Dual-objective optimization for cost and carbon emissions of green residential buildings based on SVM-NSGA-II coupling

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Abstract. In order to further reduce the life cycle cost and carbon emissions of green residential buildings, this paper proposes a dual-objective optimization framework based on the coupling of Support Vector Machine (SVM) and Non-dominated Sorting Genetic Algorithm II (NSGA-II). The framework simulates the design process and calculates the corresponding life cycle cost and carbon emissions from a design perspective. By using the SVM-NSGA-II algorithm, optimal solutions for green residential building designs are obtained. This approach is then applied to a green building project in Beijing, aiming to achieve a win-win situation in terms of economic and environmental benefits.

Keywords: Green residential, cost, carbon emissions, optimization research

1 Introduction

In the 9th chapter of the Intergovernmental Panel on Climate Change's Sixth Assessment Report (AR6) [1], it is pointed out that global greenhouse gas emissions in the construction industry continue to increase. Among these emissions, 57% are indirect emissions generated by electricity generation and heating, 24% are direct emissions, and 18% are carbon emissions produced by construction materials. From this, it can be inferred that there is significant potential for low-carbon development in the construction industry. In recent years, the Chinese government and researchers have been conducting a series of studies centered around the keywords 'green' and 'low-carbon' in the field of construction. The 'Action Plan for Carbon Peak before 2030' [2] emphasizes the need to continuously promote the transition to green and low-carbon practices, setting requirements for the low-carbon sustainable development of the future construction industry.

There are many research studies on multi-objective optimization of green buildings in China. Scholars such as W Wang[3], Ren Jiqin[4], and Yang Wenling[5] have conducted optimization studies on green buildings using various intelligent algorithms. However, in the field of energy efficiency optimization, China is still in its early stages and lacks research on the impacts of buildings from economic and environmental perspectives. Specifically, there are relatively few case studies on the costs

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and carbon emissions of green buildings. Therefore, this article establishes a multi-objective optimization model by coupling SVM and NSGA-II.

2 Construction of an Optimization Model for Whole Life Cycle Costs and Carbon Emissions of Green Residential Buildings

2.1 Optimization Algorithm Mechanism

The NSGA-II [6] algorithm was chosen. In the execution process, this algorithm introduced strategies like elite preservation, fast nondominated sorting, and individual crowding distance estimation to enhance the performance and execution efficiency of the NSGA algorithm. This means that the NSGA-II algorithm requires less computation, is simpler and faster, prevents the loss of excellent individuals, and provides a more objective computation. The computational process of the NSGA-II algorithm is illustrated in Figure 1 below.

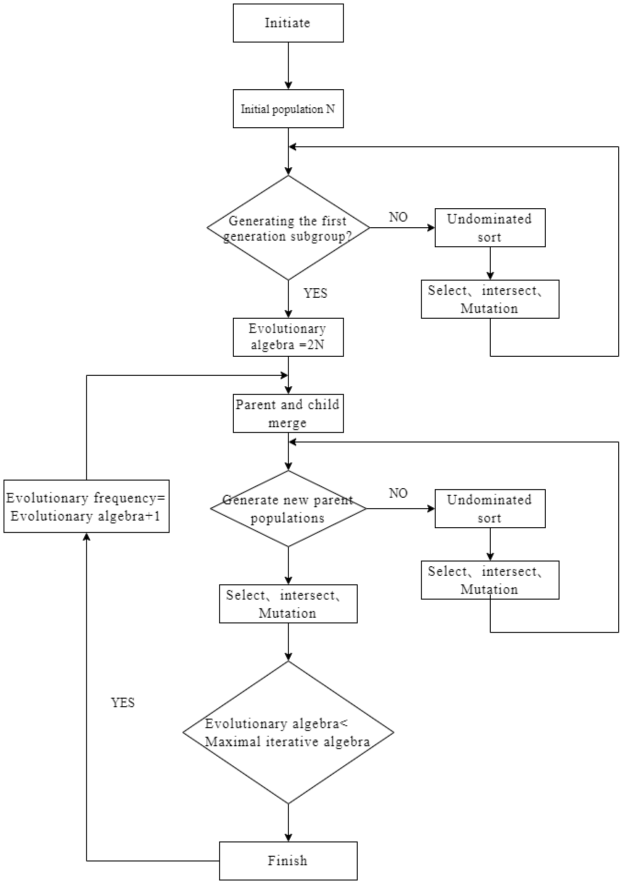

Fig. 1. Flowchart of the NSGA-II

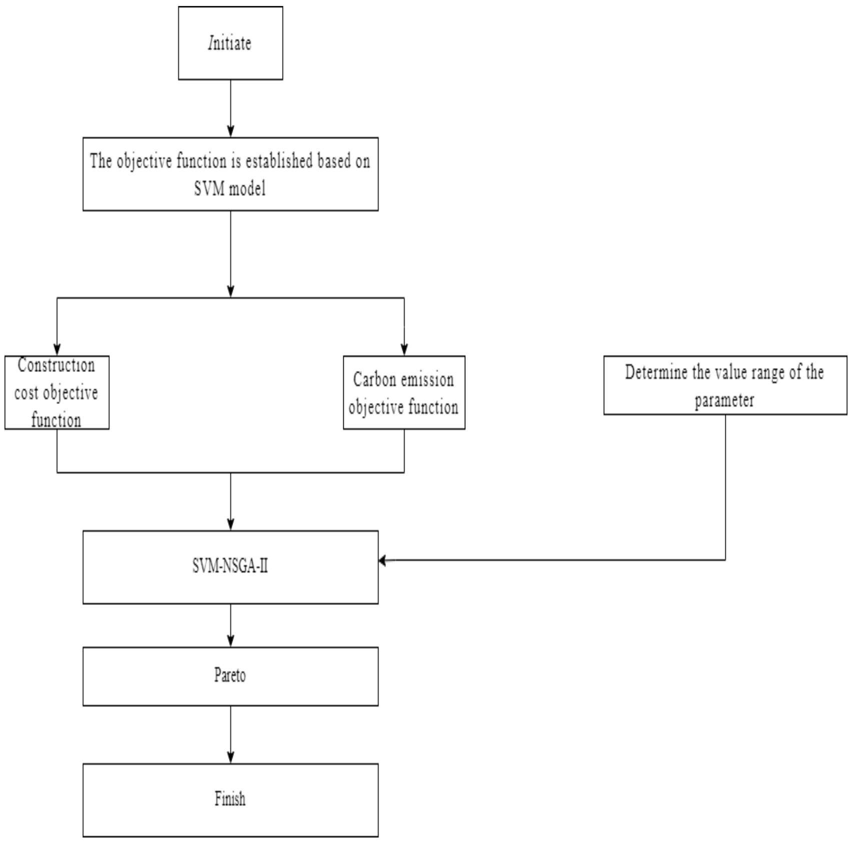

Fig. 2. multi-objective optimization flow algorithm chart based on SVM-NSGA-II

2.2 Objective Optimization Based on SVM-NSGA-II

After determining the fitness of the objective function and constraints based on the Support Vector Machine (SVM) model[7], the objective function is then optimized, as shown in Figure 2. Once the optimal solution is obtained, further analysis is conducted.

2.3 Optimization Metrics and Value Ranges

In this study, six optimization metrics were selected, focusing on aspects like building envelope, wall-to-window ratio, external shading, and building orientation. These were finalized based on national standards such as the "Green Building Evaluation Standard" (GB/T 50378-2019) and the "Thermal Design Code for Civil Buildings" (GB 50176-2016), or through reference to relevant literature when parameters were not explicitly defined in the standards. Table 1 lists the selected optimization metrics and their respective value ranges.

Table 1. Optimization index and value norm.

ID	Design variable	Value range	Unit
1	Wall-window ratio	0.16-0.7	%
2	Heat transfer coefficient of exterior window glass	1-3.5	K (W/m^2 k)
3	Thickness of external wall insulation layer	30-80	mm
4	Thickness of roof insulation layer	20-70	mm
5	Outer shade length	0.2; 0.4; 0.6; 0.8; 1.0	m
6	Building orientation	0~-90	◦

2.4 Construction of the Objective Function

Based on the SVM model, the objective function can be derived as follows:

$$\min f_1 = (SVM_{\text{building cost}}(x_1, x_2, x_3, x_4, x_5, x_6)) \tag{1}$$

$$\min f_2 = (SVM_{\text{CO}_2}(x_1, x_2, x_3, x_4, x_5, x_6)) \tag{2}$$

Where:
x1 represents the wall-to-window ratio.
x2 represents the thermal transmittance of external window glass.
x3 represents the thickness of the external wall insulation.
x4 represents the thickness of the roof insulation.
x5 represents the length of external shading.
x6 represents the building orientation.

These value ranges are used as constraints for multi-objective optimization, and they are set as follows:

$$s.t.\begin{cases} 0.16 \le x_1 \le 0.7 \\ 1 \le x_2 \le 3.5 \\ 30 \le x_3 \le 80 \\ 20 \le x_4 \le 70 \\ 0.2 \le x_5 \le 1 \\ 0 \le x_6 \le \text{-}90 \end{cases} \tag{3}$$

3 Case Study

3.1 Project Overview

This paper presents a case study of a one-star green residential building located in a specific area in Beijing. The building was constructed in accordance with the latest Chinese standards and regulations, and it complies with Beijing's "Green Building Evaluation Standard" DB11/T825-2015, with the goal of achieving a one-star green building rating. The building consists of six stories, with a floor height of 2.8 meters.

3.2 Prediction of Green Residential Building Costs and Carbon Emissions Based on SVM

Based on the SVM model, predictions were made for the costs and carbon emissions of the green residential building for both the training and testing datasets. Evaluation results were obtained using assessment metrics such as Mean Squared Error (MSE) and R-squared (R^2), as shown in Figures 3 and 4.

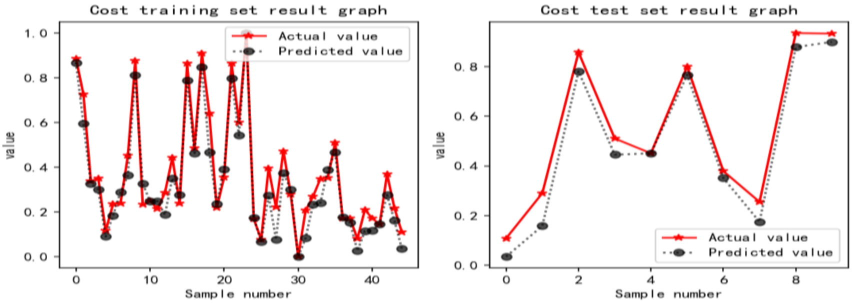

Fig. 3. Construction cost forecast results

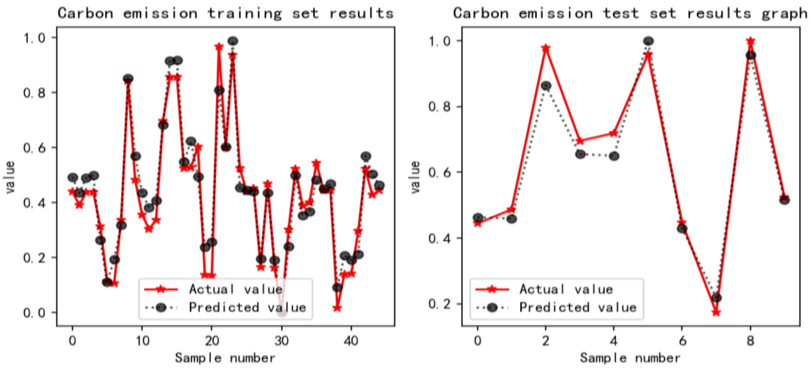

Fig. 4. Prediction results of building carbon emission

Table 2. MSE and R2 values of carbon emissions.

	MSE	R^2
Training dataset for Costs	0.0038855703067448657	0.9272706178300055
Testing dataset for Costs	0.0045605217	0.945797340991647
Training dataset for CO_2	0.0038855703067448657	0.9272706178300055
Testing dataset for CO_2	0.002670522426616946	0.9610297779339214

As shown in Figures 3 and 4, the predicted values for costs and carbon emissions are generally consistent with the actual values, indicating a good overall alignment. Predicting the training dataset effectively reflects the variations in building costs and carbon emissions, with a good fit between actual and predicted values. The results from the testing dataset, as shown in Figures 3 and 4, exhibit a similar trend between actual and predicted values.

From Table 2, it can be observed that the Mean Squared Error (MSE) for the training dataset is close to zero for both costs and carbon emissions, with values of 0.005035428 and 0.0038855703067448657, respectively. The R-squared (R^2) values for the training dataset are both close to 1, with values of 0.9223256464 and 0.9272706178300055, indicating a good predictive performance.For the testing dataset, the MSE for costs and carbon emissions are relatively small with values of 0.0045605217 and 0.002670522426616946, respectively. The R^2 values are close to 1 for both, with values of 0.945797341 and 0.9610297779339214, suggesting that the model's predictions for green residential building costs have a relatively small error, indicating a good overall performance.

3.3 Optimization of Green Residential Building Costs and Carbon Emissions Based on SVM-NSGA-II

Using the objective function and constraints, an optimization study was conducted on the costs and carbon emissions of the green residential building with the NSGA-II algorithm. The optimization program ran particle searches approximately 1000 times before stabilizing. After running the NSGA-II algorithm several times, the Pareto optimal solution set was obtained, as shown in Figures 5. Considering practical considerations, the red point in the figure (12329413.4368, 3462447.2693) is the closest to the ideal point, indicating that the design corresponding to this point is the optimal design solution.

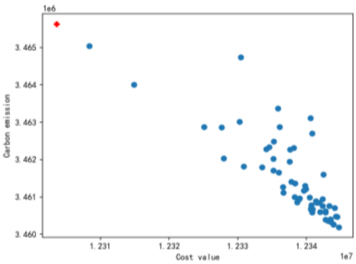

Fig. 5. Two-dimensional diagram of Pareto optimal solution

Table 3 provides a comparison between the original design and the optimized design, along with the target values. Compared to the original building design, the optimized design achieved a cost reduction of 25.25% and a carbon emissions reduction of 4.24%, demonstrating the effectiveness of the optimization efforts.

Table 3. Comparison table between original scheme and optimized scheme.

	original scheme	prioritization scheme
Wall-window ratio (%)	30%	70%
Heat transfer coefficient of exterior window glass(K(W/m^2 k))	1.9	1.70
Insulation thickness of external wall(mm)	90	50
Insulation thickness of roof(mm)	80	80
Outer shade length(m)	0	0.9
Building orientation(。)	0	17
Cost	16,511,158.75	12,341,696.81
Carbon emission	3,617,346.90	3,463,700.42

4 Conclusion and Analysis

(1) This paper conducted a case study based on the dual-objective optimization model and algorithm for the whole life cycle costs and carbon emissions of green residential buildings. The study focused on a one-star green residential building in Beijing, a cold region in China. Using the optimization model, a comprehensive optimal design solution that balances costs and carbon emissions was obtained.

(2) The case study validates the effectiveness and feasibility of the model and algorithm developed in this study. It provides insights for optimizing costs and carbon emissions in other climate regions and building types. Furthermore, it serves as a reference for cost control and carbon emission reduction in green residential buildings in the Beijing area.

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