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Research Article

Decomposition based multi-objective evolutionary algorithm for energy-saving design of homestay buildings

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Abstract. To improve the prediction accuracy of energy-saving design for homestay buildings, a multi-objective optimization model is studied. A model of multi-objective optimization algorithm for energy efficiency design of home stay buildings based on decomposition multi-objective evolutionary algorithm is proposed. Decomposition based multi-objective evolutionary algorithm is selected. To select the preliminary algorithm for achieving energy-saving design of homestay buildings, it divides the objectives into algorithm determination and model construction and uses multi-objective optimization algorithms to solve the proposed optimization model. The validation results show that the minimum discomfort time calculated using the non-dominated sorting genetic algorithm is 555.30 and the energy consumption is 7.68, while the minimum discomfort time calculated using the non-dominated sorting genetic algorithm method is 896 and the energy consumption is 8.92. With alternative model, the speed of multi-objective Evolutionary algorithm is the fastest, reaching 6105.44 seconds, which is 68.80% lower than the proposed method. With the help of substitutes, the computational speed of the multi-objective particle swarm optimization algorithm has been greatly improved. Its computational speed has reached 1217.231 seconds, while the fastest multi-objective particle swarm optimization algorithm among the four comparison methods is only 3868.591 seconds. Although the individual improvement is not significant, the overall optimization is still considerable and has strategic foresight in the decision-making plan of decision-makers.

Keywords: MOEAD; Homestay buildings; Energy-saving design; Sa-MOOSO; Multi-objective optimization

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1. Introduction

With the increasingly severe global shortage of energy resources and environmental pollution, promoting energy-efficient design in buildings has become one of the important ways to achieve sustainable development. According to the "China Building Energy Consumption Research Report (2022)", in 2020, the total energy consumption of buildings and construction accounted for 45.5% of the total national energy consumption, and carbon emissions accounted for 50.9% of the national total. Among them, the energy consumption and carbon emissions during the operation phase of buildings both exceeded 20% (Yugank *et al.* 2022). At present, the proportion of building energy consumption is increasing significantly, and strengthening effective management of building energy consumption has become one of the important contents to improve energy utilization and guide building energy conservation (Du *et al.* 2022). The physical structure and parameter performance of buildings are largely related to their energy performance and residential suitability, especially in small and medium-sized buildings such as homestays. Energy saving design can not only reduce operating costs, but also help improve user comfort and environmental friendliness, thus having significant social and economic benefits (Ebrahimi *et al.* 2021). The issue of building energy efficiency includes various performance indicators such as building shape coefficient, heat transfer coefficient, exterior wall area, and so on. In traditional building energy-saving design problems, most scholars have also attempted to apply optimization methods such as genetic algorithm, particle swarm optimization, simulated annealing, etc. Although these methods have improved the efficiency and effectiveness of building energy-saving design to a certain extent, they still face problems such as slow convergence speed, insufficient diversity of solutions, and severe constraints in dealing with multi-objective optimization problems. They face difficulties in sample selection and complex model construction (Liang *et al.* 2022). Therefore, the study introduces the Decomposition based Multi Objective Evolutionary Algorithm (MOEA/D) algorithm for building energy efficiency analysis. MOEAD can decompose multi-objective problems into multiple single objective subproblems for parallel solving, and its diversity strategy based on decomposition and constraints on the problem can effectively improve operational efficiency, making it suitable for diverse and complex building energy-saving design problems. The issue of building energy-saving design itself contains many contradictory performance indicators, such as building energy consumption and environmental thermal comfort, lighting effect and lighting energy consumption, ventilation demand and heat loss, etc. (Serat *et al.* 2023); Janus *et al.* 2021). However, currently, the vast majority of multi-objective optimization

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models generally suffer from problems such as long iteration times and high operating costs, which seriously affect the cost control of construction teams. Therefore, innovative research proposes the idea of combining surrogate models with evolutionary algorithms to achieve energy-saving design in buildings. The structure of homestay buildings includes single house structures and multi house structures, with complex data types. The study uses multi-objective design methods to analyze real homestay buildings, and establishes relevant mathematical algorithms and optimization conditions using multi-objective optimization models, ultimately achieving the goal of reducing construction period and cost.

2. Literature review

Mazlomi *et al.* (2022) optimized the QoS indicators of wireless sensor networks based on this, thereby improving the performance and reducing energy consumption. It studied the mathematical models and optimization problems of various indicators in the network. Simulation experiments have shown that the proposed model can effectively optimize the parameters and indices of the network. The Samarasinghalage *et al.* (2022) research team involved many parameters in the design of solar cell and building integrated enclosure structures, and there were contradictions with photovoltaic related performance indicators. A new integrated photovoltaic (BIPV) design method was proposed based on MOO, which comprehensively optimized its lifetime energy consumption and cost. Research has shown that simulation findings have certain guiding significance for the mid-term design of products, but cannot serve as a decision-making basis for product design. The subjectivity, taste, preferences, and other factors of users had a significant impact on the energy-saving effect of the system. Scholars such as Ebrahimi A found that in the future of sustainable development, the development of renewable energy became inevitable. This energy competed with conventional energy sources that could fully utilize wind and solar energy. The hybrid renewable energy power generation system could not only improve the economic efficiency of renewable energy generation, but also improved its environmental performance. To address this issue, this project planed to establish a distributed renewable energy system scale optimization model based on MOO. The whole system included wind turbines, photovoltaic panels, batteries, Diesel generator, etc. This project planed to use the Non domain Sorted Genetic Algorithm (NSGA) to solve the MOO problem, while ensuring the energy utilization rate of the system and minimizing the energy consumption and carbon emissions of the system. And it was compared with other multi-objective optimal algorithms. Through comparison, this plan was feasible. The calculation results denoted that under the selected climate and building environmental conditions, the renewable energy utilization rate of the residential building could reach about 78%, meeting the requirements (Ebrahimi *et al.* 2021). Wang *et al.* (2021)found that early design decisions were crucial in building energy efficiency. However, due to its poor applicability in real environments, its practicality has been questioned. The calculation outcomes indicated that after using MOOSAS, the energy efficiency of the system was significantly improved, and the average energy density decreased by 8%. In addition, researchers have found that during the research, they could obtain more energy-saving new design solutions and make better choices between the "best" and "near best" options. 8% of participants believed that Moosa was effective, while 58% of participants indicated that they were willing to use MOOSAS in the future. This also meant that being responsible for and utilizing auxiliary tools during the pre-set process was beneficial for design practice. Du *et al.* (2022) established a dynamic temperature adjustment mode for each partition based on different levels of user needs. The research findings expressed that by dynamically adjusting the set temperature every day, the load demand could be reduced by 6.17% without affecting user comfort. At the application and control levels, a comprehensive approach of operational optimization and model predictive control was adopted to achieve an overall energy-saving index of 12.75% for the air conditioning system .

Scholars such as Pu have established a MOO based speed curve model for urban rail transit and provided a 3D Pareto boundary model suitable for urban rail transit. The research results confirmed the correctness of the method proposed in this article, and also suggested that when using comfort, one could not use only one method (Pu *et al.* 2022). Zhang *et al.* (2020) designed an objective function energy-saving mode for energy consumption, lighting, and ventilation in buildings, and used genetic algorithms to optimize building parameters. The results showed that this method can effectively reduce building energy consumption, increase the lighting coefficient by more than 10%, and effectively achieve building energy-saving effects. Elsheikh *et al.* (2023) used a multi-objective genetic algorithm model to analyze the energy efficiency of residential buildings under different climates, and considered various design variables related to energy efficiency, such as exterior wall type, window to wall ratio, building direction, and so on. The results indicate that the research design method can achieve a good balance of energy consumption and ensure good thermal comfort conditions in semi-arid climates. Pioppi *et al.* (2020) believed that the energy efficiency of buildings is related to factors such as personnel energy behavior and environmental perception. They modeled and analyzed an office building and found that eliminating energy waste behavior can effectively reduce energy demand, and improving indoor environmental conditions can enhance energy efficiency. Egwim *et al.* (2024) introduced a hybrid stacked ensemble method to evaluate building energy efficiency, and found that using ensemble machine learning can effectively analyze and predict building energy efficiency data. Considering the complexity of building energy, Yu *et al.* (2021) conducted a literature review and analysis of the application ideas of deep reinforcement learning, and concluded that this technology has significant control optimization performance. Buturache *et al.* (2022) utilized the Six Sigma stage approach for building energy consumption prediction analysis and designed data processing and hyperparameter selection. The results indicate that the model has good application scalability and significant advantages in digital analysis of energy consumption data. Bagholinizad *et al.* (2022) conducted multi-objective optimization on photovoltaic sunshades, including the selection of position and geometry, and completed function design using Morris sensitivity analysis and artificial neural networks. The results indicate that shading the southern direction of the building and adjusting the tilt angle appropriately according to the seasonal cycle can effectively reduce power consumption. The optimal photovoltaic shading tilt angle is 19.6 °. In summary, scholars and scientists have made contributions in neural networks and feature sequence extraction. Many improved algorithms were designed to meet more efficient dataset processing and optimization algorithms. At the same time, considering the good data processing performance of the sequence feature model and the shortcomings of current advertising recommendation algorithms, using this method to optimize the efficiency of advertising recommendation should have significant application value in the operational decision-making of large internet companies and advertising companies.

3. Optimization of multi-objective algorithm for ESD of homestay buildings based on MOEAD

This study adopts multi-objective algorithms to optimize the ESD of homestay buildings, and determines the recommended model and construction algorithm based on actual situations and ESD cases. Through the analysis of MOEAD algorithm, multi-agent assisted MOEAD and scientific control, the model differentiation comparison is realized by compiling software. Ultimately, an ESD model is obtained for that is suitable for real situations can provide valuable reference for the design of homestay buildings and provide forward-looking strategic value for the development of the industry.

3.1 Design of multi-objective evolutionary optimization algorithm for ESD of homestay buildings based on MOEAD

Compared with single objective optimization problems, MOO problems require simultaneous optimization of multiple indicators, and there are contradictions between multiple indicators (Do *and* Ohsaki 2021; Pu *et al.* 2022). There is no single way to solve such problems once and for all, and only a compromise approach can be adopted. It takes the minimized MOO as an example, as shown in equation (1).

$$\begin{cases} \min F(X)=\left(f_1(X), f_2(X), \mathrm{K}, f_M(X)\right) \\ h_j(X)=(\leq)0, j=1,2,\mathrm{K}, J \\ X=\left(x_1, x_2 \mathrm{L}, x_D\right)\in\Omega \end{cases} \tag{1}$$

In equation (1), Ω means the decision space; $X=(x_1, x_2 \cdots, x_D)$ denotes the D dimensional solution; F(X) indicates the performance indicator; $h_j(X)$ refers to the equality or inequality constraint; M means the number of objectives. It researches a method based on decomposing MOO that can obtain the optimal solution of Pareto's law for each suboptimal problem. One of the solving methods is shown in equation (2).

$$mig^{ws}\left(X\,|\,\lambda\right)=\sum_{i=1}^{M}\lambda_i f_i(X) \tag{2}$$

In equation (2), λ refers to the reference weight vector, which is the weighted sum approach (WS), while the other method is the Tchebycheff method. The aggregation form of this method is expressed in equation (3)(Pereira *et al.* 2020; Polo-Mendoza *et al.* 2023).

$$\min g^{tche}\left(X\,|\,\lambda, Z^*\right)=\max_{1\leq i\leq M}\left\{\lambda_i\left|f_i(X)-Z_i^*\right\}\right. \tag{3}$$

In equation (3), Z^* denotes $min\{f_i(X)|X\in\Omega\}, i\in\{1,2,\dots,M\}$, which belongs to the position of the reference point. Based on the penalty boundary crossing method, the objective function aggregation form of this method is denoted in equation (4).

$$\begin{cases} \min g^{pbi}\left(X\,|\,\lambda, Z^*\right)=d_1+\theta d_2 \\ d_1=\dfrac{\left\|\left(Z^*-F(X)\right)^T\lambda\right\|}{\|\lambda\|} \\ d_2=\left\|F(X)-\left(Z^*-d_1\lambda\right)\right\| \end{cases} \tag{4}$$

In equation (4), θ expresses the penalty factor, and $d_1\theta$ and d_2 control the distribution and convergence of the population. Usually, the optimal solution set obtained by the boundary crossing method is more uniform (Sohani *et al.* 2022; Ma *et al.* 2023). A multi-objective energy-saving model for homestay buildings is established based on indicators such as annual energy consumption and user discomfort hours, as shown in equation (5).

$$\begin{cases} min\,F=\left(BEC(X), UDE(X)\right) \\ s.t.X=\begin{pmatrix} x_{or}, x_{tolw}, x_{srar}, x_{ghtc}, x_{shgc}, \cdots \\ x_{lwl}, x_{lww}, x_{bww}, x_{kwl}, x_{kww}, \dots \\ x_{wwl}, x_{www}, x_{lepd}, x_{bepd}, \dots \\ x_{kepd}, x_{wepd}, x_{hst}, x_{cst} \end{pmatrix} \end{cases} \tag{5}$$

In Formula (5), BEC and UDE express the annual energy consumption and the annual user uncomfortable hours, respectively. x in $s.t.X$ is the room orientation, the thickness of external insulation layer of the wall, the solar absorption rate of the external wall, the Heat transfer coefficient of the window, the solar heat gain coefficient of the window, the length of the living room window, the width of the bedroom window, the length of the kitchen window, the length of the bathroom window, the lighting density of the living room, the lighting density of the bedroom, the lighting density of the bathroom, the heating setting temperature of the air conditioning system and the cooling setting temperature of the air conditioning system (Liu et al. 2021; Liu et al. 2020). It utilizes fuzzy decision-making technology to provide decision-makers with a new choice scheme for the compromise solution of the target value, and the satisfaction level is shown in equation (6).

$$\mu^k=\begin{cases} 1 \\ \dfrac{f_i^{\max}-f_i\left(X_k\right)}{f_i^{\max}-f_i^{\min}} \\ 0 \end{cases} \tag{6}$$

In equation (6), f_i^{max} and f_i^{min} are the max and mini values of the i objective function, respectively, and the normalized membership function corresponding to X_k is indicated in equation (7).

$$\mu^k=\frac{\sum_{i=1}^{M}\mu_i^k}{\sum_{k=1}^{|SET|}\sum_{i=1}^{M}\mu_i^k} \tag{7}$$

In equation (7), M expresses the amount of objective functions; $|SET|$ means the amount of elements in the set SET, and the compromise solution is the solution with the highest μ^k value in SET. The specific implementation of this algorithm is expressed in Fig. 1.

In Fig. 1, the specific implementation of the proposed algorithm is shown. Firstly, it uses Sketchup software to draw a 3D model of the building to be optimized, and uses it as one IDF files for storage; Secondly, using the MOEA/D method in MATLAB software, a new single point positioning problem is generated, which is a new solution. Then, it utilizes the Visual C++interface program to decode the new solution and generate EnergyPlus; It runs EnergyPlus and outputs two performance indicators: energy consumption of buildings and minimum discomfort time; Then, MATLAB is applied to calculate the performance parameters of the new solution and modify the results of the new solution to achieve the desired results. Finally, the Pareto optimal solution retained in the external population is utilized as the final result of the algorithm (Pavankumar *et al.* 2021). The algorithm performance is evaluated using the hypervolume measure. The increase of hypervolume means that the distribution or convergence of the results become better, as shown in equation (8).

$$HV=\delta\left(\mathrm{U}_{i=1}^{|S|}v_i\right) \tag{8}$$

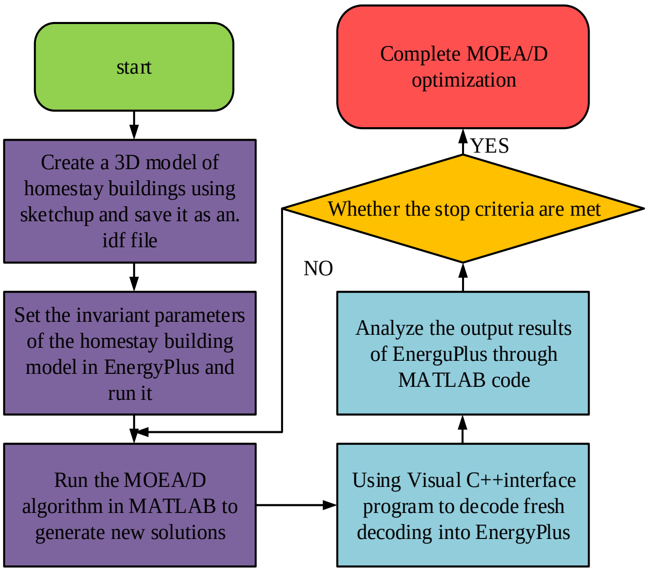


Fig. 1 MOEAD algorithm implementation

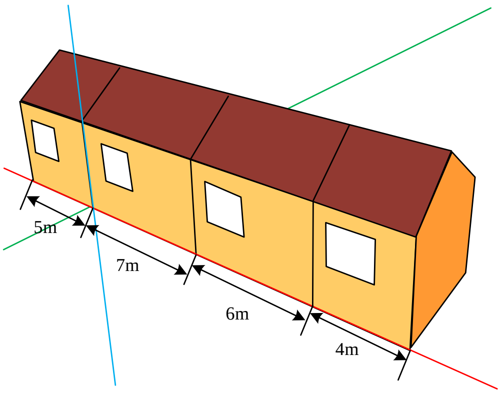


Fig. 2 The SketchUp simulation results of the exterior of a residential building

In equation (8), δ means the Lebesgue measure; $|S|$ denotes the amount of non dominated solution sets; v_i expresses the hyper volume formed by the i −th structure of the reference point and solution set. It uses the SC measure for MOO of convergence, as shown in equation (9).

$$S_C(A,B) = \frac{|\{b \in B : \exists a \in A, a \prec b\}|}{|B|} \tag{9}$$

In equation (9), $|g|$ means the amount of elements in the set; $S_C(A,B) = 1$ denotes that all solutions of the set B are dominated by the solutions of the set A. When $S_C(A,B) = 0$ is used, it indicates that no solution of set B is dominated by any solution of set A.According to different functions, residential buildings are divided into four hot zones, namely living room, bedroom, kitchen, and bathroom. The initial length and width of the window are 1.8m and 1.2m, respectively. According to the recommendations in the EnergyPlus software manual, set their return air coefficient to 0, radiation coefficient to 0.37, visible light coefficient to 0.18, and coefficient of heat transfer from light to the surrounding air to 0.40. The Fig. 2 shows the SketchUp simulation results of the exterior of a residential building.

Consider building orientation, window length and width in each hot zone, heat transfer coefficient and solar heat gain coefficient of windows, thickness of wall insulation layer, external wall solar absorption rate, lighting power density and other parameters as decision variables for this model. Based on the reference to the "Building Energy Efficiency Design Standards", the variable range of the building has been preliminarily determined, as shown in Table 1 (Najafi *et al.* 2023).

Among them, the length and width of the windows are determined by the size of the rooms in the building model, and the range of values for the remaining variables is determined by the specific design of building energy efficiency. When conducting building energy consumption simulation, EnergyPlus first needs to preserve the 3D geometric model in.

Table 1
Range of Building Decision Variables

Decision variables	Range	Reference value
Building orientation/°	[0,360]	0
Insulation layer thickness/m	(0.0001,0.1)	0.0523
Window heat transfer coefficient/w/(m^2 · k)	(2,6)	4.5
Lighting density/w/m^2	[4.5,6]	5.0
Air conditioning system heating/cooling set temperature	[18,24]/[24,28]	8/20
Personnel density/w/m^2	(0.1,1.0)	0.2
Equipment energy consumption density/w/m^2	[10,18]	15

idf file format, and then set parameter information based on design requirements and actual situations, including maintenance structure information, operating time, lighting equipment, air conditioning system, etc. It can also download required weather files for operation, and output building energy consumption, project load, and other content (Egwim *et al.* 2024). Subsequently, the Matrix Laboratory (MATLAB) can be connected to the EnergyPlus engine to optimize building energy-saving design. MATLAB can use the performance indicators of the scheme as objective function values for constraint execution analysis, generate new positions until the constraint conditions are met, and finally obtain the Pareto optimal solution in the external population.

3.2 Design of MOO algorithm for ESD of homestay buildings based on multi-agent assisted MOEAD

In response to the drawback of high computational complexity in existing evolutionary optimization methods, this project plans to study multi-agent MOEAD based on multi-agent models, which is referred to as the MS-MOEAD algorithm. On this basis, an individual evaluation method based on neighboring agent aggregation is proposed, and a reference point update method that integrates prediction results is proposed for the problem of single search without valuable targets (Liu *et al.* 2022; Najafi *et al.* 2023). The basic framework of the proposed MS-MOEAD algorithm is expressed in Fig. 3.

Fig. 3 shows the basic framework of the proposed MS-MOEAD algorithm. On this basis, four modules are proposed: multi-agent modeling and management based on agents, group update based on MOEAD, individual evaluation based on neighboring agents, and reference point update. The function of the "Multi-agent Model Establishment and Management" module is to synchronously establish representative multiple Agent models and continuously update them based on newly added samples, to ensure their accuracy as much as possible. On this basis, a group update algorithm based on MOEA/D algorithm is proposed. The "Personal Evaluation Based on Adjacent Subject Aggregation" module aims to independently integrate multiple basic subject models using the adjacent subject aggregation mechanism for the evaluated object, and then comprehensively evaluate a single subject, thereby achieving accurate prediction of a single subject (Altekin *et al.* 2022; Egwim *et al.* 2024; Sharma and Kumar 2022;). The function of the 'Management of Filling Samples' module is to select high-quality new individuals from the population, conduct real evaluations of them, and update the sample training set used for the alternative model based on this (Mazloomi et al. 2022; Zvyagina and Zvyagin 2022). The uncertainty of individual X is shown in equation (10).

$$u(X)=\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{\tau+1}\sqrt{\frac{\left(\hat{f}_i^{j}(X)-\bar{f}_i(X)\right)^2}{\tau+1}} \tag{10}$$

In Formula (10), M denotes the number of targets; $\bar{f}_i(X)$ means the surrogate model evaluation value of the individual X; τ indicates the neighborhood size of the individual; $\bar{f}_i(X)$ expresses the average approximate value of X on the ith target. Only when the optimization results of a certain weighted vector have not changed within several generations, the basic vector model corresponding to this weighted vector is updated. Evaluation indicators are utilized to obtain the final target value, as shown in equation (11).

$$\hat{f}_m(X_i)=\sum\nolimits_{j=0}^{\tau}\varpi_j\times\hat{f}_m\left(X_i\left|SM\_\lambda_i^j\right.\right), m=1,2,K,M \tag{11}$$

In equation (11), ϖ_j indicates the weight of $SM_{\lambda_i^j}$; λ_i^j denotes the reference weight vector. The weight value is determined by the distance between the weight vector and the reference weight vector, as shown in equation (12).

$$\varpi_j=0.5\frac{\left|\lambda_i^0-\lambda_i^j\right|^{-1}}{\sum_{q=1}^{\tau}\left|\lambda_i^0-\lambda_i^q\right|^{-1}} \tag{12}$$

In equation (12), $\left|\lambda_i^0-\lambda_i^j\right|^{-1}$ expresses the reciprocal of the distance between λ_i^0 and λ_i^j. The closer the distance between λ_i^j and λ_i^0, the closer the sub optimization problems represented by $SM_{\lambda_i^j}$ and $SM_{\lambda_i^0}$ are, and the greater the weight of the objective function predicted by $SM_{\lambda_i^j}$. In MOEAD, the properties of the reference point Z 'are related to the distribution and convergence of the Pareto front-end obtained. Unlike general numerical optimization problems, the objective function of this algorithm has two types: one is practical, and the other is predictive. In view of this, the new reference point is determined by referring to two objective functions, as shown in equation (13).

$$\text{¢}_m^{*}=\begin{cases} f_m^{\min} \\ \frac{t}{T_{\max}}\times f_m^{\min}+\left(1-\frac{t}{T_{\max}}\right)\times\hat{f}_m^{\min}\end{cases} \tag{13}$$

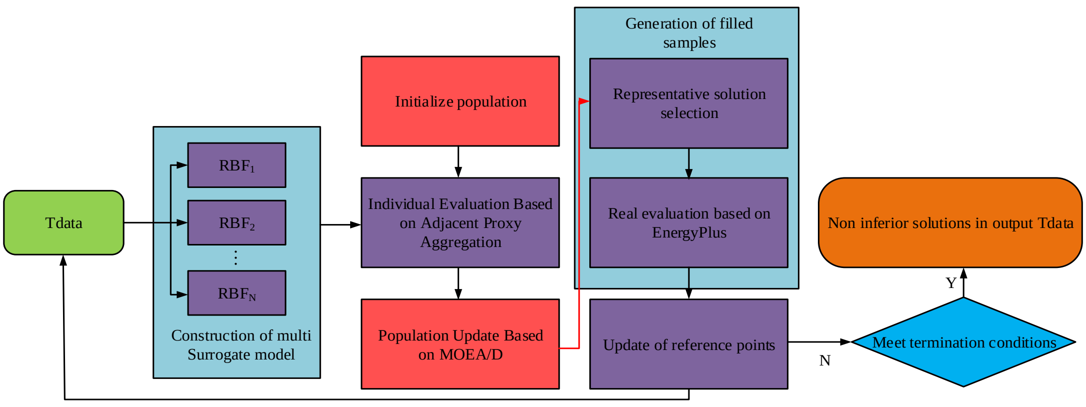


Fig. 3 Basic framework of MS-MOEAD

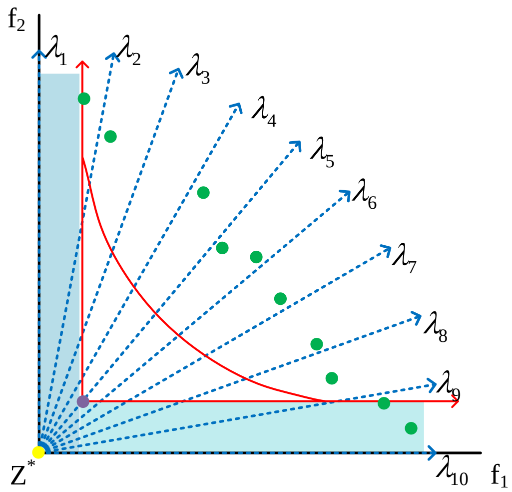


Fig. 4 Schematic diagram of the effectiveness of reference point selection

In equation (13), f_m^{min} indicates the true minimum value and $\hat{f}_m^{min}$ refers to the predicted minimum value. This example will obtain a more ductile real Pareto front-end, as shown in Fig. 4.

In Fig. 4, the red curve means the real Pareto front, the purple and yellow dots mean the reference points determined by f_m^{min} and the surrogate model, and the green dots refer to10 individuals in the population. When selecting the yellow point defined by the alternative model as the reference point, the two edge individuals always search for the best solution in the blue shadow area. But this shadow is useless, which leads to a decrease in the search efficiency of the population (Atanassov 2022). Write the MS-MOEAD algorithm in the MATLAB environment, and the running framework of the algorithm is shown in Fig. 5.

In Fig. 5, first, Sketchup software is utilized to draw a 3D model of the building that needs to be optimized, and stored as an idf file; Secondly, MATLAB is applied to perform initial value operations on the algorithm to obtain the initial population and initial sample set, and then this initial value is used to establish N basic substitution models. Then, the MS-MOEAD algorithm is utilized to generate new single cells and predict their objective function. Secondly, whether necessary updates have been made to the alternative model. If necessary, it uses the Visual C++interface program to pass the solutions to these problems to Energy Plus, and then outputs two objective functions during the operation of Energy Plus, namely the energy consumption of the building and the minimum discomfort time; After obtaining the new function, it needs to updates the sample set Tdata using MATLAB and reconstruct the required basic alternative model; If not necessary, it proceeds to the next step (Belgacemet *al.* 2024; Nguyen *et al.* 2022). On this basis, the MS-MOEAD method is used to continuously generate new individuals. Repeating this process until the algorithm reaches the end condition. Finally, the Pareto optimal solution in the T data is used as the final result of the algorithm. The complexity calculation of the reference algorithm is denoted in equation (14).

$$C = RFEs \cdot C_F + C_S + C_g + C_{other} \cdot t_{\max} \quad (14)$$

Among them, C_F expresses the calculation cost of the real evaluation target individual; $RFEs$ indicates the amount of times the real evaluation individual is evaluated; t_{max} refers to the total amount of iterations of the algorithm; C_S represents the generated fill sample; C_{other} stands for other operators required for updating the population.

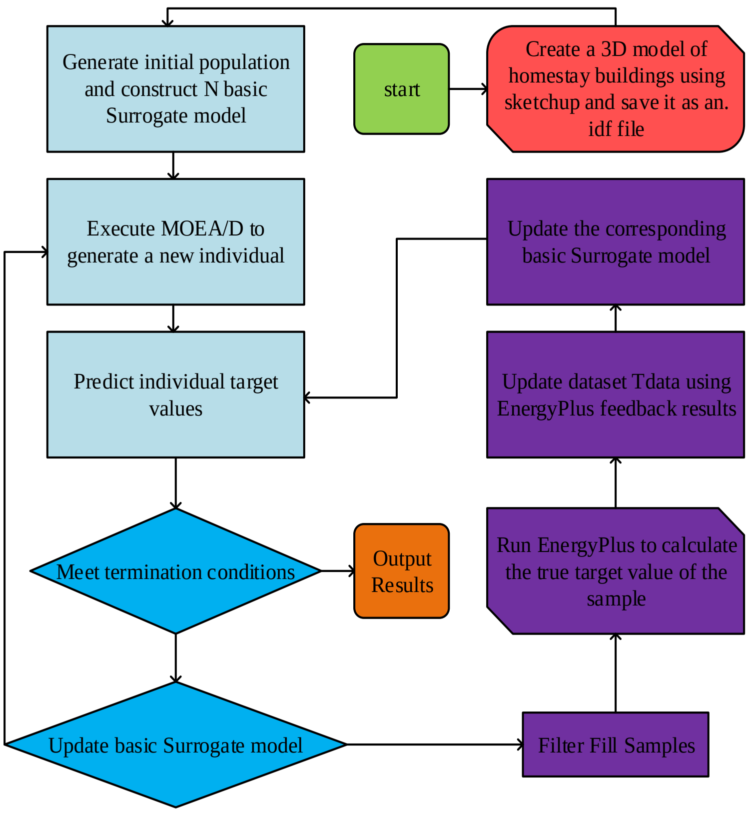


Fig. 5 Execution framework of MS-MOEAD algorithm

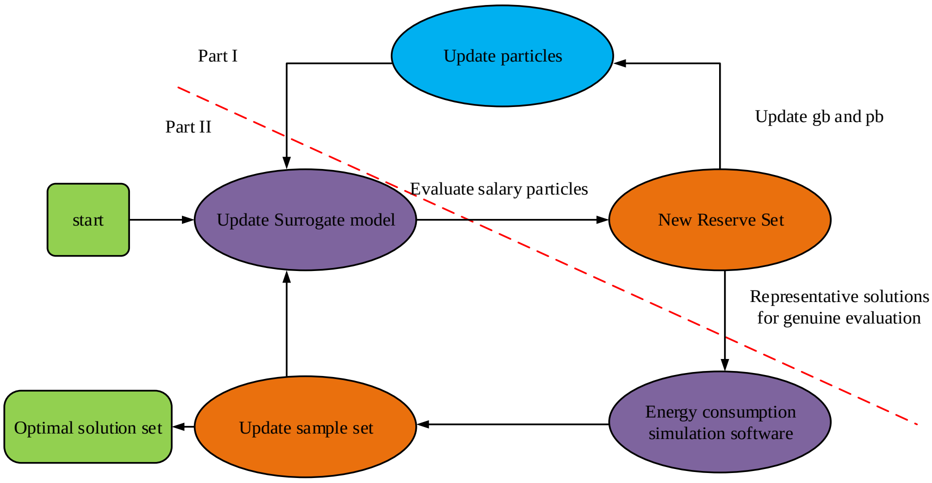


Fig. 6 Sa-MOOSO framework

3.3 Model design of MOOPSO algorithm based on multi-agent assistance

Firstly, theoretical framework of Sa-MOOSO is introduced. On this basis, a particle position update method based on Agent and a method for establishing and managing Agent models are proposed. Similar to other multi-objective PSO algorithms, particle position update is also an important component of PSO (Lu *et al.* 2023; Khodadadi 2022). It can continuously update the position of particles in the particle swarm to generate new particle swarm, while also maintaining the local optimal solution in the particle swarm. The framework structure diagram is shown in Fig. 6.

In Fig. 6, the Agent model management section is used to maintain and update the Agent model used in the previous section. In other words, this paragraph is used to generate high-quality new particles or to fill the sample. Within a given time interval, it selects a representative and high-quality solution set from the backup library, and uses EnergyPlus to solve its actual target; Then, each representative solution and their actual target values form a new filled sample. All new sampleset data are added to the sampleset data (Alghamdi *et al.* 2022; He *et al.* 2023; Lu *et al.* 2023). Finally, it extracts all non optimal solutions from the dataset and optimize them accordingly. To enhance the search ability of the population, conventional PSO algorithms often use an inertia weighting and two learning factors. The particle position is updated by the Gaussian distribution relative to the two navigator, so it is unnecessary to set the above control parameters. Specifically, the update rules for particle X_i are shown in equation (15).

In equation (15), $N(\cdot)$ denotes a Gaussian distribution function; r_3 indicates a random number from 0 to 1; pb_i and pb_i mean the local and global guides of the current particle; t_{max} expresses the maximum number of iterations; x_j^{low} and x_j^{up} refer to the lower and upper limits of the x_j^{up} variable; $f^{\max}_{m}$ and $f^{\max}_{m}$ stand for the maximum and minimum values of the m-th objective function of the population; δ_j means the interference factor determined by the similarity between pb_i and pb_i; ph refers to a probability determined by the difference between $f_m(gb_i(t))$ and $f_m(pb_i(t))$ (Muhiuddin *et al.* 2022). On this basis, the Sa-MOOSO algorithm is developed using MATLAB, and the energy consumption of buildings is simulated using Energy Plus to obtain the actual initial value. In other words, in MATLAB, the Sa-MOOSO algorithm will continuously generate new solutions, and then the Energy Plus algorithm will solve the actual target of the selected representative solution. A data exchange interface between Matlab and Energy Plus is established using isualC++ (Qiao *et al.* 2022; Ramzanpoor *et al.* 2022). The Sa-MOOSO execution framework is shown in Fig. 7.

In Fig. 7, the specific implementation steps of the algorithm are shown. Firstly, SketchUp is utilized to perform 3D modeling of the optimized building. Then, the Sa-MOOSO algorithm in MATLAB is used to solve the original population and sample set,

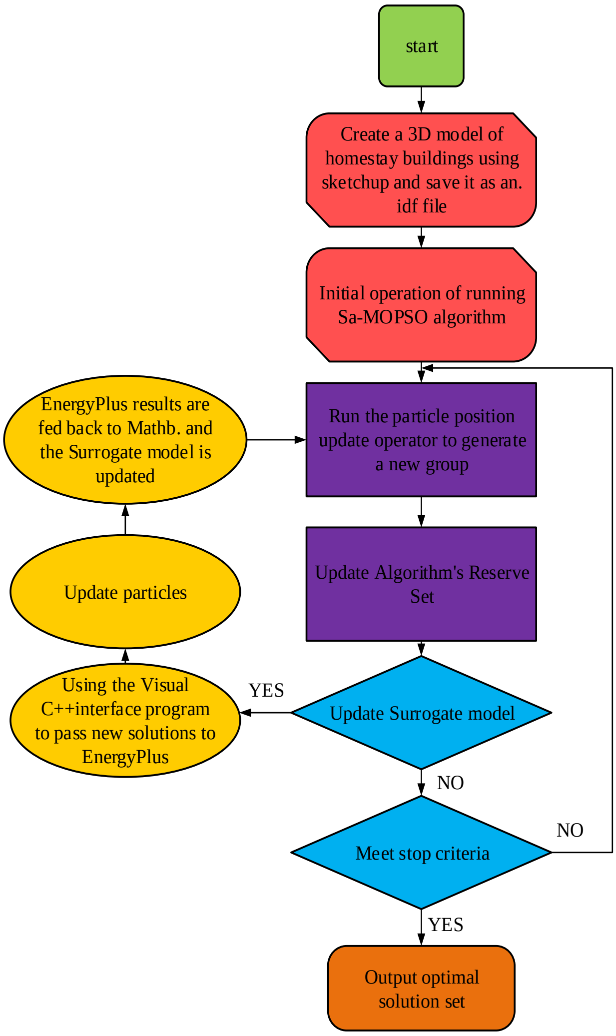


Fig. 7 Execution framework of Sa-MOOSO

and the original RBF replacement model is established. On this basis, the Sa-MOOSO algorithm is used to obtain new particle positions and update the candidate particle set through this algorithm. It needs to redetermine whether to update the Surrogate model. If so, a new representative solution will be selected from the backup set and passed to Energy Plus. Finally, the actual target values obtained are evaluated through Energy Plus and the results are fed back to Matlab; Then, with MATLAB, these target values are added to the dataset to obtain a new sample set, and the alternative model is updated. If there is no need to update, then it proceeds to the next step. In this algorithm, the particle update operator continuously generates new solution results. Repeating this process until the algorithm meets the termination condition. Finally, the non inferior solutions in the dataset are output as the final result of the algorithm.

4. Model analysis of MOO algorithm for ESD of homestay buildings based on MOEAD

By constructing sequence data, sampling sequence data, and training sequence feature vectors, the feature vectors of sequence nodes were obtained. The next step was to process the sequence composed of the feature vectors. A self attention model was built to assist in extracting information from advertising sequences, and then it concatenated and fused it with a front term network that can extract low-level features to form a complete model. It compared and tested this complete model with the other five models.

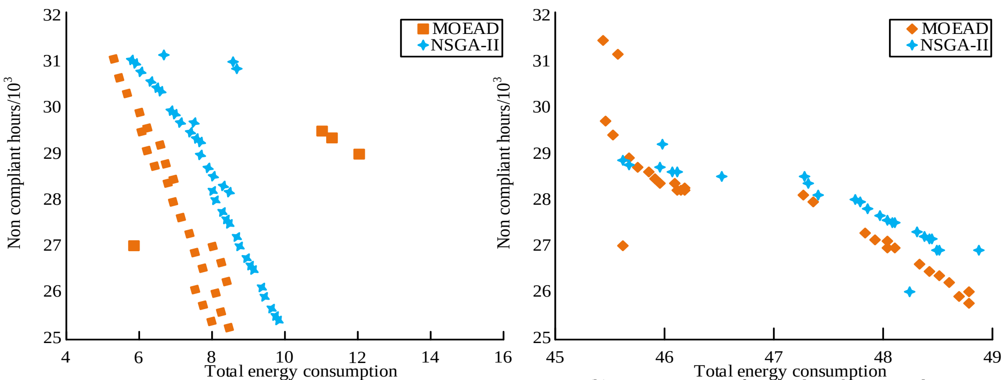
4.1 Model analysis of MOO for ESD of homestay buildings integrated with MOEAD

The MOEAD and NSGA-II algorithms were run 40 times respectively, and the differences between the algorithms were verified using t-test. The significance level of the t-test was set to 0.5, where "R+" indicated that the performance of the MOEAD algorithm was significantly better than the compared algorithms. Two algorithms wee used for the HV value, SC value, and compromise solution of single room homestay buildings, as shown in Table 2.

In Table 2, it compared the results of the two methods. Regarding HV measurement, although the stability displayed by MOEAD was slightly worse than that of NSGA-II, the average value of NSGA-II was 12743.38, which was 19691.18 higher than the average value of the MOEAD algorithm proposed in this chapter; Compared to NSGA II, MOEA/D had greater advantages. In terms of SC measurement, there was SC (MOEA/D, NSGA-II) =0.52, indicating that MOEA/D accounted for 52% in NSGA-II; NSGA-II only accounted for 24% of MOEAD, with SC=0.21. From the above results, the rate of convergence of this method was much faster than that of NSGA - II method. Then, using these two algorithms, a compromise was made on the one room oriented building. Research has found that the minimum discomfort time calculated using the NSGA-II method was 555.30 and the energy consumption was

Table 2
Two algorithms for HV value, SC value, and compromise solution of single room homestay buildings

/	MOEAD	NSGA-II	SC(NSGA-II,MOEAD)	SC(NSGA-II,MOEAD)
HV(BEST)	32840.08	16724.69	/	/
HV(Average)	19691.18	12743.38	/	/
HV(Std)	7372.89	5565.90	/	/
T-tset	\	R+	/	/
Best	/	/	0.37	1.00
Average	/	/	0.21	0.53
Std	/	/	0.30	0.57
Compromise solution	0.0,2.5,1.2,0.7,0.1,0.1,0.1,6.0,10.7,26.2	4.2,2.5,2.1,3.6,0.4,0.0,0.7,0.1,9.6,15.2,20.1,26.1,	/	/
Target value	7.68,555.30	8.92,896.00	/	/



(a)Pareto Frontiers of Two Algorithms in Single Room Homestay Buildings
(b)Pareto Frontiers of Two Algorithms in Multi room Homestay Buildings

Fig. 8 Pareto frontiers of two algorithms in single room and multi-room homestay buildings

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Table 3
Shows the running time comparison between MS-MOEAD and five multi-objective evolutionary algorithm.

Case	Algorithm	Best	Worst	Averge	Std
Single room homestay building	MS-MOEAD	1666.44	2203.69	1774.59	194.28
	MOEAD	2994.73	3270.96	3114.67	112.42
	MOABC	3043.70	3908.08	3425.26	344.80
	MOOSO	3099.54	3868.60	3415.30	353.92
	NSGA-II	3673.42	4275.59	3940.46	239.64
	BBMOOSO-A	3086.94	4854.86	3685.66	711.97
Multi room homestay building	MS-MOEAD	3485.23	3784.16	3616.97	138.57
	MOEA/D	5797.84	6319.07	6105.55	224.80
	MOABC	6039.16	6825.57	6471.38	339.75
	MOOSO	6422.77	7191.60	6735.33	295.88
	NSGA-II	6250.50	6963.36	6542.66	298.07
	BBMOOSO-A	6162.72	6833.23	6473.02	294.50

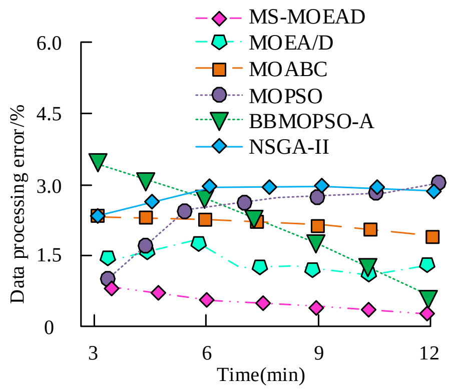


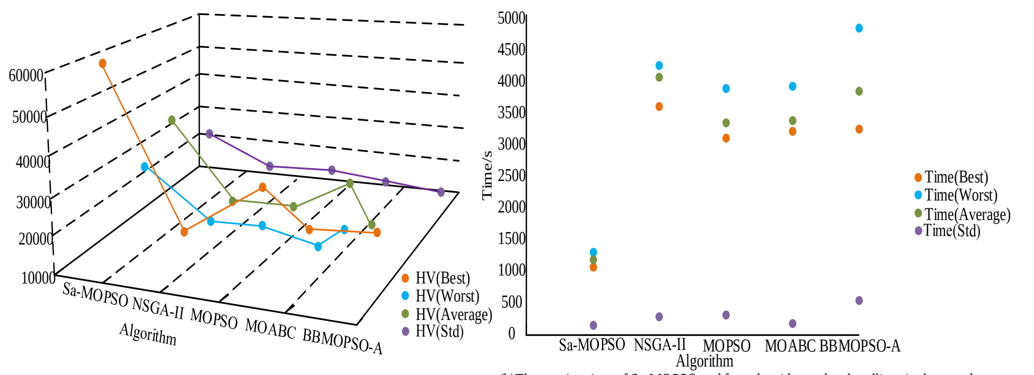
Fig. 9 Data processing error results

7.68, while the minimum discomfort time calculated using the NSGA-II method was 896 and the energy consumption was 8.92. From this point of view, it has greatly improved both in comfort and power saving. The Pareto front of two algorithms in multi room homestay buildings is shown in Fig. 8.

In Fig. 8 expresses the optimal Pareto frontier obtained by the two algorithms. The results denoted that this method had fast convergence and good distribution performance. Research has found that using the MOEA/D method to solve the problem of multi room houses had better convergence and effectiveness than the NSGA-II method. For better comparison, the population size of the two control algorithms was set to 20, and the maximum number of iterations was set to 50. Each control algorithm was executed 20 times, while the other parameters used recommended values. Finally, by analyzing the simulation results of five representative multi-objective evolutionary algorithms, corresponding simulation results were provided. "R+" indicated that MS-MOEAD performed better than the control algorithm; "=" denoted that the two algorithms had the same performance; "one" expressed that the calculation was meaningless.

In Table 3, with alternative model, the execution speed of the MS-MOEAD program significantly decreased to 1774.58 seconds. This speed was almost twice the fastest among the other five algorithms; In computational time, the average execution time of the MS-MOEAD algorithm in practical applications was 3616.96 seconds. Among other methods, the MOEAD method had the fastest speed, reaching 6105.44 seconds, which was 68.80% lower than the proposed method. Subsequently, the error situation of the above algorithm under data processing was analyzed, and the results are shown in Fig. 9.

The results in Fig. 9 indicate that in the data processing results, the error results of the above algorithms show different trends with increasing time. Among them, the overall error results of the proposed model do not exceed 1%, and the minimum value can reach 0.3%. The algorithm with the second smallest error is MOEA/D, and its error processing results vary within a range of (1.3%, 1.6%), with some fluctuations. The error curves of MOABC and MOPSO algorithms have relatively high variation values, with maximum values reaching 2.45% and 2.97%, respectively. The reason for the large error result may be that these algorithms are prone to getting stuck in local optima problems (*Zhou et al.* 2022). Although the maximum error of BBMOPSO-A algorithm is greater than that of NSGA-II algorithm, its subsequent error curve shows a downward trend, and the algorithm with the worst data processing performance is NSGA-II algorithm. The above results indicate that the proposed model has good data processing performance and can



(a)Sa-MOPSO and HV values of four algorithms for handling single room homestays (b)The running time of Sa-MOPSO and four algorithms when handling single room homestays
Fig. 10 The HV values and runtime of Sa-MOOSO and four algorithms for handling single room homestays

improve computational performance while considering data differences.

4.2 MOO model for ESD of homestay buildings based on agent assisted backbone MOOSO

It compared the proposed algorithm with four traditional MOO algorithms for single room office buildings. Firstly, the energy consumption, comfort, safety, and environmental performance of a single room office building were taken as the objective functions for optimization, and transformed into multiple optimization problems, which were then solved using the proposed algorithm. The comparison of HV values obtained when dealing with single room homestay buildings is shown in Fig. 10.

In Fig. 10 (a), although the calculation results of the Sa-MOOSO algorithm varied greatly, its average HV was 35928.55, which was significantly higher than the other four comparison algorithms. In Fig. 10 (b), the execution cycle of the algorithm was shown. With the assistance of substitutes, the calculation speed of Sa-MOOSO has been greatly improved, reaching 1217.231 seconds, while the fastest MOOSO among the four comparison methods was only 3868.591 seconds. The comparison of HV values between Sa-MOOSO and proxy assisted algorithms for multi room homestay buildings is shown in Fig. 11.

The results in Fig. 13 (a) indicate that the SC values of Sa MOEO algorithm are higher than those of MS-MOEA/D algorithm and ParEGO algorithm at different running times, and the average SC values are generally greater than 0.5. The average SC values of MS-MOEA/D algorithm at 4, 8, 12, 16, and 20 runs are 0.431, 0.455, 0.568, 0.522, and 0.495. The SC measure curve of the ParEGO algorithm changes smoothly, with the maximum value approaching 0.4. Overall, the performance comparison of Sa MOEO algorithm is significantly better than the other two proxy models. In Fig. 13 (b), compared to the other two proxy models, the proposed model has better energy consumption prediction performance, with a relative prediction error based on less than 0%, and the overall curve nodes have smaller fluctuations. The maximum prediction errors exhibited by MS-MOEA/D algorithm and ParEGO algorithm can reach 0.038% and 0.007%, respectively, and the energy consumption prediction results vary greatly at different testing time intervals. The adaptability originally designed by MS-MOEA/D and ParEGO may not be sufficient to handle the specific and variable constraints and goals of building energy consumption. The objective function involved in optimizing building energy consumption may be nonlinear, non convex, or have multiple peaks. MS-MOEA/D and ParEGO may require significant

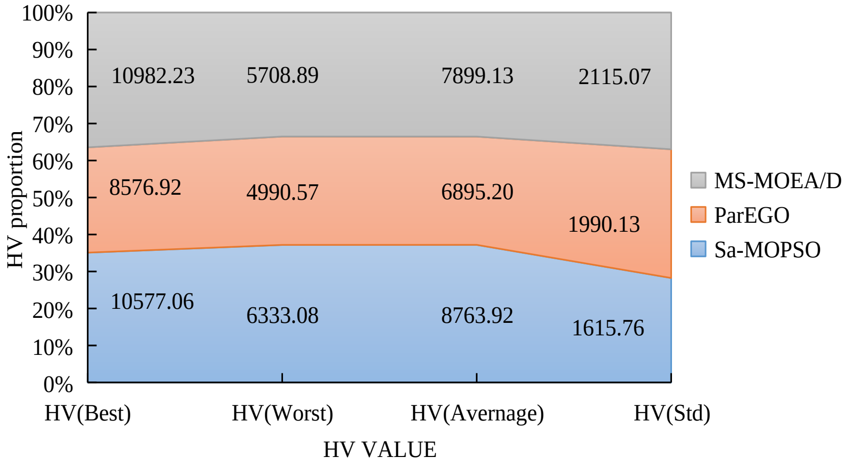


Fig. 11 HV values obtained from Sa-MOOSO and two proxy assisted algorithms when processing multi-room homestay buildings

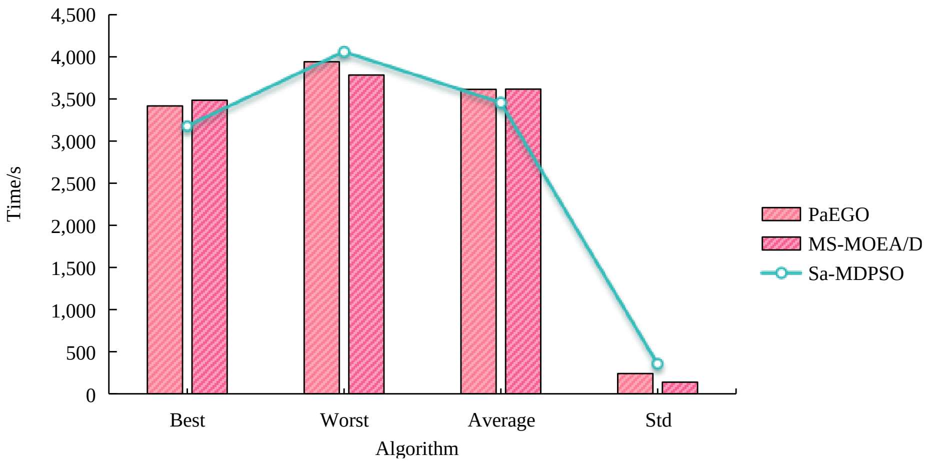
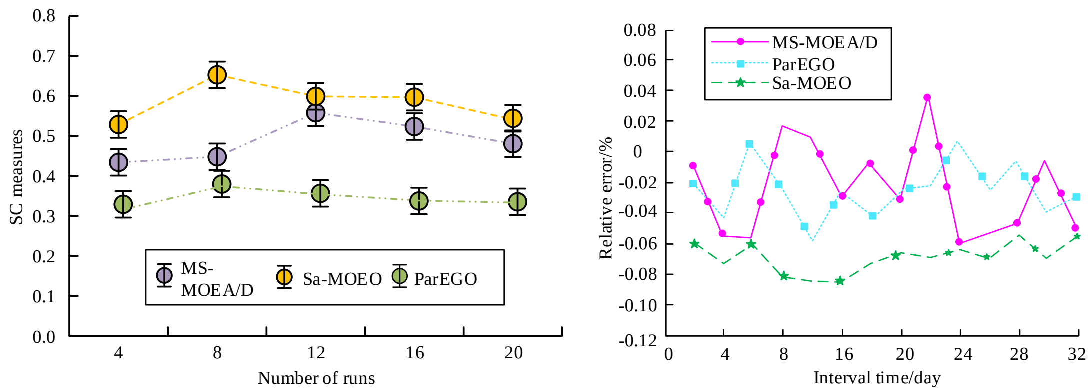


Fig. 12 Running time obtained from Sa-MOOSO and two proxy assisted algorithms when processing multi room homestay buildings



(a) Measurement of Building Energy Efficiency SC (b) Building energy consumption prediction error

Fig. 13 Results of Building Energy Efficiency SC Measurement and Energy Consumption Prediction

computational resources to handle complex building energy optimization problems, resulting in poor performance and difficulty in quickly obtaining effective solutions (Qiao *et al.* 2022); Sharma *et al.* 2022)。 The above results indicate that the proposed model has good energy consumption analysis results, good data processing performance, and small data error values.

In Fig. 11, the advantages and disadvantages of this method were analyzed by combining it with methods such as ParEGO and MS-MOEA/D. Although the optimization effect of Sa-MOOSO was not as significant as the two comparison methods, it achieved the optimal average HV. When dealing with multi room homestay buildings, the running time obtained from Sa-MOOSO and two proxy assisted algorithms is shown in Fig. 12.

In Fig. 12, compared to MS-MOEAD, the Sa-MOEO algorithm had a much slower computational speed, perhaps due to its lower cost. Among them, Sa-MDPSO had the least computation time for best, while Sa-MDPSO took much longer on the worst problem. Overall, compared to existing alternative assisted high-dimensional adaptive evolutionary algorithms, Sa-MOOO had strong advantages in solving high-dimensional problems. Subsequently, the algorithm proposed by the research institute was subjected to building energy-saving SC measurement and energy consumption prediction analysis, and the results are shown in Fig. 13.

5. Conclusion

For the ESD of homestay buildings, an optimization model based on MOEAD and Sa-MDOSO was adopted, and various indicators were verified. The research results indicated that the minimum discomfort time calculated using the NSGA-II algorithm was 555.30 and the energy consumption was 7.68, while the minimum discomfort time calculated using NSGA-II was 896 and the energy consumption was 8.92. With models, Sa-MDPSO had the fastest speed, reaching 6105.44 seconds, which was 68.80% lower than the proposed method. With the help of substitutes, the calculation speed of Sa-MDPSO algorithm has been greatly improved, reaching 1217.231 seconds, while the fastest multi-objective PSO algorithm among the four comparison methods was only 3868.591 seconds. The convergence and effectiveness of using the MOEAD method to solve the problem of multi room houses were superior to the NSGA-II method. For better comparison, the population size of the two control algorithms was set to 20, and the maximum number of iterations was set to 50. Each control algorithm was executed 20 times, while the other parameters used recommended values. Finally, by analyzing the simulation results of five representative multi-objective evolutionary algorithms, corresponding simulation results were provided. In the practical application process, in addition to efficiently optimizing the ESD of homestay buildings, cost was also a crucial consideration goal. Future research can explore the impact of cost factors on energy-saving optimization of homestay buildings. Therefore, the results of this study have great reference value for guiding the energy-saving optimization of homestay buildings.

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