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Multi-Objective Optimization Technology for Building Energy-Saving Renovation Strategy based on Genetic Algorithm

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ABSTRACT

Abstract Building energy-saving design is significant for the industry to achieve carbon reduction and sustainable development. Firstly, a multi-objective model for energy consumption, cost, and carbon emissions is established based on the three-dimensional perspectives of society, nature, and economy. Then, a polynomial operator is used to improve the non dominated sorting genetic algorithm to calculate the optimal solution set. The low computational efficiency caused by direct coupling of algorithms in traditional optimization processes is expected to be addressed. Based on the results, the algorithm proposed in this study showed significant improvement in the reverse distance and convergence metrics for both the Square1 and Iris datasets, with an improvement of over 70% compared to the support vector machine-genetic algorithm and multi-objective clustering algorithm. The values obtained were closer to 0. The solution solved by this algorithm had lower building costs, energy consumption, and carbon emissions, with values of 345,200 yuan, 2,374 KWh/year, and 26 tons, respectively. This validates the effectiveness of the multi-objective model and solving algorithm in obtaining the optimal energy-saving design scheme for buildings. The results provide a reference for low-carbon optimization.

1. Introduction

With the economic transformation and urbanization development, people's demands for living environment are constantly increasing. The current proportion of residential energy consumption will reach 30% -40%. As an emerging energy building, green buildings not only rely on the building itself, but also on the user's behavioral awareness and lifestyle habits. Reducing building energy consumption and improving economic efficiency will comply with China's development strategy. Improving the living environment also needs to meet the urgent needs of the people for a better life [1-2]. In the new era, multi-objective optimization (MOO) research on building energy efficiency inevitably attracts widespread attention. Traditional research on building energy consumption optimization mainly focuses on certain specific research areas. The optimal research results are selected through a series of simulations, experiments, and evaluations, providing improvement

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strategies and suggestions. With the improvement of the life quality, the requirements for buildings are becoming more diverse. Energy efficient buildings with single or dual objectives are difficult to meet the various requirements of residents for building economy, comfort, and energy efficiency [3-4]. To achieve optimal control of residential energy conservation with multiple indicators, firstly, a mathematical model with multiple optimal indicators is established. The multi index comprehensive evaluation method for building energy-saving design is a technically complex and large-scale system engineering, involving the intersection and penetration of multiple fields. How to establish a multi index optimal control mode is a key link in building energy efficiency optimization [5]. The optimization of building energy design is very challenging because it is a multi-disciplinary problem involving multiple fields such as architecture, engineering, mathematics, and economics. Multiple opposing objective functions need to be solved. Particle swarm optimization and artificial bee colony algorithm are helpful for solving, but their computational complexity is relatively high. To optimize the coupling calculation of the social, natural, and economic levels included, while considering the competitive characteristics of various building performance indicators, the Non-Dominant Sorting Genetic Algorithm-II (NSGA-II) has become a hot algorithm for comprehensive optimization of building performance due to the ease of use and variability. In view of this, the NSGA-II is applied as the solving algorithm. A building energy-saving renovation model is designed with cost, energy consumption, and carbon emissions as multiple objectives.

The paper presents an innovative building energy-saving optimization model that encompasses not only buildings but also engineering, mathematics, design, and other related fields. To address the complexity and specificity of the model, the NSGA-II algorithm is utilized for solving it. The study's primary contribution is the design and implementation of a model for optimizing building energy savings. This model effectively reduces construction losses and costs while improving construction efficiency. This paper has four parts. The first part is a literature review on building energy conservation. The second part is the construction of building energy-saving models and solving algorithms. The third part is the result analysis of the MOO model for building energy conservation. The fourth part is a conclusion.

2. Related Work

In the research direction related to building energy conservation, scholars such as Langevin *et al.,* [6] considered that building operational efficiency and flexibility could provide value for the power system. The impact of optimal available building efficiency and flexibility measures on the technological potential of annual electricity has been estimated. When discussing the energy-saving renovation of buildings, the scholar has only considered the parts related to the power system. Berawi *et al.,* [7] proposed an intelligent integrated workspace design framework. The building programming system using Internet of Things (IoT) technology was integrated into the value engineering process to evaluate the design solutions for future intelligent office buildings. The results showed that this method could achieve high efficiency and comfort in buildings. The author only considered the energy-saving design and renovation of the office area, which is not universal. More building types needed to be analyzed. Loengbudnark *et al.*, [8] investigated the relationship between residents' perception control and building automation. On-site experiments conducted in the same building demonstrated the potential impact of residential controllability on energy conservation. The author analyzed the feasibility of energy-saving renovations for the building but did not provide a clear solution. Copiello [9] aimed to study the thematic intersection between discount rates and building energy efficiency. The conclusion showed that the positions of private stakeholders involved in the decision-making process were related to the energy-saving measures adopted in buildings. The author analyzed only the importance of the discount rate and building energy efficiency in architectural design, without addressing how to balance the two. Zhong *et al.,* [10] used spatial regression models to test the correlation between building environment and building energy consumption. The positive and differential impact of building environment on building energy consumption was analyzed and compared. The conclusion showed that the building environment should be incorporated into urban planning to reduce building energy consumption. The scholar analyzed only the impact of the building environment on building energy consumption and did not propose ways to transform the environment to reduce energy consumption levels.

For the MOO of buildings, Yu *et al.,* [11] minimized the energy costs of heating, ventilation, and air conditioning systems in multi area commercial buildings while considering random area occupancy, thermal comfort, and indoor air quality comfort. A multi agent deep reinforcement learning-based HVAC control algorithm with attention mechanism was proposed to solve Markov game. It could run without establishing a thermodynamic model. The real trajectories demonstrated the effectiveness, robustness, and scalability. The author analyzed the thermal comfort level of the building but did not consider its carbon emissions or the potential for energy-saving transformations. Satrio *et al.,* [12] aimed to study the optimization of heating, ventilation, and air conditioning system operation and other building parameters, minimizing annual energy consumption and maximizing thermal comfort. The study used artificial neural network and multi-objective genetic algorithm (MOGA) to optimize the operation of a dual cooling system in a certain building. Compared to the basic scheme design, the optimization considering two objectives performed the best in thermal comfort and energy consumption. The author's analysis of the building's energy consumption only focused on the cooling system and failed to consider the building's overall situation. Vukadinović *et al.,* [13] discussed the optimization of independent passive building structures and building parameters. Non-explicit sorting genetic algorithm obtained optimization results. The results showed that the window to wall ratio was the most influential factor on energy performance in passive solar design. In their analysis of optimizing the structural parameters of independent buildings, the author solely focused on the impact of window walls on energy-saving renovations, neglecting the influence of other structures such as eaves. Zhai *et al.,* [14] proposed a MOO method combining non dominated crowding sorting with genetic algorithm for window design optimization. This method considered many parameters and optimized several objectives to evaluate their overall performance. The results showed that this method could obtain the best window design solution to minimize building energy consumption. The author focused on optimizing the window design when improving the building structure, but did not analyze the overall structure of the building. This approach may not be universally applicable. Zhao and Du [15] aimed to optimize the important role of windows and shading systems in building energy efficiency. A simple, practical, and efficient MOO method was proposed, which used the NSGA-II and combined with Design Builder energy simulation software for experiments. The results showed that the Pareto optimal solution could also provide different scheme choices according to the designer's preferences. It had great significance for providing guidance and suggestions for designers in the early design of buildings. The author analyzed the window and shading system of the building structure and optimized their role in the building's energy-saving transformation. However, no corresponding transformation scheme was proposed.

In summary, scholars mainly focus on optimizing heating, ventilation, and air conditioning systems in MOO of buildings. Energy-saving design mainly focuses on the economic aspect, with less emphasis on comprehensive optimization of energy conservation, cost, and energy consumption. In view of this, a multi-dimensional energy-saving design model is constructed based on MOGA.

3. Design of Building Energy-Saving Model and Solution Algorithm based on MOO

The construction industry consumes a lot of energy. In response to this situation, a MOO model for building energy-saving design is proposed from an interdisciplinary perspective to balance building energy consumption, lifecycle cost, and lifecycle carbon emissions. Additionally, the study utilizes NSGA-II as an optimization tool to achieve the seamless integration of optimization goals and energy-saving strategies.

3.1 A Multi-Objective Model for Building Energy Conservation based on Energy Consumption, Cost, and Carbon Emissions

Based on the sustainable development concept of the "value triangle", this paper explores the environment-friendly development of buildings from multiple perspectives including society, nature, and economy. The basic concept is to ensure that the building performs its normal functions while achieving the best comprehensive benefits in terms of social, economic, and environmental aspects through reasonable operation and maintenance technology. Throughout the entire construction process, there will be many different stages and participants. Different expectations are conflicting. Therefore, in the optimal selection, it is necessary to ensure the balance and consistency of multiple objectives. From a social perspective, advocating for every household to cultivate an atmosphere of energy conservation and environmental protection is an important measure to build a resource-saving society. Therefore, energy conservation and emission reduction is considered as optimization goals at the social level. From an individual perspective, reducing construction costs can achieve maximum economic benefits when the quality of the building meets the standards. Therefore, the lowest construction cost is considered an economic goal. From a national perspective, to achieve the grand goal of carbon neutrality in the construction industry as soon as possible, the country has recently launched a series of measures to promote decarbonization in the construction industry. Therefore, reducing carbon dioxide emissions is a natural indicator. The optimal indicators of overall performance are constructed from three aspects: social, economic, and natural, exploring the dynamic equilibrium relationship between various dimensions to achieve optimal overall performance. Figure 1 shows a schematic diagram of energy consumption, cost, and carbon emission.

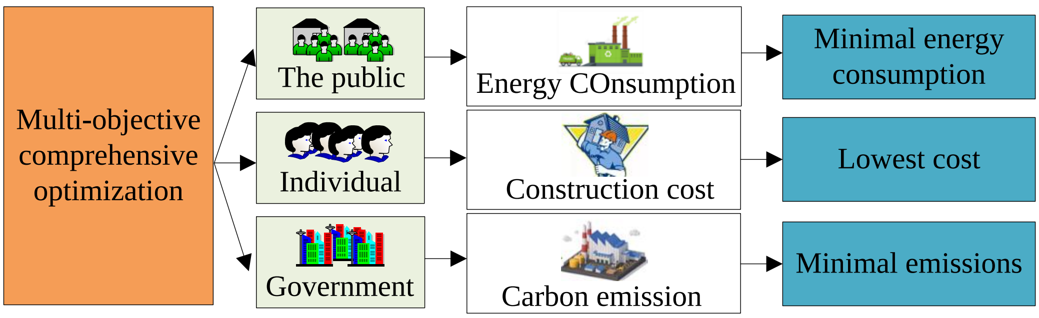


Fig. 1. Energy consumption, cost, and carbon emission targets

The overall value of building energy consumption is the measurement standard, mainly because it not only reflects the equipment energy consumption during the service, but also the operational impact brought by renewable energy generation. The calculation limits include the energy consumption of internal control equipment, the equipment energy consumption that maintains the basic functions of the building, and the renewable energy utilization capacity. The energy consumption of cold and heat sources belongs to indoor control energy consumption. The energy consumption of basic equipment refers to the domestic hot water, lighting, and other household equipment [16]. In buildings, renewable energy compensation generates the same amount of energy as new energy generation. Eq. (1) is the overall value of building energy consumption.

$$E_{total} = E_E - \frac{\sum E_r * f_i}{A} \tag{1}$$

In Eq. (1), E_{total} represents the overall value of the building energy consumption. E_E represents the total energy consumption of buildings without new energy. E_r represents the annual power generation of sustainable energy on buildings. A represents the building area. f_i represents the energy conversion coefficient, as shown in Eq. (2).

$$E_E = \frac{f_i}{A}\left(E_h + E_c + E_l + E_w + E_e\right) \tag{2}$$

In Eq. (2), E_h represents the annual heating energy consumption. E_c stands for annual cooling energy consumption. E_l denotes annual lighting energy consumption. E_w represents the annual hot water energy consumption. E_e represents the annual power consumption of household appliances. The E_h is shown in Eq. (3).

$$E_h = \frac{Q_h}{COP_h * H} \tag{3}$$

In Eq. (3), Q_h represents the annual heating load. COP_h represents the total heating efficiency. H denotes the calorific value of the fuel used for heating. The E_c is shown in Eq. (4).

$$E_c = \frac{Q_c}{COP_c} \tag{4}$$

In Eq. (4), Q_c represents the annual cooling load. $\frac{Q_c}{COP_c}$ represents the comprehensive efficiency of the cooling system. From the perspective of building energy efficiency, life cycle cost is the optimization objective for measuring costs. It includes the total cost of various building components and renewable energy generation systems required during the construction phase, operation phase, demolition and disposal phase, as well as the energy consumption cost during the operation period [17]. The cost of building life cycle is calculated as Eq. (5) (denoted as Cbuild).

$$C_{build} = \frac{IC + OC + RC}{A} \tag{5}$$

In Eq. (5), IC represents the cost during engineering manufacturing and construction. OC represents the cost during the construction and operation period. RC represents the cost of building demolition and disposal stages. Eq. (6) is the cost calculation during the production and construction stages.

$$IC = IC_0 + \sum_{i}^{n} IC_{Mi} \tag{6}$$

In Eq. (6), IC_0 represents the cost of selecting a reference building during the construction phase. IC_{Mi} represents the additional cost of components of Class and building during the construction process. Eq. (7) is used to calculate the operating cost of a building.

$$OC = \sum_{y=1}^{n} a_y \left[E_h W_1 + \left(E_c + E_l + E_w + E_e \right) W_2 - E_r W_3 \right] + \sum_{z=1}^{n} a_z dw_z \tag{7}$$

In Eq. (7), a represents the compensation coefficient that takes into account fluctuations in fuel prices and electricity prices. W denotes the unit price of heating fuel. W_2 denotes the residential electricity price. W_3 represents the selling price of renewable electricity connected to the grid. dw represents the cost required for component replacement. Eq. (8) represents the cost of demolition and disposal stages.

$$RC = \left(RC_D + RC_T + RC_C \right) a_y \tag{8}$$

In Eq. (8), RC_D represents the cost of alternative building solutions. RC_T represents the cost of waste transportation. RC_C represents the disposal cost. Buildings release significant carbon emissions after construction, use, and demolition. Carbon emissions during the life cycle are used as a measure of carbon emissions based on the concept of life cycle. Table 1 shows the carbon emission sources for each stage of the life cycle.

Table 1
Carbon emission sources at various stages of the life cycle

Stage	Carbon source category		
	Artificial	Material	Machinery
Production and Construction	Personnel respiratory carbon emissions	Implied carbon emissions from prefabricated component composition materials	Carbon emissions generated by energy consumption in the production, transportation, and construction of prefabricated components
Working		Implied carbon emissions from materials required for maintenance, refurbishment, and replacement	Carbon emissions generated by energy consumption in renewable energy systems, indoor living equipment, etc
Demolition and disposal		Implied carbon emissions from consumables such as oxygen and acetylene required for dismantling	Carbon emissions generated by energy consumption of excavators, trucks, and other machinery

From Table 1, the carbon dioxide generated during the production and construction process mainly includes personnel respiration, material production, material transportation, and machine consumption. During the operation, it mainly comes from personnel respiration, material production and transportation, machine consumption, and backup energy inside the building. The carbon dioxide generated during the dismantling and reuse process includes personnel respiration, material handling and handling, mechanical consumption, etc. At present, there are two methods for estimating carbon dioxide emissions in China: the quota method and the actual measurement method. Considering that the construction quota is mainly applicable to the construction stage, it is difficult to calculate the operation stage, demolition and disposal stage. Therefore, the actual measurement method is adopted.

3.2 MOO Algorithm based on NSGA-II Competitive Screening

The MOO problem includes multi-dimensional decision variables x and total m objective functions $\left(Obj_1(x),...,Obj_m(x)\right)$. The task of solving MOO problems is to maximize (or minimize) multiple objective functions. A multi-dimensional decision variable is searched within the selectable range of the solution set. The multi-dimensional decision variable is in Pareto optimization when it no longer reinforces all objective functions and does not affect them. Figure 2 shows the Pareto optimal front matrix.

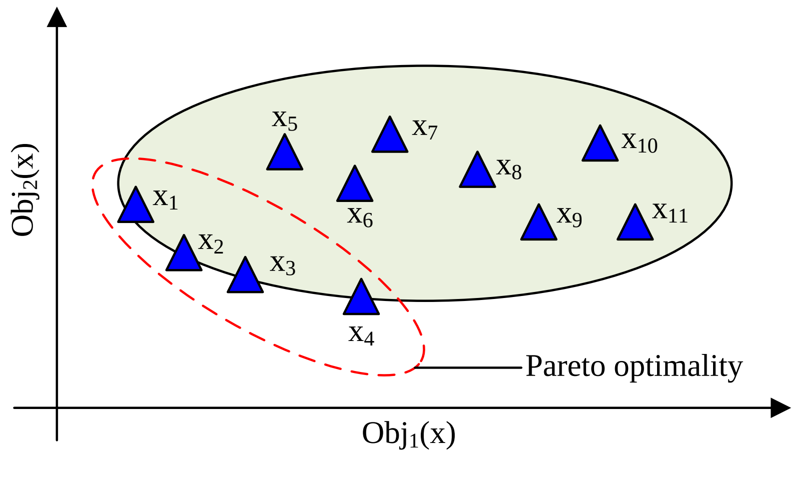


Fig. 2. Pareto optimal front matrix

Assuming two objective functions $Obj_1(x)$ and $Obj_2(x)$ are selected, the two decision variables within the range of values are x_1 and x_2. If $Obj_1(x_1) < Obj_1(x_2)$ and $Obj_2(x_1) < Obj_2(x_2)$, then the decision variable x_1 dominates x_2, and the decision variable x_2 is dominated by x_1. If a variable is not affected by other variables, it is the Pareto optimal solution. In MOO problems, the best Pareto solution is usually a set rather than one. This combination is called a Pareto optimal solution set, also known as a Pareto matrix. Genetic algorithm is an optimization method based on natural selection and the principle of natural inheritance. This method simulates the evolutionary laws of organisms, writing individual genetic information into chromosomes. When the suitability of the species is determined, these genes will be deciphered [18]. In the simulation evolution process, each individual can represent a consensus and obtain the optimal solution by solving the objective function of the problem. Among these methods, NSGA-II is the most efficient and widely used high-dimensional MOGA. Figure 3 shows the NSGA-II competitive screening process.

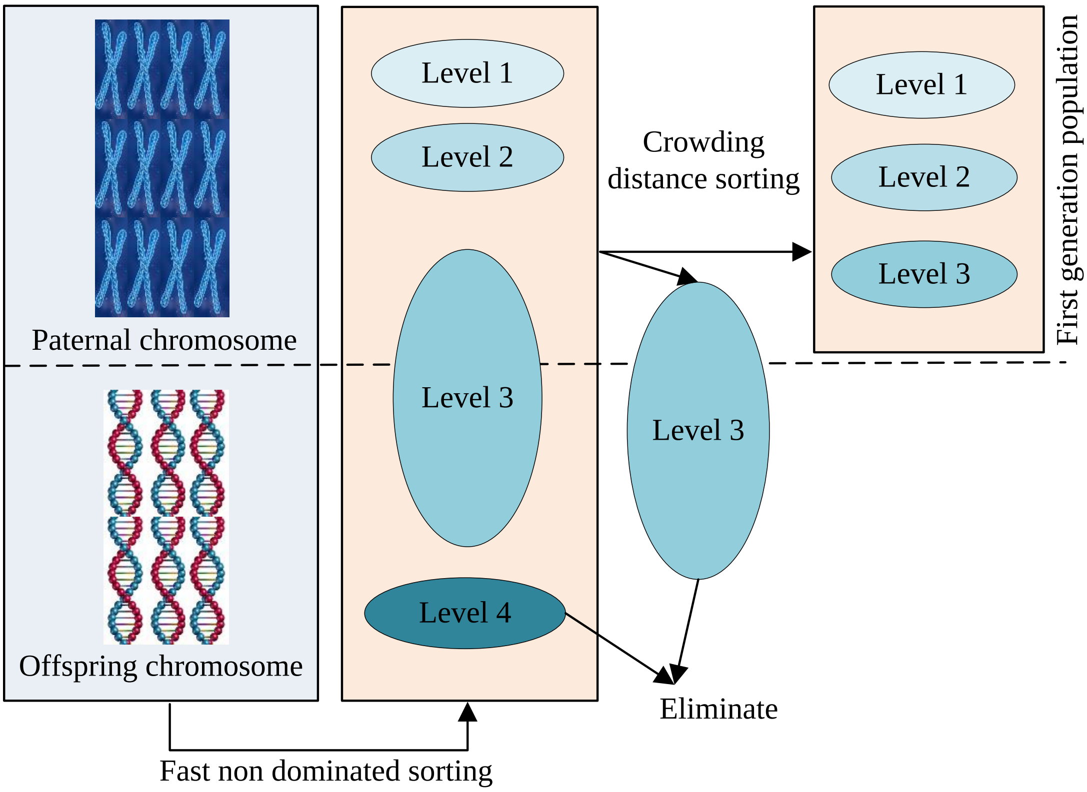


Fig. 3. NSGA-II competitive screening process

The NSGA-II method is aimed at multi-objective programming problems. After determining a population and its offspring, a competitive screening method is used to generate a new generation of population. It utilizes a fast non dominated sorting algorithm to retrieve and control the front matrix. It uses the distance of crowding to classify groups. NSGA-II adopts a selective approach, dividing each population into several levels. The populations with higher status survive, while the populations with lower status are eliminated [19]. However, individuals within the same taxonomic group do not dominate each other. Their order is determined based on their level of crowding. Eq. (9) is the expression for calculating the crowding distance.

$$P[i]_{distance} \leftarrow P[i]_{distance} + \left(P[i+1].m - P[i-1].m\right) / \left(f_m^{\max} - f_m^{\min}\right) \tag{9}$$

In Eq. (9), $P[i+1].m$ represents the m -th objective function value of the $i+1$ -th individual. $P[i-1].m$ represents the *m*-th objective function value of the $i-1$-th individual. $f_m^{\max}$ and $f_m^{\min}$ denote the maximum and minimum values of the *m*-th objective function in the solution set, respectively. Genetic algorithms typically include two types of operators. One is the selection operator and the other is the recombination operator. The former performs directional control on the algorithm. The latter generates new search scopes. Both of these methods can ensure the implicit parallelism of genetic algorithms, thereby finding a near optimal solution within a larger problem range. Chromosome crossover and mutation are two implementation methods of operators. Eq. (10) is the calculation method for the binomial crossover operator.

$$\beta_{qi} = \begin{cases} (2u_i)\dfrac{1}{\eta_c + 1}, u_i \le 0.5 \\ \left(\dfrac{1}{2(1-u_i)}\right)^{\frac{1}{\eta_c+1}}, u_i > 0.5 \end{cases} \tag{10}$$

In Eq. (10), β_{qi} represents the crossover operator. u_i represents a random number with a value between 0 and 1. η_c represents the cross distribution index. Eq. (11) is the calculation method for polynomial variation.

$$\delta_k = \begin{cases} (2r_k)^{\frac{1}{\eta_m+1}} - 1, r_k < 0.5 \\ 1 - \left[2(1-r_k)\right]^{\frac{1}{\eta_m+1}}, r_k \ge 0.5 \end{cases} \tag{11}$$

In Eq. (11), r_k represents a random number that follows uniform sampling, with values ranging from 0 to 1. η_m represents the variation distribution index. From Eqs. (10) and (11), the crossover operator is the exchange of genetic information between two parent individuals through certain methods, forming two new offspring [20]. The polynomial variant achieves genetic diversity of the population by setting mutation rules. Figure 4 shows the flowchart of the NSGA-II.

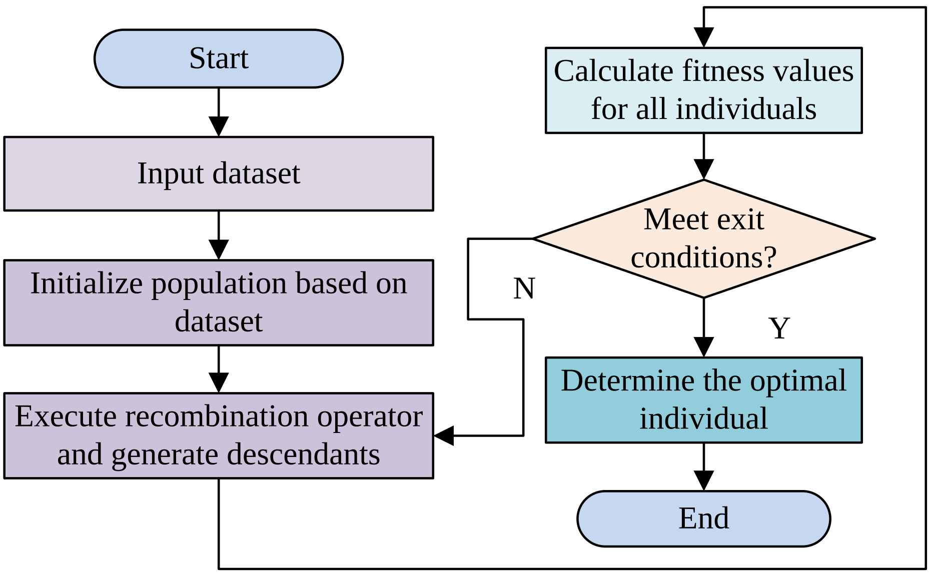


Fig. 4. Algorithm flowchart of NSGA-II algorithm

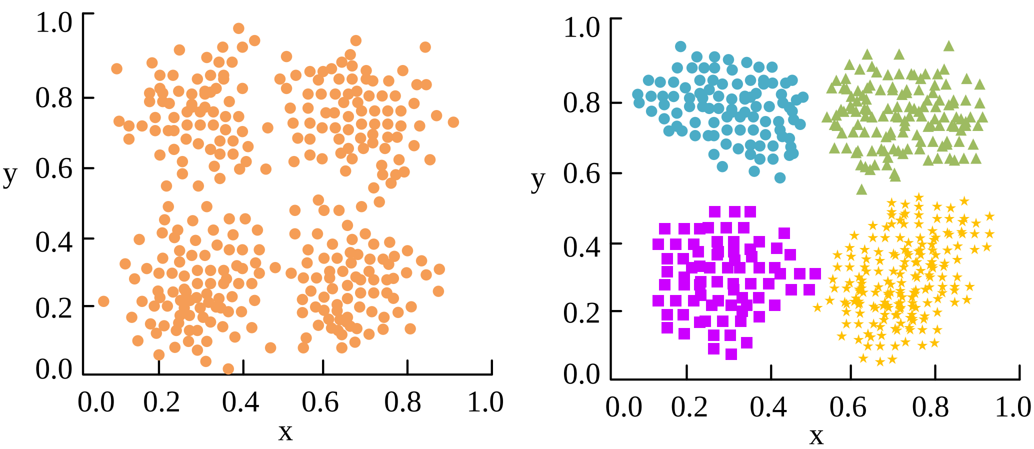
From Figure 4, after establishing a new sample set, each sample is initialized according to the prototype encoding method. On this basis, the refactoring operation is performed and an appropriate fitness function is introduced to continuously evolve and form a new population. This algorithm adopts two methods, cross operation and mutation operation. Finally, the recommended individuals are selected from the population as the output.

4. Result Analysis of MOO Building Energy Efficiency Model based on NSGA-II

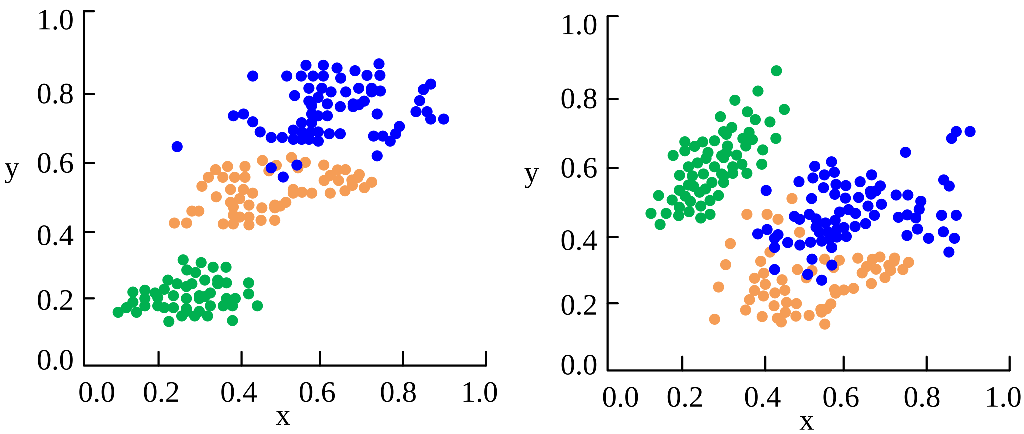
To verify the effectiveness of the MOO model based on cost, energy consumption, and carbon emissions, as well as the MOGA, artificial datasets and machine learning datasets were selected. The performance of different algorithms was compared from multiple indicators. Finally, the solution results of the MOO model were obtained.

4.1 Performance Analysis of MOGA

To present a visual comparison analysis of algorithm performance, the Square1 dataset and Iris dataset were selected for experiments from both manual datasets and machine learning databases. The Square1 dataset contained 4 clusters of the same size, totaling 103 data points. Each cluster appears as a cube, with some overlap between clusters. The Iris dataset included three types, Vericolor, Virginia, and Setosa. The number of samples in three clusters was 50. The data points between the first two clusters overlapped significantly. Genetic algorithm required setting parameter values for four factors, i.e. population size, iterations, chromosome crossover, and mutation probability. The study used the expert experience method, selecting 200, 100, 0.8, and 0.2. The comparison methods were Multi-Objective Clustering with Automatic K-determination (MOCK) and Support Vector Machine Genetic Algorithm (SVM-GA). The evaluation indicators included the clustering effect of the solution set, Inverse Generation Distance (IGD), and Convergence Metric (CM). IGD represented a comprehensive evaluation index for algorithm performance. It was used to evaluate the convergence rate and population difference. A low IGD value indicated that the algorithm had a high convergence rate and good population diversity. CM was used to evaluate the convergence performance of the solution set obtained by the algorithm. This convergence measure referred to the difference between a set of approximated optimal solutions and the true optimal solution set. Therefore, a small indicator indicated that the algorithm had better convergence. Figure 5 shows the partitioning performance of the proposed algorithm on the selected dataset.



(a) Actual data distribution of Square1 (b) Square1 Data Distribution Based on NSGA - II

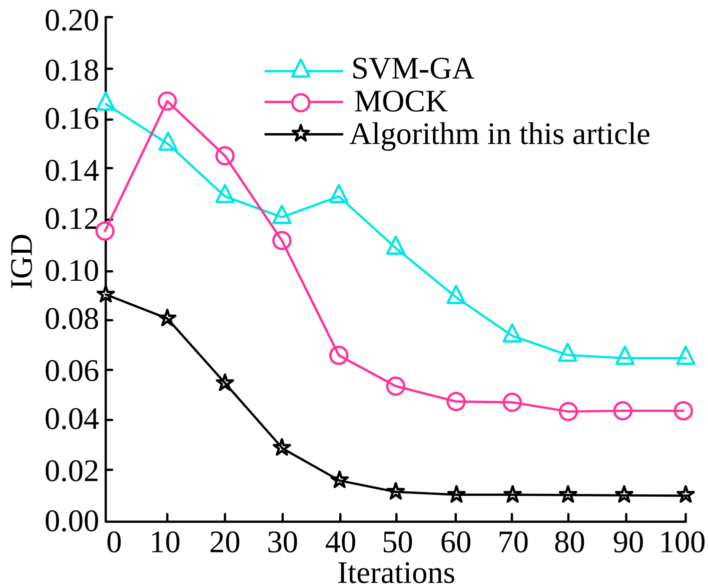


(c) Actual data distribution of Iris

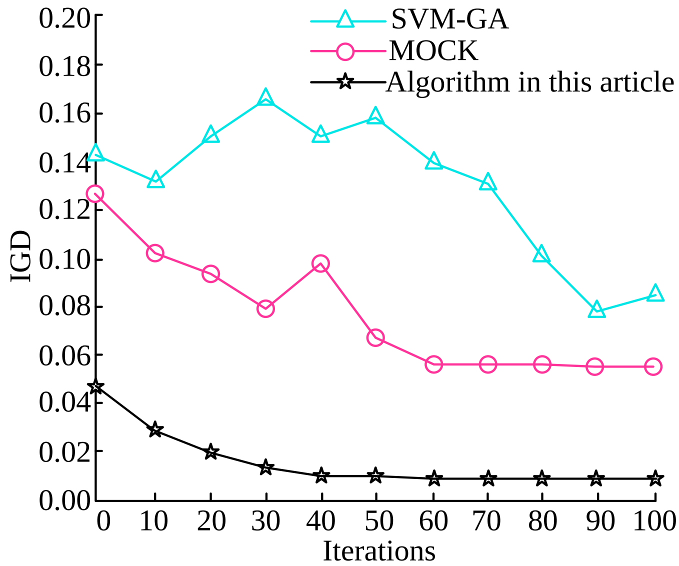
(d) Iris Data Distribution Based on NSGA - II

Fig. 5. The partitioning effect of the dataset

From Figure 5, the actual Square1 dataset presented a four cluster data distribution of two rows and two columns. There was slight overlap between the clusters. The Square1 data based on NSGA-II also presented four distinct approximate clusters. Although the overlap between square clusters was not obvious, there was a trend of convergence. The Iris actual dataset presented a three row distribution of data clusters. There was a significant overlap between the data clusters in the previous two rows. The Iris data cluster based on NSGA-II was also divided into three clusters. The overlapping treatment was more prominent. The above results show that the proposed model has a better performance when distinguishing the data structure, and can realize the complete differentiation of the data. Figure 6 shows the comparison curve of IGD mean.



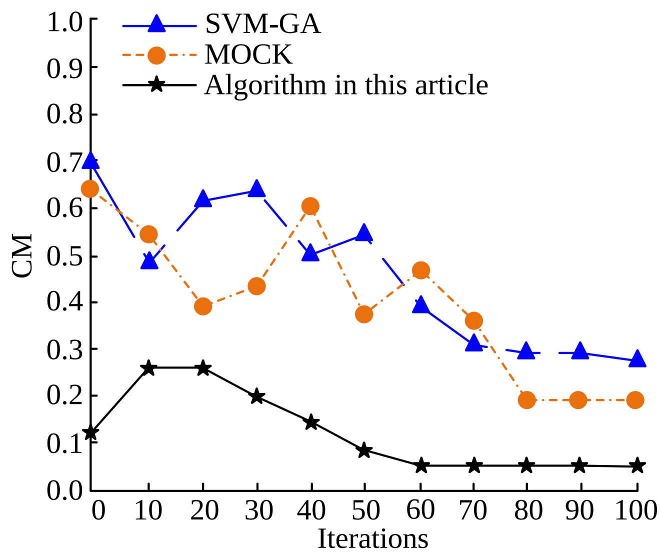
(a) Square1 dataset



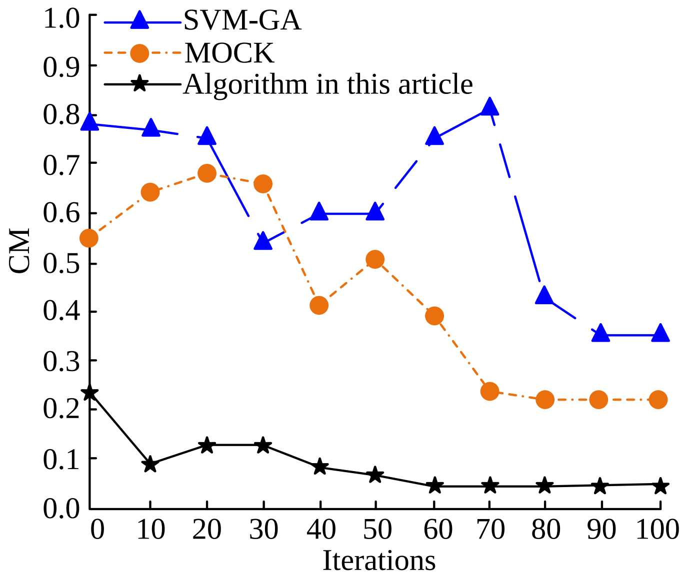
(b) Iris dataset

Fig. 6. IGD mean comparison curve

From Figure 6, on the Square1 dataset, the IGD index value curve obtained by the MOGA converged faster. It had smaller convergence values. The number of iterations to start convergence was 40, and the IGD value to complete convergence was 0.01. The SVM-GA and MOCK algorithms converged in the later stages of iteration. The convergence only started after 70 iterations. The final IGD values obtained were 0.063 and 0.042, respectively, which were 84.1% and 76.2% higher than the proposed algorithm. On the Iris dataset, the proposed method had a lower initial convergence value for the IGD metric value. The convergence process was more stable. The final obtained IGD value was 0.008. The comparison algorithm had a larger fluctuation range. The SVM-GA algorithm ultimately failed to obtain a convergence value. The IGD value of the MOCK algorithm was 0.058. The above results show that the proposed algorithm has obvious advantages in both convergence speed and data miniature. Figure 7 shows the CM mean comparison curve.



(a) Square1 dataset



(b) Iris dataset

Fig. 7. CM mean comparison curve

From Figure 7, the proposed multi-objective algorithm achieved smoother convergence curves and lower CM convergence values on both the Square1 and Iris datasets. The SVM-GA algorithm and MOCK algorithm exhibited significant fluctuations in the early and mid stages. There was also a significant difference in convergence speed and convergence value compared to the proposed algorithm. For example, on the Square1 dataset, the CM convergence values of the three algorithms were 0.05, 0.18, and 0.28, respectively. On the Iris dataset, the CM convergence values of the three algorithms were 0.06, 0.22, and 0.35, respectively. On the CM metric, the proposed algorithm was 70% lower than the comparison algorithm on both datasets. Therefore, it indicates that the algorithm has more advantages in convergence performance. The study further analyzed the results of comparing the proposed model with SVM-GA and MOCK models on different size datasets, as shown in Figure 8.

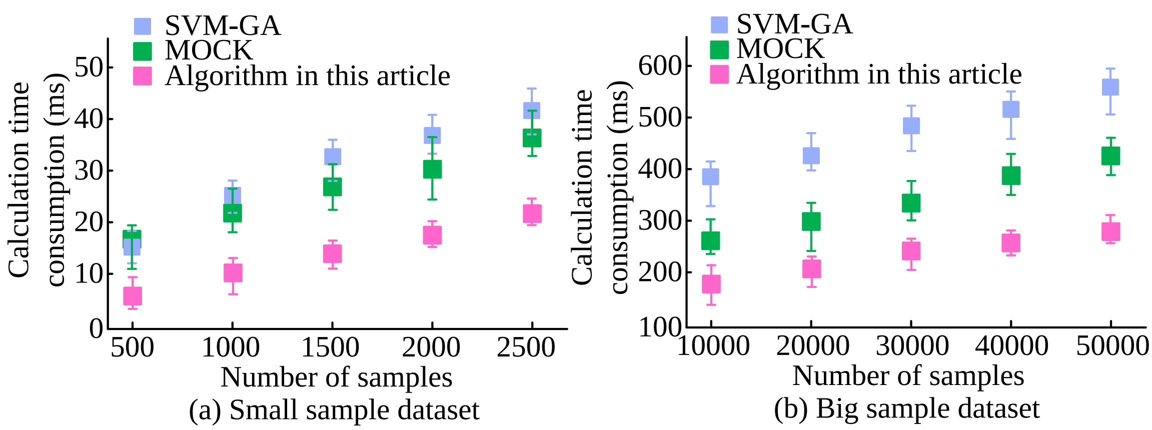


Fig. 8. Comparison of model running time

Figure 8 (a) showed the running time results of the three models on small sample data sets. With the increase of sample data, the running time of the three models was increasing, but the running time of the model used in the study was always lower than that of the other two models. The proposed model had the highest running time of about 20ms, while the remaining two models were higher than 30ms. Figure 8 (b) showed the running time results of the three models on large sample data sets. The running time of the research model was still significantly better than the other two models. The research model could complete the target task more quickly and realize the optimization goal. The study also compared the accuracy of the three models on the size sample data sets, and the results are shown in Figure 9.

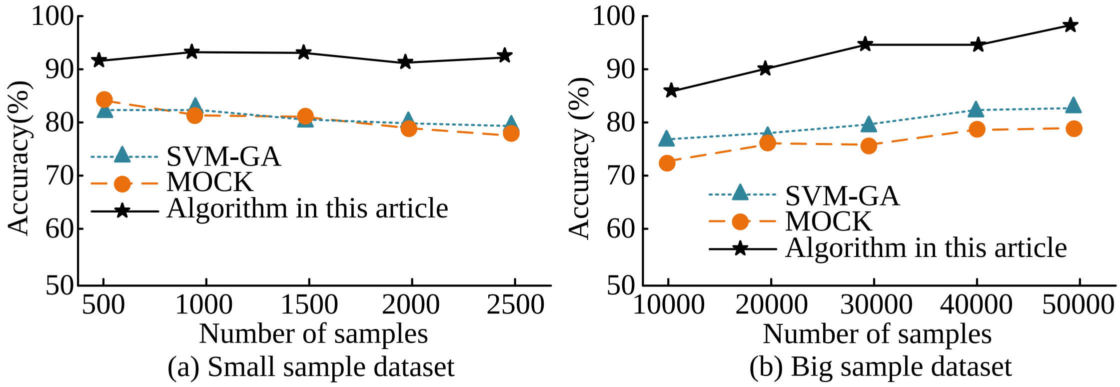


Fig. 9. Comparison of the model accuracy rate

Figure 9 (a) showed the results of the accuracy comparison of the three models in small sample data sets. With the increase of the number of samples, the accuracy of SVM-GA model and MOCK model was constantly decreasing, but the accuracy of the research model basically did not change with the number of samples, and always remained above 90%. Figure 9 (b) showed the change of the accuracy of the three models on large sample data sets. When the data sample was large enough, the accuracy of the model would show an upward trend with the increase of the sample data, and the accuracy of the proposed model could reach 98.6%. The proposed model not only has a lower running time than the other two models but also has a higher accuracy than them.

4.2 The application effect analysis of multi-objective building energy-saving model

To verify the effectiveness of the building energy efficiency optimization objective function established in the research and the MOGA in practical applications, a typical residential building in a certain province was taken as the research object. The building had a height of 2.8 meters and a total of 15 floors. The total construction area was 4850 m2. The range of values for basic building variables was displayed in Table 2.

Table 2
Range of values for building basic variables

Entry name	Variable value	Unit
South window to wall ratio	0.1-0.45	-
North window to wall ratio	0-0.3	-
Building area	90-160	m2
Thermal conductivity of walls	0.1-0.6	W/(m2·k)
Roof thermal conductivity	0.1-0.45	W/(m2·k)
Door thermal conductivity	0.1-1.5	W/(m2·k)
Thermal conductivity of window	0.1-3.0	W/(m2·k)

After on-site research and statistics, the heat transfer coefficient of the door was mainly 1.5W/(m2 k). The ratio of the north and south window walls to the building area was set to 0.25. This study mainly examined the optimization situation without significant changes to the original design. Therefore, the similarity variation diagram of each part of the building was first obtained, as shown in Figure 10.

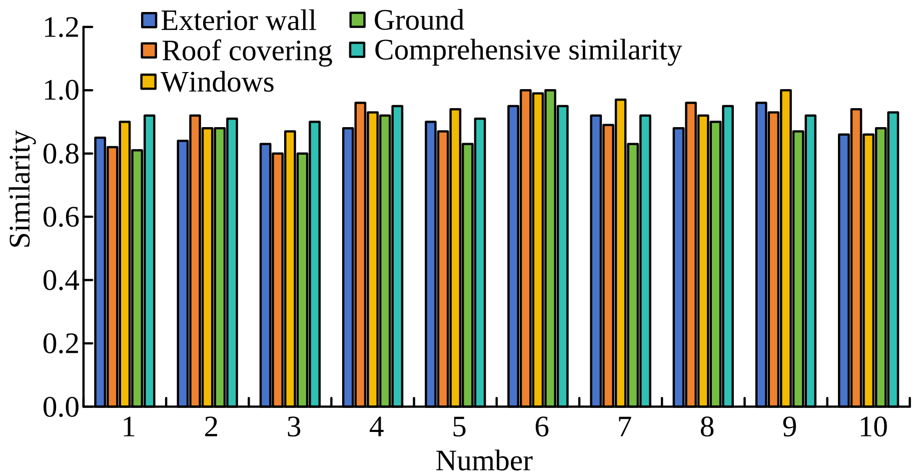


Fig. 10. Similarity curve

From Figure 10, the similarity between the exterior walls, roofs, windows, doors, and floors was maintained between 0.8 and 1. Among them, the ground and roof had larger fluctuations, with fluctuations within 0.2. The overall similarity curve had the smallest fluctuation and the overall value was also above 0.9. This indicates that the proposed optimization techniques can ensure minimal modifications to the original building. It is effective to study the optimized structure of the doors, which can obviously reduce the energy consumption of buildings. Table 3 shows the design parameters under different optimal solutions.

Table 3
Design parameters under different optimal solutions

Category	Thermal conductivity of external walls	Roof thermal conductivity	Thermal conductivity of window	Door thermal conductivity
Energy saving optimization	0.3	0.15	1.5	1.5
Economically optimal	0.7	0.3	2.5	1.5
Comfort optimal	0.2	0.08	0.8	1.5
Optimal carbon emissions	0.4	0.3	1.5	1.5
Comprehensive optimal	0.2	0.1	1.5	1.5

Category	Construction cost (10000 yuan)	Total energy consumption (KWh/year)	Carbon emissions (tons)	Comfort
Energy saving optimization	36.85	2155	32	0.39
Economically optimal	33.48	2274	35	0.10
Comfort optimal	37.13	2716	30	1.05
Optimal carbon emissions	34.65	2553	18	-0.54
Comprehensive optimal	34.52	2374	26	0.28

From Table 3, there were differences in the design parameters obtained from the energy conservation, economy, and carbon emissions. If energy conservation was considered the best, the construction cost was the highest, with a size of 368,500 yuan. However, its total energy consumption was the lowest, with a size of 2,155 KWh/year. Considering the economic optimum alone, the construction cost was 334,800 yuan, but the comfort level was also reduced to 0.10. Considering the optimal carbon emissions alone, the carbon emissions were significantly reduced, but the comfort level was also reduced to a negative value, with a magnitude of -0.54. Under the comprehensive optimal solution, the comfort value, construction cost, and carbon emissions all achieved lower values of 0.28, 345,200 yuan, and 26 tons, respectively. This indicates that single objective optimization has significant limitations. MOO can obtain global optimization and a more comprehensive design solution. Figure 11 shows the construction cost, carbon emissions, and energy consumption curves of different algorithms for MOO.

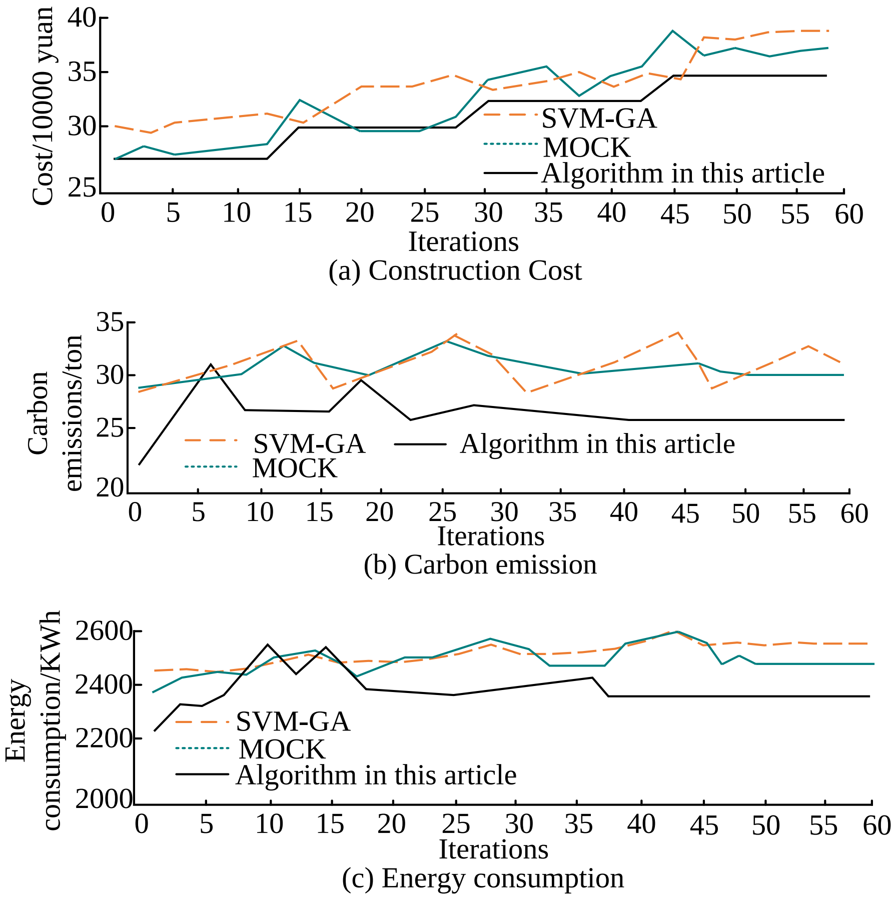


Fig. 11. Construction cost, carbon emissions, and energy consumption curve

From Figure 11, compared with the SVM-GA and MOCK algorithm, the proposed method had the lowest building cost, carbon dioxide emissions, and energy consumption. Although there were some fluctuations in the early and middle stages of convergence, the curve tended to stabilize in the later stage. The convergence performance was good. The SVM-GA algorithm did not obtain convergence values in the carbon emissions. Compared to the proposed algorithm, the construction cost and energy consumption had increased by 11.5% and 7.8%, respectively. The MOCK algorithm had increased construction costs and energy consumption by 7.2% and 5.1% compared to the proposed algorithm. This indicates that the multi-objective model established in the study has good optimization effects.

5. Conclusion

The current energy-saving design in the construction industry is difficult to balance multiple performance goals, such as energy consumption, cost, and carbon emissions. The MOO model is established to adjust design parameters for this problem. The multi-objective solution algorithm based on NSGA-II was designed to achieve comprehensive optimization of buildings. According to the results, for the Square1 dataset, the algorithm proposed in the study had a value of 0.01 for the IGD metric. The SVM-GA and MOCK algorithms were 0.063 and 0.042, respectively. The proposed algorithm had improved by 84.1% and 76.2%. For the CM indicator, the proposed algorithm had a value of 0.008 on the Iris dataset, while the comparative algorithm MOCK was 0.058. The proposed algorithm had improved by more than 70%. In addition, the MOO model designed in the study achieved higher comprehensive benefits than the single objective model. It could achieve a balance of multi-objective values. Under the comprehensive optimal solution, the comfort value, construction cost, and carbon emissions all achieved lower values of 0.28, 345,200 yuan, and 26 tons, respectively. The numerical values were better than single objective optimization algorithms. In terms of building energy consumption, the model proposed in the research had reduced by 7.8% and 5.1% compared to the comparison algorithm. Therefore, this indicates that the multi-objective design method has more advantages in energy conservation, emission reduction, and cost reduction, which is feasible. At the same time, the multi-objective solving algorithm based on NSGA-II achieves the global search ability and local development ability of the balanced algorithm, making the multi-index performance better. The study's model consistently demonstrates strong performance during the training process and achieves excellent results across various datasets, successfully meeting the goal of energy-efficient building transformation. In practical applications, the model also exhibits exceptional performance, enhancing comfort levels while reducing construction costs and carbon emissions.

While a MOO model for building energy-saving transformation has been constructed and solved, the development of IoT technology means that building construction projects must now consider both design and time construction. This can make it difficult for some architectural designs to be realized in actual construction. In the future, the building information model technology should be combined with building energy-saving transformation design to analyze the feasibility of building energy-saving transformation in detail. This will optimize the design and improve the effectiveness of the research and constructed model on building energy-saving transformation.

Author Contributions

Conceptualization, S.D. and L.L.; methodology, S.D.; software, S.D. and L.L.; validation, S.D. and L.L.; formal analysis, L.L.; investigation, S.D.; resources, S.D. and L.L.; data curation, L.L.; writing—original draft preparation, S.D. and L.L.; writing—review and editing, S.D. and L.L..; visualization, S.D. and L.L..; supervision, S.D. and L.L. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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References

[1] Kumar, A., Pant, S., Ram, M., & Negi, G. (2022). Multi-Objective Optimization of Complex Bridge Network by MOPSO-CD. In 2022 International Conference on Advances in Computing, Communication and Materials (ICACCM) (pp. 1-6). IEEE. https://doi.org/10.1109/ICACCM56405.2022.10009336

[2] Xue, Q., Wang, Z., & Chen, Q. (2022). Multi-objective optimization of building design for life cycle cost and CO2 emissions: A case study of a low-energy residential building in a severe cold climate. Building simulation. Beijing: Tsinghua University Press, 15(1), 83-98. https://doi.org/10.1007/s12273-021-0796-5

[3] Kumar, A., Pant, S., Ram, M., & Yadav, O. (2022). Meta-heuristic Optimization Techniques: Applications in Engineering. Berlin, Boston: De Gruyter. https://doi.org/10.1515/9783110716214

[4] SS, V. C., & HS, A. (2022). Nature inspired meta heuristic algorithms for optimization problems. Computing, 104(2), 251-269. https://doi.org/10.1007/s00607-021-00955-5

[5] Shen, T., Teng, L., Hu, Y., & Shen, W. (2022). Systematic screening procedure and innovative energy-saving design for ionic liquid-based extractive distillation process. Frontiers of Chemical Science and Engineering, 17(1), 34-45. https://doi.org/10.1007/s11705-022-2234-3

[6] Langevin, J., Harris, C. B., Satre-Meloy, A., Chandra-Putra, H., Speake, A., Present, E., Adhikari, R., Wilson, E. J. H., & Satchwell, A. J. (2021). US building energy efficiency and flexibility as an electric grid resource. Joule, 5(8), 2102-2128. https://doi.org/10.1016/j.joule.2021.06.002

[7] Berawi, M. A., Kim, A. A., Naomi, F., Basten, V., Miraj, P., Medal, L. A., & Sari, M. (2023). Designing a smart integrated workspace to improve building energy efficiency: an Indonesian case study. International Journal of Construction Management, 23(3), 410-422. https://doi.org/10.1080/15623599.2021.1882747

[8] Loengbudnark, W., Khalilpour, K., Bharathy, G., Voinov, A., & Thomas, L. (2023). Impact of occupant autonomy on satisfaction and building energy efficiency. Energy and Built Environment, 4(4), 377-385. https://doi.org/10.1016/j.enbenv.2022.02.007

[9] Copiello, S. (2021). Economic viability of building energy efficiency measures: A review on the discount rate. AIMS Energy, 9(2), 257-285. https://doi.org/10.3934/energy.2021014

[10] Zhong, H., Wang, J., Jia, H., & Huang, L. (2019). Vector field-based support vector regression for building energy consumption prediction. Applied Energy, 242, 403-414. https://doi.org/10.1016/j.apenergy.2019.03.078

[11] Yu, L., Sun, Y., Xu, Z., Shen, C., Yue, D., Jiang, T., & Guan, X. (2020). Multi-agent deep reinforcement learning for HVAC control in commercial buildings. IEEE Transactions on Smart Grid, 12(1), 407-419. https://doi.org/10.1109/TSG.2020.3011739

[12] Satrio, P., Mahlia, T. M. I., Giannetti, N., & Saito, K. (2019). Optimization of HVAC system energy consumption in a building using artificial neural network and multi-objective genetic algorithm. Sustainable Energy Technologies and Assessments, 35, 48-57. https://doi.org/10.1016/j.seta.2019.06.002

[13] Vukadinović, A., Radosavljević, J., Đorđević, A., Protić, M., & Petrović, N. (2021). Multi-objective optimization of energy performance for a detached residential building with a sunspace using the NSGA-II genetic algorithm. Solar Energy, 224, 1426-1444. https://doi.org/10.1016/j.solener.2021.06.082

[14] Zhai, Y., Wang, Y., Huang, Y., & Meng, X. (2019). A multi-objective optimization methodology for window design considering energy consumption, thermal environment and visual performance. Renewable energy, 134, 1190-1199. https://doi.org/10.1016/j.renene.2018.09.024

[15] Zhao, J., & Du, Y. (2020). Multi-objective optimization design for windows and shading configuration considering energy consumption and thermal comfort: A case study for office building in different climatic regions of China. Solar Energy, 206, 997-1017. https://doi.org/10.1016/j.solener.2020.05.090

[16] Kumar, A., Vohra, M., Pant, S., & Singh, S. K. (2021). Optimization techniques for petroleum engineering: A brief review. International Journal of Modelling and Simulation, 41(5), 326-334. https://doi.org/10.1080/02286203.2021.1983074

[17] Chaube, S., Singh, S. B., Pant, S., & Kumar, A. (2018). Time-dependent conflicting bifuzzy set and its applications in reliability evaluation. Advanced mathematical techniques in engineering sciences, 4, 111-128. https://doi.org/10.1201/b22440-6

[18] Kumar, A., Pant, S., Singh, M. K., Chaube, S., Ram, M., & Kumar, A. (2023). Modified wild horse optimizer for constrained system reliability optimization. Axioms, 12(7), 693. https://doi.org/10.3390/axioms12070693

[19] Veasna, K., Feng, Z., Zhang, Q., & Knezevic, M. (2023). Machine learning-based multi-objective optimization for efficient identification of crystal plasticity model parameters. Computer Methods in Applied Mechanics and Engineering, 403, 115740. https://doi.org/10.1016/j.cma.2022.115740

[20] Ji, Y., Yang, Z., Ran, J., & Li, H. (2021). Multi-objective parameter optimization of turbine impeller based on RBF neural network and NSGA-II genetic algorithm. Energy Reports, 7, 584-593. https://doi.org/10.1016/j.egyr.2021.10.003