantages, including high efficiency, diversity, adaptability, and scalability (Huang et al., 2024).

(1) Efficiency. By decomposing multi-objective optimization problems into multiple single-objective subproblems, computational complexity is reduced. Utilizing neighborhood information for optimization enables rapid convergence to global optimal solutions.

(2) Diversity. By optimizing multiple subproblems, a uniformly distributed set of Pareto-optimal solutions can be generated while maintaining solution diversity.

(3) Adaptability. Applicable to diverse multi-objective optimization problems, including both linear and nonlinear objective functions, adaptable to varying problem scales and complexities by adjusting weight coefficients and neighborhood sizes.

(4) Scalability. Features a simple algorithmic structure that facilitates implementation and extension, which can be combined with other optimization algorithms (e.g., genetic algorithms, particle swarm optimization) to further enhance optimization performance.

## 3. Integrated Energy System Design for Green Buildings

### 3.1. System Architecture Design

The design objective of integrated energy systems for green buildings is to achieve efficient energy utilization and low-carbon operation. System architecture design must consider multiple stages, including energy supply, conversion, storage, and distribution (as shown in Fig. 3) to meet diverse building energy demands such as cooling, heating, and electricity (Alassaf, 2024).

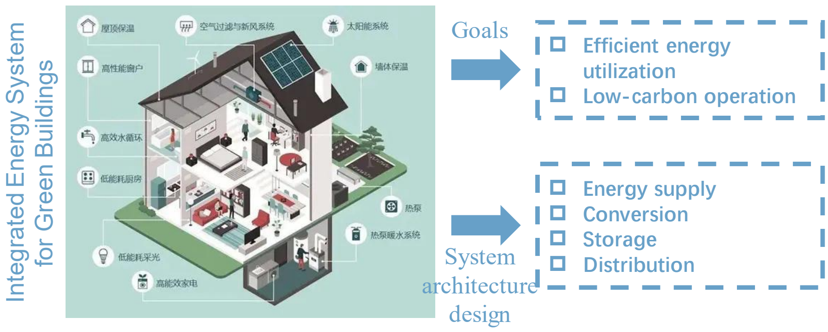


**Fig. 3.** System component diagram

#### 3.1.1. Energy supply system

The energy supply system serves as the core component of the green building's integrated energy system. It primarily comprises energy equipment such as solar photovoltaic systems, wind power generation systems, natural gas power generation systems, and biomass energy systems, as detailed in Fig. 4.

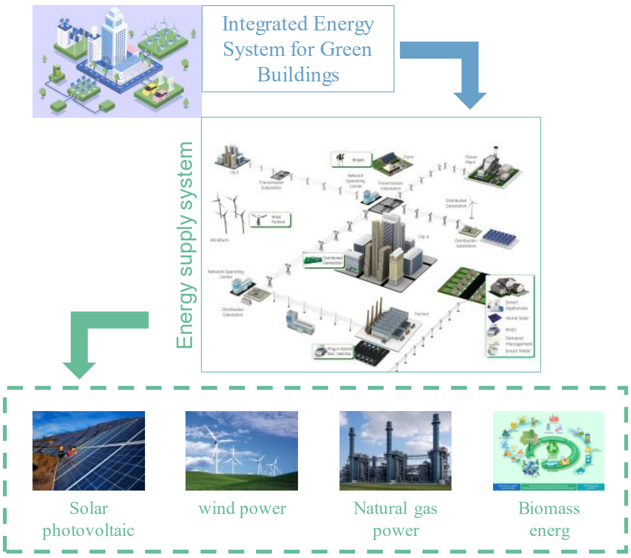


**Fig. 4.** Energy supply system

As shown in Fig. 4, the solar photovoltaic system converts solar energy into electricity via solar panels to power the building. The wind power generation system uses wind turbines to convert wind energy into electricity, making it suitable for regions with abundant wind resources. The natural gas power generation system converts natural gas into electricity through gas turbines or internal combustion engines while recovering waste heat for heating or cooling. Biomass energy systems utilize biomass (such as straw, wood chips, etc.) to generate thermal or electrical energy through combustion or gasification.

#### 3.1.2. Energy conversion equipment

Energy conversion equipment transforms one form of energy into another to meet diverse building requirements. This includes heat pumps, fuel cells, absorption chillers, and similar devices. Heat pumps use electrical energy to absorb heat from low-temperature sources (e.g., air, groundwater) for building heating or cooling; fuel cells directly convert the chemical energy of fuels (e.g., hydrogen, natural gas) into electrical energy through chemical reactions while producing thermal energy; absorption chillers utilize thermal energy to drive an absorption refrigeration cycle, generating cooling capacity for building air conditioning systems.

### 3.1.3. Energy storage systems

Energy storage systems store surplus energy to balance supply and demand. 1) Battery storage systems store electrical energy in batteries for peak shaving and emergency power supply. 2) Thermal storage systems utilize phase change materials or water as media to store thermal energy for heating or cooling. 3) Compressed air energy storage systems store energy by compressing air, releasing it for power generation when needed. Specific configurations of energy storage systems are illustrated in Fig. 5.

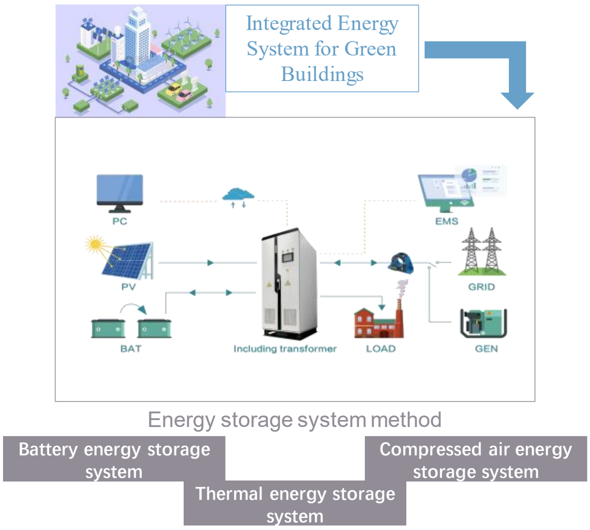


**Fig. 5.** Energy storage system configuration

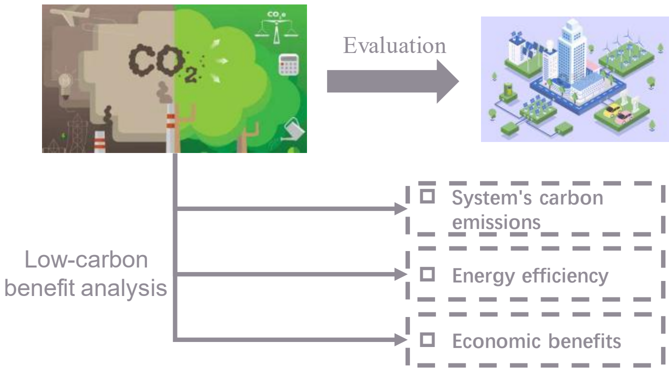


**Fig. 6.** Diagram of low-carbon benefit analysis

### 3.1.4. Energy distribution network

The energy distribution network is responsible for delivering energy from the supply end to various energy consumption points within the building. Based on energy form, the energy distribution network is categorized into electrical, thermal, and cooling distribution networks.

### 3.2. Low-Carbon Benefit Analysis

Low-carbon benefit analysis is a critical component in evaluating the performance of integrated energy systems in green buildings (Haddad and Javani, 2024). By calculating the system's carbon emissions, energy-saving benefits, and economic benefits, a comprehensive assessment of its low-carbon benefits can be achieved, as illustrated in Fig. 6.

1. Carbon emissions serve as a key indicator for assessing a system's environmental friendliness. Carbon emission calculations require consideration of the carbon emission factors for various energy sources within the system, calculated as follows:

$$C_e = \sum_{i=1}^{n} E_i \times F_i \tag{3}$$

Where: $C_e$ represents total carbon emissions. $E_i$ represents the consumption of the i-th energy source. $F_i$ represents the carbon emission factor of the i-th energy source. For power systems, the carbon emission factor can be calculated based on the power grid's energy mix. For natural gas systems, the carbon emission factor can be calculated based on the combustion efficiency of natural gas.

2. Energy-saving benefit assessment is primarily achieved by comparing energy consumption data before and after optimization. The energy-saving benefit can be calculated using the following equation:

$$R_b = \frac{C_{before} - C_{after}}{C_{before}} \times 100\% \tag{4}$$

Here, $R_b$ represents energy-saving benefits. $C_{before}$ denotes pre-optimization energy consumption. $C_{after}$ indicates post-optimization energy consumption. Higher energy-saving benefits indicate more significant improvements in the system's energy utilization efficiency.

3. Economic benefit analysis primarily considers the system's investment costs and operational maintenance costs (Wei, 2024). Investment costs include equipment procurement, installation fees, and related expenses. Operational maintenance

costs include energy expenses, equipment maintenance fees, and related costs. Economic benefits can be calculated using the following equation:

$$E_b = \frac{I_c}{S_m} \times 100\% \tag{5}$$

Here, $E_b$ represents the payback period, primarily used to calculate economic benefits; $I_c$ denotes total investment cost; $S_m$ indicates annual savings. A shorter payback period indicates better economic benefits for the system.

4. Environmental benefit analysis primarily evaluates the system's contribution to reducing greenhouse gas emissions and improving environmental quality. By comparing traditional energy systems with optimized, integrated energy systems in green buildings, the environmental benefits of the latter can be assessed.

### 3.3. Optimization Model Construction

Optimization modeling is key to achieving integrated energy system design for green buildings (Afroozeh, 2024). By constructing a multi-objective optimization model, the system's economic viability, environmental performance, and energy utilization efficiency can be considered simultaneously.

#### 3.3.1. Objective functions

The objective functions of the optimization model include economic, environmental, and energy-efficiency targets.

The economic objective minimizes the total investment cost and operation and maintenance cost of the system (Mohamed Ali and Akka, 2024), calculated as follows:

$$\text{Minimize } C_{total} = C_{investment} + C_{operation} \tag{6}$$

where $C_{investment}$ represents the total investment cost. $C_{operation}$ represents the operation and maintenance cost. The environmental objective minimizes the carbon emissions of the system, calculated as follows:

$$\text{Minimize } C_e = \sum_{i=1}^{n} E_i \times F \tag{7}$$

The energy utilization efficiency objective maximizes the renewable energy utilization rate of the system (Ben Mohammed, 2023), calculated explicitly as follows:

$$\text{Maximize } \eta_{renewable} = \frac{E_{re-e}}{E_e} \tag{8}$$

Where $E_{re-e}$ denotes renewable energy consumption, and $E_e$ denotes total energy consumption.

#### 3.3.2. Constraints

The optimization model's constraints include energy supply-demand balance constraints, equipment operation constraints, and environmental constraints (Yao et al., 2024). The energy generated by the system must satisfy the building's energy demand.

$$E_{supply} = E_{demand} \tag{9}$$

Equipment operation constraint. Equipment operating parameters must remain within permissible ranges.

$$P_{run} \in \left[ P_{\min}, P_{\max} \right] \tag{10}$$

Environmental constraints. The system's carbon emissions must comply with environmental protection requirements.

$$C_e \le C_{e,limit} \tag{11}$$

## 4. Design Method for Green Building Integrated Energy Systems Based on the MOEA/D Algorithm

In designing green building integrated energy systems, multi-objective optimization algorithms effectively balance system economics, environmental performance, and energy utilization efficiency. This section introduces a design methodology based on multi-objective optimization algorithms, covering the definition of decision variables, the construction of objective functions, and specific optimization steps.

### 4.1. Decision Variables

In the design of green building integrated energy systems, decision variables are parameters that require adjustment during optimization and directly impact system performance and benefits. Key decision variables include equipment capacity, operational parameters, and energy allocation ratios, structured into three main categories.

Specifically, equipment capacity includes solar panel area, wind turbine power, heat pump power, energy storage system capacity, and natural gas power generation system capacity. Equipment operating parameters include operating time, energy storage system charge/discharge power, and energy conversion efficiency. Energy allocation ratios include the distribution of different energy sources for heating, cooling, and power supply, along with the priority given to renewable energy.

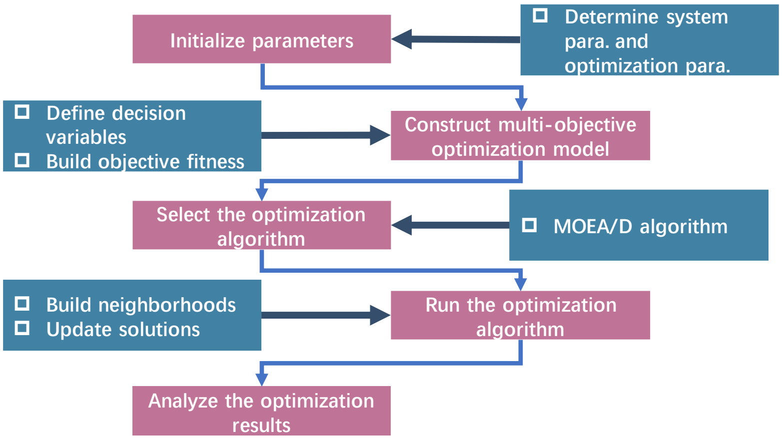


**Fig. 7.** Method flowchart

### 4.2. Objective Functions

Objective functions represent the metrics to be optimized during the process. Designing integrated energy systems for green buildings typically necessitates simultaneous consideration of economic viability, environmental sustainability, and energy utilization efficiency. Consequently, the objective functions encompass economic, environmental, and energy utilization efficiency targets.

### 4.3. Methodological Steps

The flowchart illustrating the design methodology for integrated energy systems in green buildings based on multi-objective optimization algorithms is shown in Fig. 7. The specific steps are as follows:

Step 1: Initialize parameters. Determine system parameters, including building energy demand, equipment performance parameters, energy prices, and other relevant factors. Randomly generate an initial population of size N. Set optimization algorithm parameters such as maximum iteration count and neighborhood size.

Step 2: Construct the multi-objective optimization model. Define decision variables, including equipment capacity, operational parameters, and energy allocation ratios, based on system design requirements. Establish a multi-objective optimization model considering economic efficiency, environmental performance, and energy utilization efficiency. Set constraints including energy supply-demand balance, equipment operation, and environmental limitations.

Step 3: Select the optimization algorithm. Choose the MOEA/D algorithm as the optimization tool based on the characteristics of green building integrated energy systems.

Step 4: Execute the optimization algorithm. Construct a neighborhood for each subproblem based on weight coefficients. For each subproblem, select several individuals from its neighborhood to perform crossover and mutation operations, generating new solutions. Replace the current solution with the new solution if it outperforms existing solutions within the neighborhood. Terminate the algorithm if termination conditions are met. Otherwise, return to the subproblem optimization step.

Step 5: Analyze optimization results. Output optimal solutions for all subproblems to form the Pareto front. Comprehensively evaluate the system's low-carbon benefits by calculating carbon emissions, energy savings, and economic benefits. Compare optimization results with those from traditional design methods to validate the optimization approach's effectiveness.

## 5. Experimental Validation

### 5.1. Experimental Setup

Validate the performance of the MOEA/D-based green building integrated energy system design method in terms of economic efficiency, environmental friendliness, energy utilization efficiency, and compare it with other optimization algorithms. A typical green building project is selected as the experimental subject, with its main parameter settings shown in Table 1.

This paper employs the MOEA/D algorithm to address the optimization design of integrated energy systems for green buildings. The specific parameter settings for the algorithm are detailed in Table 2.

To demonstrate the superiority of the green building integrated energy system optimization design method based on the MOEA/D algorithm, this paper employs NSGA-II (Non-Dominated Sorting Genetic Algorithm) and MOPSO (Multi-Objective Particle Swarm Optimization) as comparative algorithms.

**Table 1.** Experimental subject parameter settings

| No. | Project | Parameter Name | Value |
|---|---|---|---|
| 1 | Building Scale | Area | 10000m² |
| 2 | Energy Demand | Electricity Demand | 500kW |
| | | Heating Demand | 300kW |
| | | Cooling Demand | 200kW |
| 3 | Energy Price | Electricity Price | 0.15CNY/kWh |
| | | Natural Gas Price | 3.5CNY/m³ |
| 4 | Equipment Parameters | Solar PV Efficiency | 18% |
| | | Wind Turbine Power | 100kW |
| | | Heat Pump COP | 3.5 |
| | | Energy Storage Capacity | 100kWh |

**Table 2.** MOEA/D optimization algorithm parameter settings

| No. | Parameter Name | Value |
|---|---|---|
| 1 | Population Size | 100 |
| 2 | Max Iterations | 100 |
| 3 | Neighborhood Size | 20 |
| 4 | Crossover Probability | 0.9 |
| 5 | Mutation Probability | 0.1 |

### 5.2. Result Analysis

This section provides a detailed analysis of the performance of the green building integrated energy system design method based on the multi-objective optimization algorithm (MOEA/D). By comparing with NSGA-II and MOPSO, the effectiveness and superiority of the proposed method are evaluated across multiple dimensions, including total system cost, carbon emissions, renewable energy utilization rate, and algorithm convergence characteristics. Specific results are presented in Figs. 8 to 12 and Table 3.

Fig. 8 presents the comparison results of total costs for integrated energy systems in green buildings under different optimization algorithms. The figure indicates that the MOEA/D algorithm delivers the best performance in improving system economics, with its optimized total cost significantly lower than those achieved by NSGA-II and MOPSO. Specifically, the total system cost obtained by MOEA/D is 1.2×10^6 yuan, while NSGA-II and MOPSO yield values of 1.4×10^6 yuan and 1.5×10^6 yuan, respectively. This demonstrates that MOEA/D can effectively reduce investment and operational maintenance expenditures while ensuring regular system operation. Its advantage stems from the algorithm's rapid convergence speed and balanced solution set generation capability when handling multi-objective optimization problems. This enables better coordination among energy supply, storage, and distribution segments, thereby minimizing economic objectives.

Further analysis reveals that during cost optimization, MOEA/D not only reduces total investment but also achieves synergistic effects in energy operational efficiency. Compared with alternative algorithms, the results demonstrate that the system can achieve a higher proportion of renewable energy use at lower cost, thereby indirectly reducing reliance on high-cost fossil fuels. In contrast, NSGA-II and MOPSO, due to slower convergence rates and insufficient solution diversity, are prone to getting stuck in local optima, leading to suboptimal cost control in the final optimization results.

Fig. 9 presents the comparative results of three optimization algorithms regarding carbon emissions in green building integrated energy systems. The figure demonstrates that the MOEA/D-based optimization yields the optimal outcome, with carbon emissions as low as 150 tons, which is significantly lower than the 180 tons from NSGA-II and 200 tons from MOPSO. This demonstrates MOEA/D's outstanding performance in eco-friendly optimization, enabling more effective reduction of fossil fuel consumption and associated emissions during system operation. Its superiority stems from the precise scheduling of energy allocation and equipment operating parameters, maximizing renewable energy utilization. Consequently, it significantly reduces total carbon emissions while ensuring building energy demands are satisfied.

During optimization, the MOEA/D algorithm not only directly reduces carbon emissions but also achieves a superior balance in overall system energy efficiency. While NSGA-II and MOPSO can reduce emissions to some extent, their slow convergence and poor distribution of solutions prevent them from finding optimal solutions, resulting in persistently high carbon emissions. The results in Fig. 9 demonstrate that MOEA/D effectively balances economic viability and environmental sustainability through its multi-objective optimization strategy. This approach not only reduces system costs but also significantly enhances low-carbon benefits.

Fig. 10 presents the comparative results of three optimization algorithms regarding renewable energy utilization rates in green building integrated energy systems. As shown, the MOEA/D optimization yields the optimal result, achieving a renewable energy utilization rate of 0.60, which is significantly higher than NSGA-II's 0.50 and MOPSO's 0.45. This indicates that MOEA/D not only excels at reducing system costs and carbon emissions but also offers significant advantages in improving energy utilization efficiency. This stems from MOEA/D's ability to allocate cleaner energy sources like solar and wind power more rationally while optimizing the operation of energy storage systems. Consequently, it reduces reliance on fossil fuels, thereby achieving a greener, more efficient energy system.

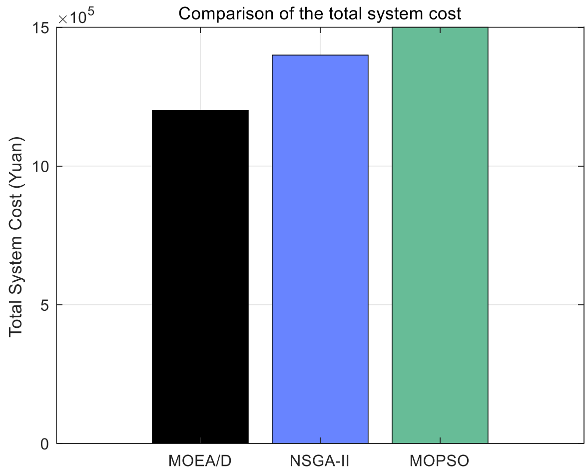


**Fig. 8.** Comparison of total system costs

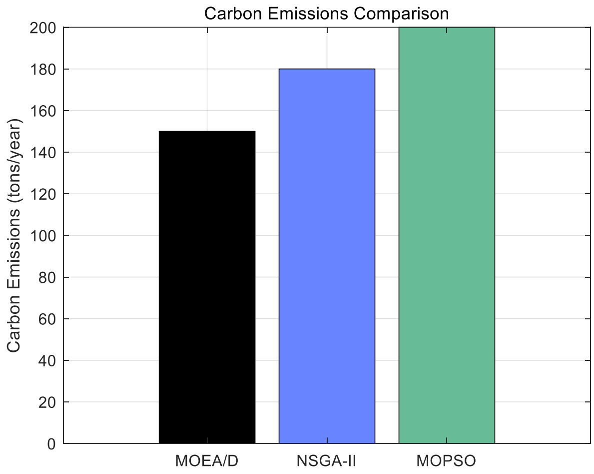


**Fig. 9.** Carbon emissions comparison

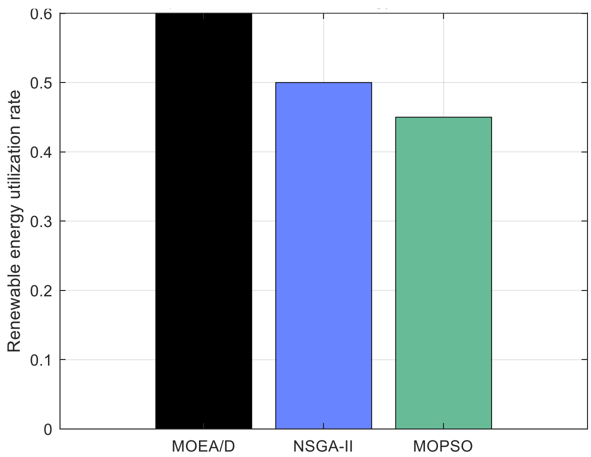


**Fig. 10.** Comparison of renewable energy utilization rates

MOEA/D's utilization advantage reflects its balanced multi-objective optimization capability. Compared to other algorithms, it achieves superior coordination between economic and environmental objectives, maximizing renewable energy usage without significantly increasing system costs. In contrast, NSGA-II and MOPSO often converge to suboptimal local solutions due to insufficient convergence speed and solution diversity, resulting in limited improvements in renewable energy utilization.

Fig. 11 displays the convergence curves of the three algorithms. Under uniform parameter settings (population = 100, maximum iterations = 100), the MOEA/D curve exhibits a steeper initial slope, rapidly descending from the high-cost region and entering the stable low-value zone earlier, with smaller iteration fluctuations. NSGA-II and MOPSO exhibit relatively slower descent rates, with noticeable plateaus and oscillatory behavior in the middle to late stages, and a tendency to linger in suboptimal neighborhoods. The curve patterns indicate that MOEA/D achieves a superior balance between "global exploration and local exploitation," ensuring search efficiency while enhancing convergence stability, thereby laying the groundwork for obtaining better compromise solutions.

MOEA/D decomposes multi-objective problems into weighted subproblems, using weight vectors to cover diverse directions. It enhances information utilization through neighborhood-based collaborative updates and solution replacement. This "decomposition + neighborhood" strategy simultaneously advances convergence toward the Pareto front while suppressing the propagation of poor solutions and reducing search randomness. With the parameters specified in this paper (neighborhood T=20, crossover probability 0.9, mutation probability 0.1), MOEA/D significantly accelerates convergence toward the low-cost/low-emission region while maintaining solution diversity, resulting in smoother curves and faster convergence.

MOEA/D's faster stabilization means acquiring higher-quality candidate solutions within the same iteration budget, reducing computational overhead and enhancing solution selection certainty. In contrast, NSGA-II and MOPSO require more iterations to escape plateaus, with oscillations increasing the risk of "false convergence" and suboptimal solution selection. Note that MOEA/D's advantages remain influenced by hyperparameters such as weight design and neighborhood size. In practice, combining early stopping criteria, restart mechanisms, and adaptive weight vectors can further enhance convergence reliability and adaptability to diverse decision preferences.

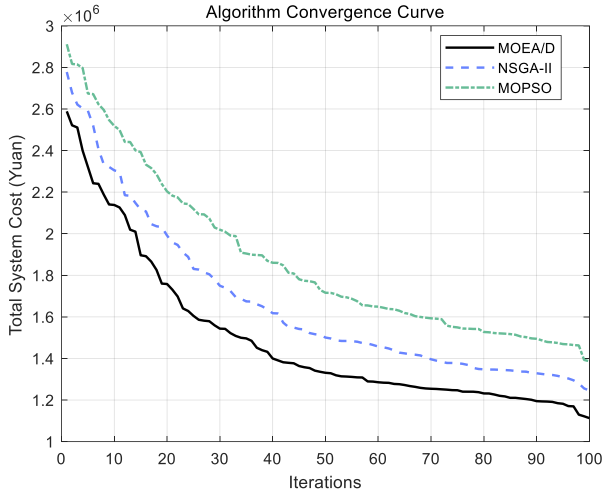


**Fig. 11.** Algorithm convergence curves

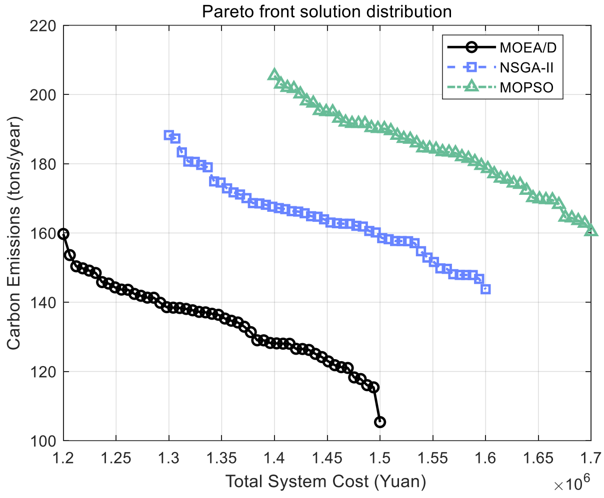


**Fig. 12.** Distribution of Pareto frontier solutions

Fig. 12 illustrates the distribution of Pareto frontiers generated by three optimization algorithms in the multi-objective space, enabling a visual comparison of solution set quality and coverage. The results show that the solution set generated by MOEA/D exhibits a more uniform distribution and is closer overall to the ideal point region (low cost, low carbon emissions). This indicates that, during multi-objective optimization, MOEA/D not only identifies more trade-off solutions but also ensures balanced development across economic efficiency and environmental sustainability. In contrast, the solution set generated by NSGA-II exhibits local clustering, making it difficult to comprehensively cover the Pareto frontier. Meanwhile, the frontier distribution generated by MOPSO is relatively sparse, with discontinuities observed in certain regions, suggesting its limitations in maintaining solution diversity.

Further analysis reveals that MOEA/D exhibits more pronounced inflection points in its solution set, enabling substantial reductions in carbon emissions at minimal cost, and is a highly valuable reference for engineering decisions. Its balanced distribution enables decision-makers to identify suitable solutions across diverse scenarios swiftly. In contrast, NSGA-II's convergence speed and solution distribution constraints lead to solutions clustering predominantly in the middle range, with insufficient coverage of extreme regions. MOPSO exhibits solution biases in certain cases, weakening the reliability of the results. These differences demonstrate MOEA/D's superior global stability and robustness in generating high-quality solution sets.

**Table 3.** Algorithm performance comparison

| No. | Algorithm | System Total Cost | Carbon Emissions | Renewable Energy Utilization Rate |
|---|---|---|---|---|
| 1 | MOEA/D | 1.2e+06 | 150 | 0.6 |
| 2 | NSGA-II | 1.4e+06 | 180 | 0.5 |
| 3 | MOPSO | 1.5e+06 | 200 | 0.45 |

Table 3 compares the optimization results of the MOEA/D, NSGA-II, and MOPSO algorithms based on three key metrics: total system cost, carbon emissions, and renewable energy utilization rate. The results demonstrate that MOEA/D achieves the best performance across all metrics. Its total system cost is 1.2×10^6 yuan, representing reductions of approximately 14.3% and 20% compared to NSGA-II (1.4×10^6 yuan) and MOPSO (1.5×10^6 yuan), respectively, significantly enhancing economic efficiency. Carbon emissions were controlled at 150 tons, markedly lower than NSGA-II's 180 tons and MOPSO's 200 tons, representing reductions ranging from 16.7% to 25% and demonstrating superior environmental benefits. Regarding renewable energy utilization rate, MOEA/D achieved 0.60, representing a 10%–15% improvement over NSGA-II's 0.50 and MOPSO's 0.45. This indicates that MOEA/D not only enables low-cost operation but also effectively promotes energy structure optimization and carbon reduction. Its comprehensive performance surpasses that of the comparison algorithms, providing robust quantitative support for low-carbon and efficient design of green building systems. It should be noted that the aforementioned results are based on specific building parameters and fixed energy pricing. Although MOEA/D demonstrates superior convergence and solution set distribution in the current deterministic scenario, the stochastic fluctuations of load demand and renewable energy output in practical engineering may affect the boundaries of the optimal solution. Therefore, this study validates the method's effectiveness under standard design conditions, while robustness analysis targeting dynamic, uncertain environments will be the focus of future research.

## 6. Conclusion

This paper proposes a system design methodology based on MOEA/D to optimize integrated energy systems for green buildings and analyze their low-carbon benefits. The research first constructs a multi-objective optimization model that comprehensively considers economic efficiency, environmental performance, and energy utilization efficiency, and defines key decision variables, including equipment capacity, operational parameters, and energy allocation ratios. Subsequently, the proposed method was experimentally validated using a typical case study and compared with NSGA-II and MOPSO algorithms. Results demonstrate that MOEA/D outperforms the comparison algorithms across three metrics, including total system cost, carbon emissions, and renewable energy utilization rate. Specifically, total cost is reduced by 14.3%–20%, carbon emissions decrease by 16.7% to 25%, and renewable energy utilization rate increases by 10% to 15%. Additionally, MOEA/D demonstrated favorable performance in convergence speed, balanced solution set distribution, and Pareto frontier approximation. The findings verify the method's effectiveness and application value in promoting low-carbon, high-efficiency operation of green buildings.

Despite achieving promising results, this study has several limitations. First, the experimental data relied primarily on a single building case, lacking validation across diverse scenarios, thereby limiting the generalizability of the findings. Second, the short research cycle focused solely on static operating conditions, failing to fully evaluate the system's stability and robustness under long-term operation and dynamic environments. Furthermore, the objective function of the optimization model is relatively narrowly defined, not yet comprehensively incorporating social indicators such as user comfort and policy constraints, which limits the method's comprehensive applicability in practical engineering.

Future research will focus on the following areas. First, expanding the diversity and scale of case studies to validate the method's universality and adaptability across different climate zones, building types, and energy pricing environments. Second, incorporating dynamic optimization and uncertainty analysis to fully account for seasonal variations in building energy consumption, energy price fluctuations, and policy constraints. Third, refine the optimization model by adding multidimensional objectives, such as comfort evaluation, system resilience, and policy alignment, to enhance its decision-making value. Concurrently, we will explore integrating deep learning and intelligent control methods with MOEA/D to establish a more intelligent and adaptive optimization framework for green building integrated energy systems.

**Funding**

This work was supported by Jilin Provincial Social Science Foundation Project "*Research on Green Construction and Management Policies and Regulations in Jilin Province*" (Grant No.: 2022B82)

**Institutional Review Board Statement**

Not applicable.

**References**

Afroozeh, P. (2024). Analyzing Energy Efficiency Strategies and Designing and Simulation Energy Efficient Systems in Buildings. *Journal of Building Materials* and *Structures, 11*(1). https://doi.org/10.34118/jbms.v11i1.3228

Akpan, F. (2024). A Framework for Industry 4.0 Related Green Concept Integration of Services Component in Commercial Buildings. *Sustainability, 16*. https://doi.org/10.3390/su16219141

Alassaf, Y. (2024). Comprehensive Review of the Advancements, Benefits, Challenges, and Design Integration of Energy-Efficient Materials for Sustainable Buildings. *Buildings, 14*. https://doi.org/10.3390/buildings14092994

Brzozka, B. (2024). Deep Learning and Data Engineering Approaches in Smart Building Decoration Automation: A Comprehensive Review. *Data Engineering and Applications*, *4*(2), 48–68. https://doi.org/10.64972/dea.2024.v4i2.14

Ben Mohammed, A. (2023). A Systematic Design Technique of Biomimicry to Correlate and Integrate Architecture and Biology to Attain Green Buildings. *Journal of Engineering Sciences, 51*(4). https://doi.org/10.21608/JESAUN.2023.181479.1190

Chadly, R., Urs, M., Wei, M., Maalouf, M., and Mayyas, A. (2023). Techno-Economic Assessment of Energy Storage Systems in Green Buildings While Considering Demand Uncertainty. *Energy and Buildings, 291*, 113130. https://doi.org/10.1016/j.enbuild.2023.113130

Choi, I., Kang, B., Lee, S., Park, S., Beck, S., and Lee, H. (2024). Empirical Study on Optimization Methods of Building Energy Operation for the Sustainability of Buildings with Integrated Renewable Energy. *Energy and Buildings, 305*, 113908. https://doi.org/10.1016/j.enbuild.2024.113908

Fan, Y., Xiong, Y., Li, X., and Tian, X. (2024). Research Progress on Multi-objective Optimization of Building Energy Consumption Based on Genetic Algorithm. *Integrated Intelligent Energy, 46*(9). https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFD and filename=ZNZN202409009

Fu, J., Sun, Y., Li, Y., Wang, W., Wei, W., and Ren, J. (2025). An Investigation of Photovoltaic Power Forecasting in Buildings Considering Shadow Effects: Modeling Approach and SHAP Analysis. *Renewable Energy, 245*, 122821. https://doi.org/10.1016/j.renene.2025.122821

Gabbar, A., and Ramadan, A. (2025). Integrated Renewable Energy Systems for Buildings: An Assessment of the Environmental and Socio-Economic Sustainability. *Sustainability, 17*(2), 656. https://doi.org/10.3390/su17020656

Gu, Q., Tang, S., Hao, J., Di Sarno, L., Wu, G., and Ren, S. (2023). Building Automation Systems for Energy and Comfort Management in Green Buildings: A Critical Review and Future Directions. *Renewable and Sustainable Energy Reviews, 179*, 113301. https://doi.org/10.1016/j.rser.2023.113301

Haddad, M., and Javani, N. (2024). Transient Analysis of a Near-Zero Energy Building with Green Hydrogen Production Integrated with Energy Storage Systems. *Journal of Building Engineering, 96*, 110541. https://doi.org/10.1016/j.jobe.2024.110541

Hoang Son, V., and Duy, H. (2023). Research on Applying Machine Learning Models to Predict the Electricity Generation Capacity of Rooftop Solar Energy Systems on Buildings. *Asian Journal of Civil Engineering, 24*(8), 3413–3423. https://doi.org/10.1007/s42107-023-00722-1

Huener, B., and Telli, E. (2023). Design and Performance Analysis of a Green House Based on Hybrid and Passive Energy Systems: A Case Study. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 45*(4), 12859–12879. https://doi.org/10.1080/15567036.2023.2276907

Leu, S., and Shi, Y. (2024). Effective Green Building Design Assessment Support Using Sequential Multidisciplinary Design Optimization. *Microelectronics Journal, 96*, 110543. https://doi.org/10.1016/j.jobe.2024.110543

Li, T. (2024). Study on the Energy Consumption Characteristics and the Self-Sufficiency Rate of Rooftop Photovoltaic of University Campus Buildings. *Energies, 17*. https://doi.org/10.3390/en17143535

Lv, Q. (2025). Intelligent Building Design Based on Green and Low-Carbon Concept. *Energy Informatics, 8*(1). https://doi.org/10.1186/s42162-025-00513-9

Meng, Y., Wei, W., and Wu, S. (2024). An Improved MOEA/D Algorithm Based on Angle Trajectory and Adaptive Weight. *Journal of Dongguan University of Technology, 31*(1), 28–36. https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CJFD and filename=DGGC202401004

Mersal, A. (2023). The Future of the Sustainable Green Architecture Through Technology. *HBRC Journal, 19*(1), 33–62. https://doi.org/10.1080/16874048.2021.19481

Mohamed Ali, B., and Akka, M. (2024). The Green Cooling Factor: Eco-Innovative Heating, Ventilation, and Air Conditioning Solutions in Building Design. *Applied Sciences, 14*(1). https://doi.org/10.3390/app14010195

Sirin, C., Goggins, J., and Hajdukiewicz, M. (2023). A Review on Building-Integrated Photovoltaic/Thermal Systems for Green Buildings. *Applied Thermal Engineering*, 120607. https://doi.org/10.1016/j.applthermaleng.2023.120607

Shum, C., and Zhong, L. (2023). Optimizing Automated Shading Systems for Enhanced Energy Performance in Cold Climate Zones: Strategies, Savings, and Comfort. *Energy* and *Buildings, 300*, 113638. https://doi.org/10.1016/j.enbuild.2023.113638

Sui, J., Chen, P., and Jiang, H. (2025). Optimizing Police Patrol Strategies in Real-World Scenarios: A Modified PPS-MOEA/D Approach for Constrained Multi-Objective Optimization. *Applied Sciences, 15*(7). https://doi.org/10.3390/app15073651

Wang, Y. (2024). Thermodynamic Efficiency and Integration Strategies in Solar-Powered Building Electrical Systems. *International Journal of Heat* and *Technology, 42*(2). https://doi.org/10.18280/ijht.420230

Wei, Y. (2024). Ecological Benefit Optimization and Design of Rural Residential Roofs Based on the 'Dual Carbon' Goal. *Buildings, 14*. https://doi.org/10.3390/buildings14123715

Xue, F., Chen, Y., Dong, T., Wang, T., Wang, P., and Fan, W. (2025). MOEA/D with Adaptive Weight Vector Adjustment and Parameter Selection Based on Q-Learning. *Applied Intelligence, 55*(6), 1–43. https://doi.org/10.1007/s10489-024-05906-z

Yao, G., Ding, D., Xie, C., and Tan, H. (2024). Optimized Design and Comparative Analysis of Double-Glazed Photovoltaic Windows for Enhanced Light Harvesting and Energy Efficiency in Cold Regions of China. *Energy and Buildings, 325*, 115011. https://doi.org/10.1016/j.enbuild.2024.115011

Zhang, L., Cao, Q., and Li, S. (2025). Robust Operation Optimization Model for Building Integrated Energy System with Demand Response Mechanism and Weighting of Consumption Responsibility. *Journal of Renewable and Sustainable Energy, 17*(1), 015901. https://doi.org/10.1063/5.0239171

Yang Yuan holds a Master's degree and is a professional Engineer. With solid teaching experience, she has focused on the field of green building. She has presided over 2 national-level and 3 provincial-level research projects, secured 2 utility model patents, and published more than 10 academic papers in the fields of teaching and research. She served as the chief editor of a digital textbook and led the development of an online course. In 2023, the course was honored with the Provincial Excellent Curriculum Ideological and Political Education Case. In addition to academic work, the author has extensive practical experience, having been deeply involved in on-site management of residential and commercial building construction, as well as metro and light rail engineering projects. This has facilitated the in-depth integration of teaching and practice, yielding remarkable accomplishments in both academic research and teaching.