A Tri-Objective Model for Optimizing Global Cost and Embodied-Operational Carbon Emission of Residential Building Envelopes

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Abstract: Building envelope materials and configurations significantly impact both embodied and operational carbon emissions. Improving thermal performance typically increases initial costs, while poor performance raises operational energy use and costs. This presents a paradox among the seven variables. This study presents a multi-objective optimization model using Rhino-Grasshopper and the BP-NSGA-II algorithm to minimize embodied and operational carbon emissions and global costs for building envelopes. A high-rise residential building in a cold region of Northern China is used as a case study. The optimization, identifies the optimal trade-offs between carbon emissions and cost. Using the entropy-weighted TOPSIS method for decision-making, the optimal solution would reduce would embodied carbon by 50.1%, operational carbon by 2.1%, and global cost by 10.8% compared to the baseline. The proposed model offers an efficient decision-support tool for reducing carbon emissions and optimizing costs in building envelope design.

1. Introduction

According to the *China Building Energy Consumption and Carbon Emissions Research Report* (2023), the total carbon emissions from the entire life cycle of residential buildings in China reached 4.07 billion tons of CO_2 in 2021, accounting for 38.2% of the nation's energy-related carbon emissions. Of this total, 43.4% originated from building material production and construction activities, while 56.6% was attributed to the operational phase[1]. Embodied carbon has received growing attention, as it is increasingly recognized that it can account for a substantial share of life-cycle carbon emissions, exceeding 50% in some cases[2].

The building envelope, as the boundary structure, improving envelope efficiency—through measures like wall insulation, high-performance windows, and optimized window-to-wall ratios-enhances energy efficiency[3]. However, building envelopes often use high-carbon materials such as aluminum, glass, and insulation, leading to significant embodied carbon emissions[4]. During operation, the envelope's thermal performance directly influences carbon emissions[5]. Enhancing thermal performance must balance environmental benefits with economic costs to ensure the sustainability of energy-saving strategies[6]. From a life-cycle perspective, the thermal performance of the envelope affects both carbon emissions and economic costs, underscoring the need for an integrated approach to balance these factors.

The mission to achieving the goals of minimizing embodied and operational carbon emissions, and reducing global costs during the design phase, poses two key challenges: First, without operational energy data, it is unclear how design parameters alone can effectively reduce emissions and costs. Second, selecting the optimal design from thousands of configurations to balance multiple objectives is complex. While existing studies on parametric life-cycle assessments consider environmental and cost factors, they often overlooked the full range of design parameters[7]. Few studies adopt an integrated approach that considers embodied carbon, operational carbon, and global costs, which is essential for understanding trade-offs between early design choices and operational emissions, thus improving both economic and environmental outcomes. Few studies address adaptive strategies for cold regions[8]. In severe cold areas, envelope optimization faces challenges like long heating seasons and high heating demand. While insulation reduces operational emissions, thicker layers and multi-glazed windows increase embodied carbon and costs. Excessive insulation also risks summer overheating.

This research aims to develop a multi-objective model for optimizing building envelope design by evaluating embodied and operational carbon emissions and economic costs over the building's life cycle, proposing low-carbon, cost-effective strategies. Focusing on residential buildings in cold regions, the study integrates numerical simulation with the BP-NSGA-II algorithm to optimize key design parameters such as insulation type, thickness, and window-to-wall ratio. The objectives are: (1) creating a parametric model to quantify the impact of design parameters on carbon emissions and costs; (2) optimizing embodied and operational carbon emissions and global cost using the BP surrogate model and NSGA-II algorithm, identifying the best trade-offs through the entropy-weighted TOPSIS method.

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2. Methods

This study proposes a tri-objective optimization model for residential building envelopes, focusing on embodied carbon emissions, operational carbon emissions, and global cost, using the Rhino-Grasshopper parametric platform. The model integrates energy performance simulation with an optimization algorithm to identify optimal solutions. Seven envelope design parameters were selected, and their variation ranges defined. To balance accuracy and efficiency, simulation was conducted on two upper floors of a high-rise building. EnergyPlus, linked via Honeybee and Ladybug plugins, was used to model operational energy consumption and carbon emissions. GH-Python scripts calculated changes in embodied carbon and global cost. Data from cross-experiments trained a BPNN surrogate model, followed by multi-objective optimization using NSGA-II. Finally, Pareto-optimal solutions were ranked and filtered using the entropy-weighted TOPSIS method to identify the most balanced design. The detailed model is illustrated in Figure 1.

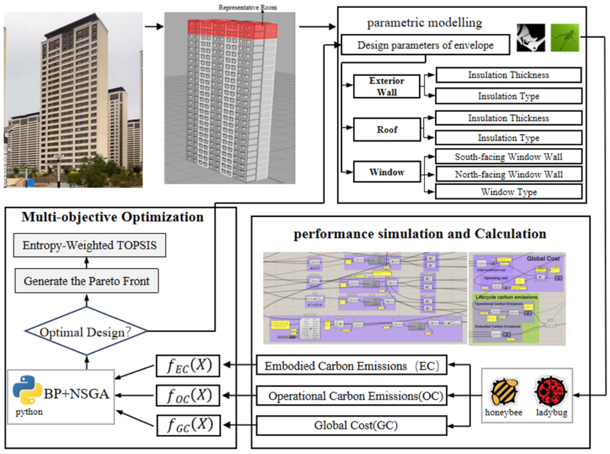

Figure 1. The optimization Model.

2.1. Backpropagation Neural Network (BPNN)

The Backpropagation Neural Network (BPNN) is a classical artificial neural network model whose core mechanism relies on iteratively updating weights through the backpropagation algorithm to achieve complex nonlinear mappings. This model exhibits strong learning and generalization capabilities[9]. Its information processing involves two stages: forward propagation of input signals to generate outputs, and backward propagation of errors to adjust the network weights. Owing to its effectiveness in modeling multivariate interactions and nonlinear relationships, the BPNN has demonstrated outstanding performance in tasks such as building performance prediction, and is therefore adopted as the predictive model in this research.

To mitigate skewness in the distribution of optimization targets and enhance the modeling stability of the BP network, this study applies a unified log1p transformation to all objective values prior to training, thereby reducing the high variance caused by positive skewness and improving numerical stability. Subsequently, the transformed targets are standardized (zero mean and unit variance) to ensure consistent scales during training. To further strengthen robustness and generalization, the Optuna framework is employed for automated hyperparameter tuning, specifically optimizing the number of hidden neurons (64–256), dropout rate (0.1–0.5), and learning rate (1e-4–1e-2). In addition, an early stopping mechanism is adopted to prevent overfitting. With these preprocessing and optimization strategies, the BP surrogate model demonstrates high accuracy and stability on both training and test sets.

2.2. Genetic Algorithms and Multi-Objective Optimization

2.2.1 Genetic Algorithms

In this research, the Non-dominated Sorting Genetic Algorithm (NSGA) was adopted as the optimization method. NSGA-II, a member of the evolutionary algorithm family, employs an elitist strategy that combines parent and offspring populations, generating the next generation through non-dominated sorting. This strategy effectively guides the evolutionary process by using crowding distance metrics, resulting in a set of well-distributed Pareto-optimal trade-off solutions[10]. NSGA-II is characterized by high precision, computational efficiency in handling large-scale and complex problems and a strong ability to maintain solution diversity due to its crowding distance and mutation mechanisms. Therefore, NSGA-II was selected for this research owing to its proven efficiency and robustness in multi-objective optimization tasks. In this research, the NSGA-II algorithm was configured as follows: the population size was set to 100, with initialization performed using random float sampling. Simulated Binary Crossover (SBX) was applied with a crossover probability of 0.9 and a distribution index of 10, while Polynomial Mutation (PM) was employed with a distribution index of 20. The termination criterion was defined as 200 generations.

2.2.2 Optimization Objectives

This research defines three optimization objectives for the building envelope: embodied carbon emissions, operational carbon emissions and total global cost, as formulated in Equation:

$$\min F(X) = f_{EC}(X) + f_{OC}(X) + f_{GC}(X)$$

In this equation, f_{EC} represents embodied carbon emissions, f_{OC} represents operational carbon emissions and f_{GC} denotes the global cost. The specific definitions of these objectives are as follows:

1) Calculation of Embodied Carbon Emissions (EC)

Calculated using the emission factor method from the *Chinese National Standard (GB/T 51366-2019)*. $EC = \sum_{i=1}^{n} M_i \times F_i$, where M_i denotes the quantity of the i-th material used and F_i represents the corresponding carbon emission factor.

2) Calculation of Operational Carbon Emissions (OC)

Calculated based on electricity consumption E_{elec} and the regional carbon emission factor β_{gird} : $OC = E_{elec} \times \beta_{gird}$

3) Calculation of Global Cost (GC)

Calculated over a 30-year period based on the *EN 15459* standard. It includes initial construction costs (C_I) and operational costs (energy consumption, $C_{e,i}$). The formula for GC is: $GC = \frac{C_I + \sum_{i=I}^{n}[C_{e,i} * R_d(i)]}{\mathrm{A}}$, $R_d(i) = \frac{1-(I+R_r)^{-i}}{2a}$, $R_r = \frac{R_i - R_e}{1+R_e}$. Where A is the building area, and $C_{e,i}$ is calculated using tiered electricity pricing in Hohhot. The real interest rate (R_r) and discount rate ($R_d(i)$) are applied for cost analysis.

2.2.3 Design Variables

This research identifies seven key parameters affecting building envelope design: 1) external wall insulation type, 2) thickness of external wall insulation, 3) roof insulation type, 4) thickness of roof insulation, 5) South-facing window-to-wall ratio (WWR), 6) North-facing WWR, and 7) window types.

To assess the impact of different envelope combinations on cost and carbon emissions, decision parameter ranges were defined using engineering standards, market conditions, and literature. Embodied carbon emissions were estimated based on GB/T 51366-2019, with material data for d costs were sourced from supplier quotes and relevant studies[11, 12].

The insulation materials include PUR, SEPS, Rock Wool, EPS, and XPS, with thicknesses ranging from 150 to 500 mm. Each material has specific U-values, carbon emission factors, and initial costs. Window types vary in U-values, ranging from 1.0 to 1.4 W/m^2·K, with carbon emission factors from 68.2 to 132.4 kgCO2e/ m^2 and initial costs between 1203.5 and 2106 yuan/m². The south-facing WWR ranges from 30% to 90%, and the north-facing WWR ranges from 10% to 40%.

3. Case Study

This study uses a representative residential building TOP part of figure 1, in Hohhot, China (40°52′26.98″ N, 111°43′29.11″ E) as a case study. Located in the severe cold climate zone, Hohhot experiences high heating demand with a 180-day heating season. The building, oriented north-south, has a window-to-wall ratio (WWR) of 0.34 (south) and 0.23 (north). The walls are insulated with 250 mm EPS and the roof with 250 mm XPS.

The building relies on air conditioning for heating and cooling, with set temperatures of 25°C in summer and 18°C in winter, and a COP of 3.0. Occupant schedules and indoor parameters follow GB 55015-2021 (General Code for Energy Efficiency and Renewable Energy Application in Buildings).

4. Results and Discussion

4.1. Reliability of simulation and surrogate model

To validate the reliability of the proposed framework, both the simulation model and surrogate model were compared with measured data. The simulation accuracy for annual heating and cooling loads was 93.3%. The BPNN model was used to predict embodied carbon emissions, global cost, and operational carbon emissions, achieving an average R^2 of 0.983 in cross-validation.

4.2. Optimization Results

A total of 20,000 optimization iterations were performed. In total, 184 Pareto-optimal solutions were obtained, with the top 20 highlighted in orange and the remaining ones depicted in blue (Figure 2).

The Pareto frontier represents a set of optimal trade-offs, not a single solution. To identify the preferred option, a multi-criteria decision-making (MCDM) method, specifically the entropy-weighted TOPSIS, was used. The weights for embodied carbon emissions, operational carbon emissions, and global cost were 36.82%, 29.95%, and 33.23%, respectively. Table 3 presents the top 10 out of 184 Pareto-optimal solutions ranked by the TOPSIS method.

The top 10 Pareto-optimal solutions show consistent trends in design parameters. The north-facing WWR is mainly 0.1, reducing heat loss, while the south-facing WWR is 0.3-0.4, balancing solar gain and overheating risks. Polyurethane (PUR) is the preferred insulation material due to its low U-value, low carbon footprint, and moderate cost. Most solutions also favor W1 windows for the best overall balance of thermal performance, shading, cost, and carbon emissions.

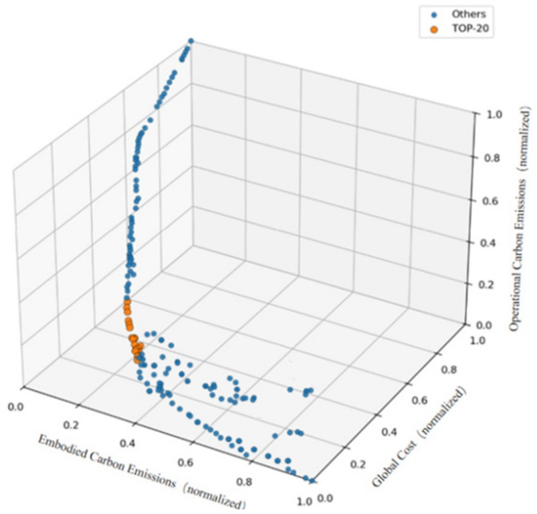

Figure 2. Optimization Results of NSGA-II

The top-ranked solution, with a composite score of 0.73, features a north WWR of 0.1, south WWR of 0.3, 0.18 m PUR insulation on the walls, 0.16 m PUR on the roof, and W1 windows. Compared to the baseline, it reduces embodied carbon emissions by 50.9 kgCO2/m², operational carbon emissions by 11.335 kgCO2/m², and global cost by ¥441.81/m², achieving reductions of 50.1%, 2.1%, and 10.8%, respectively. These results demonstrate that optimizing envelope design can balance cost control and carbon emission reduction.

5. Conclusion

This research developed a tri-objective optimization model combining a BPNN surrogate model and the NSGA-II multi-objective genetic algorithm to address trade-offs between embodied carbon emissions, operational carbon emissions, and global cost in building envelope design. A case study of a two-story section of a high-rise residential building in China's severe cold region was conducted, using energy simulations via Rhino-Grasshopper and cross-experiment data to train the BPNN, followed by NSGA-II optimization. Seven design variables were considered, including insulation type and thickness, window type, and window-to-wall ratios on the north and south walls. A total of 184 Pareto-optimal solutions were generated, and the entropy-weighted TOPSIS method was applied to identify the most balanced solution.

The optimal solution adopted a combination of PUR insulation and W1 windows, achieving a favorable balance between carbon reduction and cost-efficiency. Compared to the baseline, this solution reduced embodied carbon by 50.1%, operational carbon by 2.1%, and global cost by 10.8%. These findings demonstrate the effectiveness of the tri-objective optimization model for envelope parameter selection in cold climates. The integration of simulation-based modeling and the BP-NSGA-II evolutionary algorithm successfully identified a building envelope configuration that optimizes embodied carbon, operational carbon, and global cost, leading to substantial improvements in both economic performance and environmental impact. Future research could investigate the impacts of more variables on building carbon emissions and costs from the perspectives of diverse climate zones.

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