

Optimization method of building energy efficiency design based on decomposition multi objective and agent assisted model

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Received: 24 May 2024 / Accepted: 7 October 2024

Abstract. In today's global climate crisis, energy-efficient building design is crucial for achieving energy efficiency, environmental sustainability, and resident well-being. However, traditional architectural design is difficult to solve complex multi-objective and multivariate optimization problems. To overcome these challenges, this study proposes a solution: a strategy that combines decomposed multi-objective and agent assisted modeling. The proposed method decomposes complex architectural design problems into multiple manageable sub problems, with each sub problem optimized for a specific design objective. This method effectively simplifies the problem structure, allowing each subproblem to explore its solution space more focused and in-depth. Meanwhile, by combining proxy assisted modeling and utilizing proxy models to approximate actual physical processes or performance evaluations, the computational cost is reduced and the optimization process is accelerated. This study indicates that the improved multi-objective backbone particle swarm optimization algorithm relies on adaptive perturbation factors, with an average measured super volume of 29311 for one bedroom buildings and 49504 for three bedroom buildings. For the same building type, the average volume measurements of the multi-objective particle swarm optimization algorithm assisted by the decomposed surrogate model are 21153 and 40230, respectively. The proposed method effectively addresses complex multi-objective optimization problems in the field of building energy efficiency design, simplifies the problem structure, reduces computational costs through surrogate models, accelerates the optimization process, improves energy efficiency, and can support building construction to better cope with the challenges of climate change.

Keywords: Energy efficiency / buildings / particle swarm algorithm / agent-assisted modeling / multi-objective optimization

1 Introduction

In the building sector, there is an increasing urgency for energy-efficient building designs due to worries about environmental pollution and global energy consumption. Building energy efficiency design (BEED), as a traditional building design method, faces many challenges in solving multi-objective problems, especially when multiple conflicting design objectives are involved, how to find the optimal solution during the design process has become an urgent problem to be solved [1,2]. Methods such as the hybrid genetic algorithm, improved ant colony optimization algorithm, and distributed parallel genetic algorithm have certain drawbacks, including slow convergence speed and relatively easy local convergence. However, the decompose multi-objective (DMO) optimization is a highly advantageous method for managing multi-objective

problems. Traditional multi-objective optimization methods often attempt to directly find the optimal solution at the multi-objective level, which is particularly difficult when there are conflicts between objectives. The DMO strategy effectively decomposes complex multi-objective problems into multiple single objective sub problems, with each sub problem focusing only on one design objective, simplifying the optimization process and making it easier to find optimal solutions for each sub problem [3,4]. Agent-assisted modeling (AAM) is an auxiliary model utilized in the optimization problem-solving process for approximating the objective function or system behavior [5]. In BEED, the combined DMO and AAM approach can cope with the challenges of complex design space and multi-objective optimization (MOO). Based on this, the study proposes a BEED optimization method based on the combination of DMO and AAM. By decomposing the complex architectural design problem into multiple sub-problems and applying the MOO technique to deal with them, AAM is also introduced to improve the efficiency of the

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optimization process. The research aims to achieve a balance between multiple objectives in building design while improving design efficiency and performance. The novelty of this study lies in the MOO technique's comprehensive consideration of energy consumption, comfort, and other indicators to attain the global optimal solution. Additionally, the agent model rapidly approximates the objective function to expedite the optimization algorithm's convergence, thereby enhancing the search efficiency.

There are five sections to this research. The initial section presents the research background, issues, and solutions concerning BEED optimization. In the following part, the prior research outcomes on BEED are reviewed, and the challenges and drawbacks of those approaches are summarized. Subsequently, the BEED optimization technique that incorporates DMO and AAM is introduced in the third part. A comparative experiment for performance testing of BEED optimization is designed in the fourth part. The fifth section details the research methodology, evaluates the experimental results, and provides an analysis of the limitations and future directions of the approach.

2 Related works

BEED has become crucial in the current global climate change context for its impact on energy efficiency, environmental sustainability and human quality of life. Nevertheless, traditional building design faces serious challenges when dealing with optimization problems involving multiple objectives and variables. Yue and colleagues used the structure from motion approach to create a three-dimensional (3D) model of the urban landscape, simulating the signals in the landscape using the autocorrelation function. In addition, the study also used the fuzzy evaluation method and improved the 3D model. The results showed that different categories of green building materials have different values in urban 3D landscape design [6]. In order to analyze the response of architecture in environmental issues, Andiyan and other researchers created a harmony between the main functions of office buildings and the environment with the application of green building concepts. The results showed that the green building concept can continue to be used to solve the environmental problems that exist in buildings [7]. In order to evaluate the indoor environmental quality and energy consumption of a green office building and to provide a reference for the design of green buildings, Zhou and other researchers selected a green office building in a Chinese city as an example. They obtained the indoor environmental quality through on-site measurements and the users' satisfaction with the building through questionnaires. The experimental results indicated that the degree of energy use of this green office building is much less than the constraint value of the national standard [8]. In order to analyze the impact of occupant behavior on energy use, experts such as Almeida selected green and non-green buildings of the university with similar characteristics. They used building simulation to compare the buildings in terms of energy use and to simulate the interactions between occupants and systems in the buildings. The

study's findings indicated that residents had a 72% impact on the building's energy performance, which can serve as a guide for the construction of green buildings [9].

Multi-objective particle swarm algorithm is used as an evolutionary algorithm for solving MOO problems. It is based on particle swarm optimization algorithm and focuses on solving optimization problems with multiple conflicting objectives. For optimal energy management of microgrids, Anh and other researchers designed an improved multi-objective particle swarm optimization (MOPSO) algorithm and sought multiple objective solutions through Pareto frontiers. Experimental results revealed that the algorithm designed by this research can be optimized in real time and performs better than other heuristic algorithms [10]. To optimize the design of condenser control system in nuclear power plants, Zhi and other experts designed a control optimization method based on MOO algorithm. Under this control method, the optimization object was control parameters and the optimization objective was the step response performance. The experimental results indicated that the method designed by this research can obtain high quality control parameters with good performance [11]. To achieve the cost optimization of the stiffness parameters of the powertrain suspension system, Trng and other experts designed a combined algorithm incorporating a MOPSO algorithm and a third-generation non-dominated sequential genetic algorithm. The study transformed the cost optimization problem into a MOO problem with six optimization objectives. According to experimental findings, the algorithm developed in this work performs better on its own than either the third generation non-dominated sequential genetic algorithm or the MOPSO algorithm [12]. Xu and other researchers examined the global convergence of the MOPSO algorithm using probability theory in order to look into its convergence. Additionally, the study defined the convergence metric and converted the algorithm's global convergence into the convergence of the convergence metrics' sequence. The outcomes showed that global convergence with probability 1 is not guaranteed by the MOPSO algorithm [13].

A summary can be obtained regarding the current state of research on building energy efficiency. While significant progress has been made, there are still issues with slow convergence speeds and easy local convergence. The multi-objective particle swarm algorithm's primary objective involves an iterative search through a search space of multiple goals. This is achieved by keeping a swarm of particles and updating their positions and velocities based on their performance on various objectives. The proposed BEED optimization method is based on DMO and AAM.

3 Building energy efficiency design method based on decompose multi-objective and agent-assisted modeling

The BEED method based on DMO and AAM is a method that is expected to solve the difficulties of traditional design methods in terms of multivariate and MOO

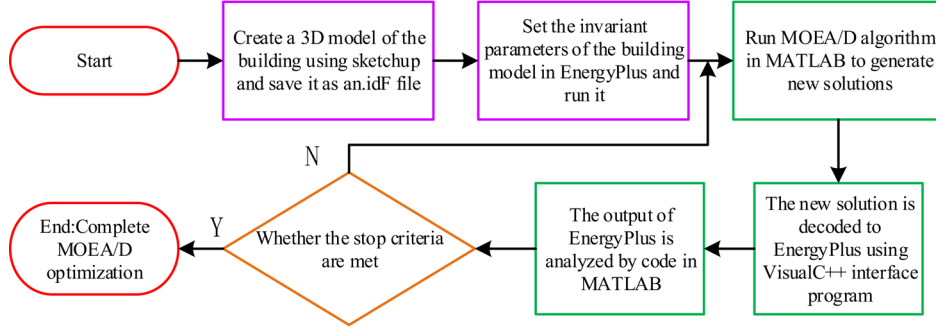


Fig. 1. Multi-objective evolutionary algorithm flow based on decomposition.

by decomposing the design objectives into relatively independent sub-objectives and combining them with the support of AAM.

3.1 Multi-agent assisted MOEA/D based optimization method for building energy efficiency design

The research suggests a BEED technique based on multi-objective evolutionary algorithm based on decomposition (M-OEAD) in order to solve the MOO, complexity, and uncertainty drawbacks of standard BEED methods [14–16]. In the M-OEAD framework, each agent handles its specific objective through an adaptive decomposition strategy and searches for a locally optimal solution in the whole design space. The multi-agent system works together in an interactive way, which makes the overall optimization process more robust and efficient. Figure 1 illustrates the implementation flow of the M-OEAD.

In Figure 1, the M-OEAD-based process includes the following steps. First, the multi-objective problem is decomposed into a set of single-objective sub problems. Then, each sub problem is optimized by an evolutionary algorithm to generate a set of solution sets; next, the solution sets of these sub problems are merged by some strategy to obtain the global Pareto optimal set [17]. Finally, the algorithm is terminated according to a predefined stopping criterion. In each evolutionary generation, the algorithm adjusts the individuals through operations such as crossover and mutation to progressively optimize the solution set of the sub problems according to the fitness function and the selection strategy. In the field of Building Energy Efficiency Design (BEED), key indicators such as energy consumption, thermal comfort, and light intensity are the cornerstone of measuring building performance. They directly affect the energy efficiency of buildings, the satisfaction of occupants, and the sustainability of the environment. Hypervolume Indicator (HV), as an indicator for evaluating algorithm performance, is closely related to the key indicators of BEED. The HV index measures the coverage range of the solution set found by the algorithm in the target space, and its value directly reflects the balance achieved by the algorithm in multiple objectives such as energy consumption, thermal comfort, and light intensity. HV is a metric used to evaluate the performance and quality of the solution set in the MOO problem. In this study, Hypervolume is used to evaluate the

algorithm, the exact mathematical expression is shown in equation (1).

$$HV = \delta(\bigcup_{i=1}^{|S|} v_i). \quad (1)$$

In equation (1), the measurement volume is denoted by δ , which represents the Lebesgue measure, i.e., the “size” of the measurable set. An increase in the value of HV represents an improvement in the distribution and/or convergence of results for a set of Pareto optimal solutions. Spearman’s Rank Correlation Coefficient (SRCC) is a non-parametric statistic commonly used to rank data or to examine relationships between variables in data analysis, especially when dealing with data that do not meet the requirements for linear correlation. The study further chose SRCC to measure the convergence of the algorithm, the exact mathematical expression of which is shown in equation (2).

$$S_c(E, F) = \frac{|\{e \in F : \exists e \in E, e < F\}|}{|F|}. \quad (2)$$

In equation (2), $|\cdot|$ is the elements in the set, and when the value of the output function is 1, it represents being dominated by the solutions in set E over all the solutions in set, F while the value of the output is 0, which means that it is not dominated. Due to the sensitive M-OEAD parameter settings, high computational effort, and load balancing issues, the research further proposes multi-stage multi-objective evolutionary algorithm based on decomposition (MS-M-OEAD), which is also known as Multi-Agent Model-Assisted M-OEAD algorithm. Multi-agent model-assisted M-OEAD refers to the improved version that introduces multi-agent modeling in M-OEAD based [18,19]. Figure 2 illustrates the basic framework of the multi-agent model-assisted M-OEAD.

In Figure 2, the basic framework of the multi-agent model-assisted M-OEAD includes the introduction of multiple agent models, each responsible for searching a different part of the problem space. These agents may cooperate with each other through mechanisms such as collaborative search and information exchange. Dynamic adjustment of the agents’ behavior enables them to adaptively adjust their strategies according to the nature of the problem or the progress of the search. In addition to focusing on the timing of updating the agent model, the

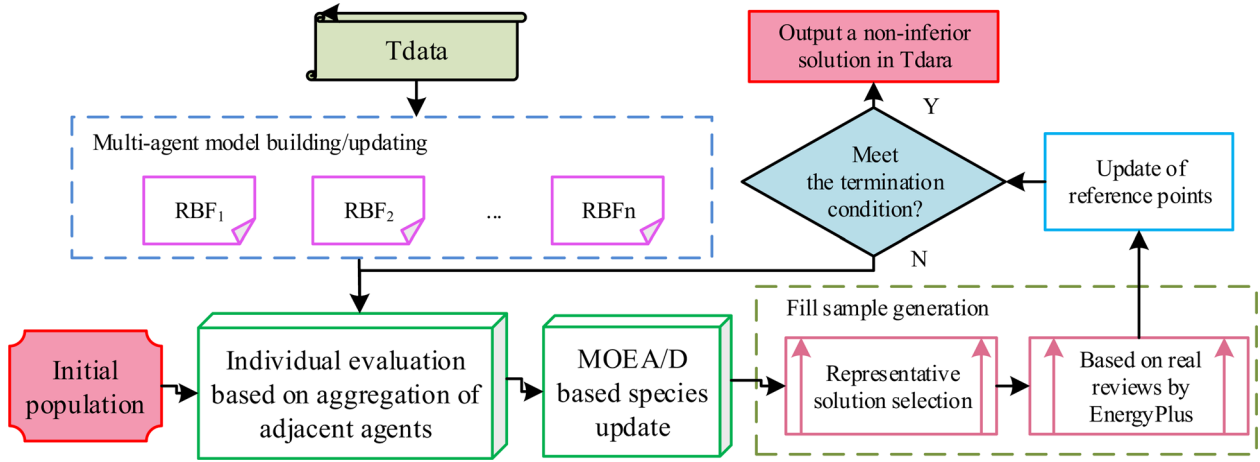


Fig. 2. Basic framework of M-OEAD assisted by multi-agent model.

management of the agent model also addresses the challenge of selecting the “right” individuals for true assessment when generating new samples. Specifically, for individual X , the expression for the degree of uncertainty is given in equation (3).

$$u(X) = \frac{\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^{\alpha+1} \sqrt{(\hat{f}_i^j(X) - \bar{f}_i(X))^2}}{\alpha + 1} \quad (3)$$

In equation (3), N denotes the number of targets and $\hat{f}_i^j(X)$ denotes the individual’s agent model evaluation value. α denotes the neighborhood size of the individual, and $\bar{f}_i(X)$ denotes the average approximation of solution X on the i th target. Since the bare-bone multi-objective particle swarm optimization-adaptive (BBMOPSO-A) disturbance factor suffers from the problem of repetitive searching of known regions by particles and waste of computational resources [20]. Therefore, the study improved the BBMOPSO algorithm by introducing the adaptive disturbance factor to form the final BBMOPSO-A algorithm. The particle update method after the introduction of the adaptive perturbation factor is shown in equation (4).

$$x_{i,j}(t+1) = \begin{cases} N\left(\frac{r_3 \times pb_{i,j}(t) + (1-r_3) \times gb_{i,j}(t)}{2}, |pb_{i,j}(t) - gb_{i,j}(t)| + \delta_D\right), & \text{if } U(0,1) < 0.5 \\ pb_{i,j}(t) & \text{otherwise} \end{cases} \quad (4)$$

In equation (4), δ_D represents the perturbation factor, N represents the total number of particles in the particle population, r_3 represents a random number between 0 and 1 used to increase the randomness of the update formula. $gb_{i,j}(t)$ is the global optimal point of i particle, and $pb_{i,j}(t)$ the individual optimal point of the i th particle. j represents the dimension, t represents the number of iterations, and $pb_{i,j}(t)$ is the j th dimension of the i th individual optimal point in the t th iteration, and the specific calculation of the perturbation factor is shown

in equation (5).

$$\delta_D = \begin{cases} (x_D^{up} - x_D^{low}) \times e^{(-5t/T)}, & \text{if } pro_d \geq rand \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

In equation (5), T represents the maximum iterations, x_D^{up} denotes the upper bound of the value taken by the D th decision variable, and x_D^{low} is the lower bound of the value taken by the D th decision variable. pro_d represents the perturbation probability, and its specific calculation is shown in equation (6).

$$pro_d = 0.5 \times \left(1 - \frac{1}{M} \sum_{m=1}^M \left| \frac{f_m(Pb_i(t)) - f_m(Gb_i(t))}{f_m^{\max} - f_m^{\min}} \right| \right) \quad (6)$$

In equation (6), M is the total objective functions, $f_m^{\max}$ and $f_m^{\min}$ denote the maximum and minimum values of all solutions in the reserve set with respect to the value of the m th objective function, respectively. $f_m(Pb_i(t))$ and $f_m(Gb_i(t))$ represent the value of the m th objective function for Gb_i and Pb_i , respectively. Decomposition-based multi-stage multi-objective evolutionary algorithm is an algorithm that efficiently tackles the MOO challenge by decomposing a complex multi-objective problem into a series of smaller sub-problems and optimizing them separately at each stage. Figure 3 illustrates the execution framework of the decomposition-based multi-stage multi-objective evolutionary algorithm.

In Figure 3, the execution framework of the MS-M-OEAD mainly consists of a diversity maintenance strategy and a multi-agent search mechanism. The algorithm promotes extensive exploration of the solution space by maintaining the diversity of the population, in which different agent models are used to be responsible for the search of the sub problems to enhance the efficiency of the global search. During the execution of the algorithm, information is exchanged between the agents through

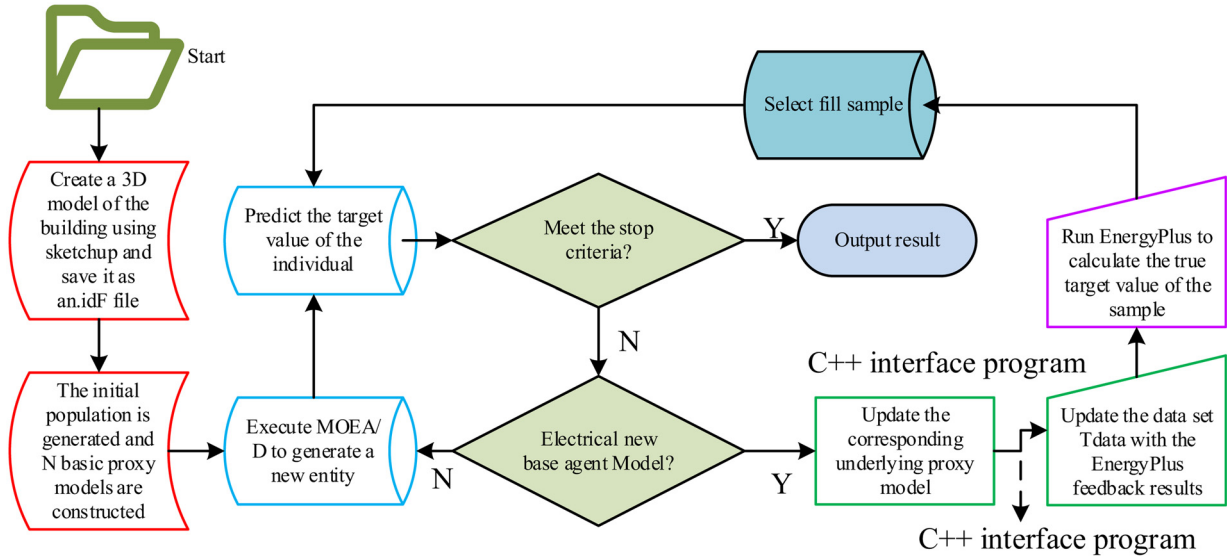


Fig. 3. Execution framework of M-OEAD assisted by multi-agent model.

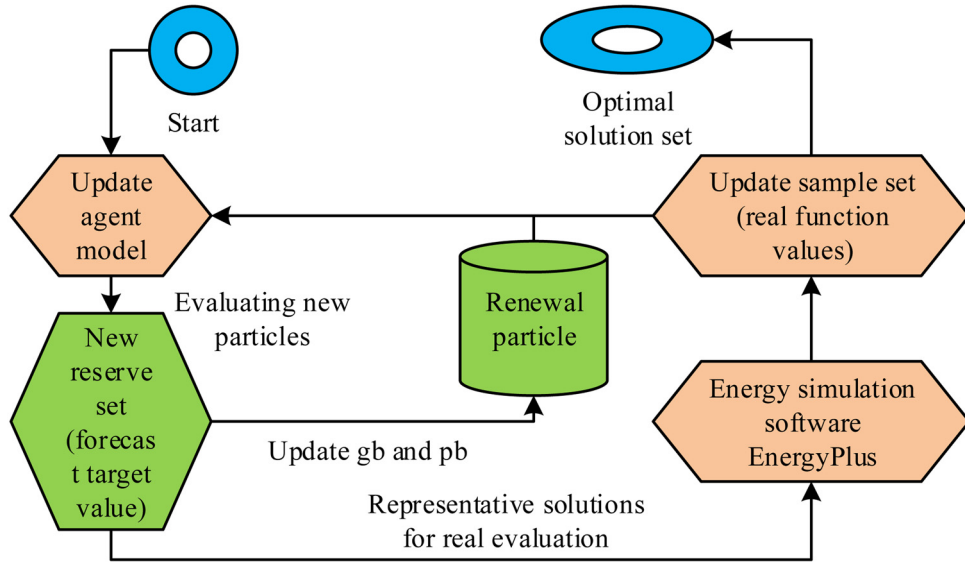


Fig. 4. Frame diagram of the agent model-assisted adaptive multi-objective particle swarm optimization algorithm.

collaborative and competitive mechanisms, and the search strategy is dynamically adjusted to adapt to the complexity of the problem.

3.2 SA-MOPSO based multi-objective optimization method for building energy efficiency design

BEED-MOO based on agent-assisted self-Adaptive multi-objective particle swarm optimization (SA-MOPSO) is an approach that combines agent technology and backbone MOPSO [21]. By introducing the agent technique, the system is able to search the solution space of an architectural design more efficiently, while the backbone MOPSO provides an effective way to deal with multiple

interrelated design objectives [22,23]. Figure 4 illustrates the framework diagram of the agent model-assisted adaptive MOPSO algorithm.

In Figure 4, the SA-MOPSO framework is mainly composed of two elements: agent-based particle position update and the construction and management of agent model. The introduction of the agent model enables the algorithm to adapt more flexibly to complex objective functions and constraints, and dynamically adjust the parameters during the search process, thus improving the global search capability of the algorithm. Figure 4 further demonstrates the execution framework of the agent model-assisted adaptive MOPSO algorithm.

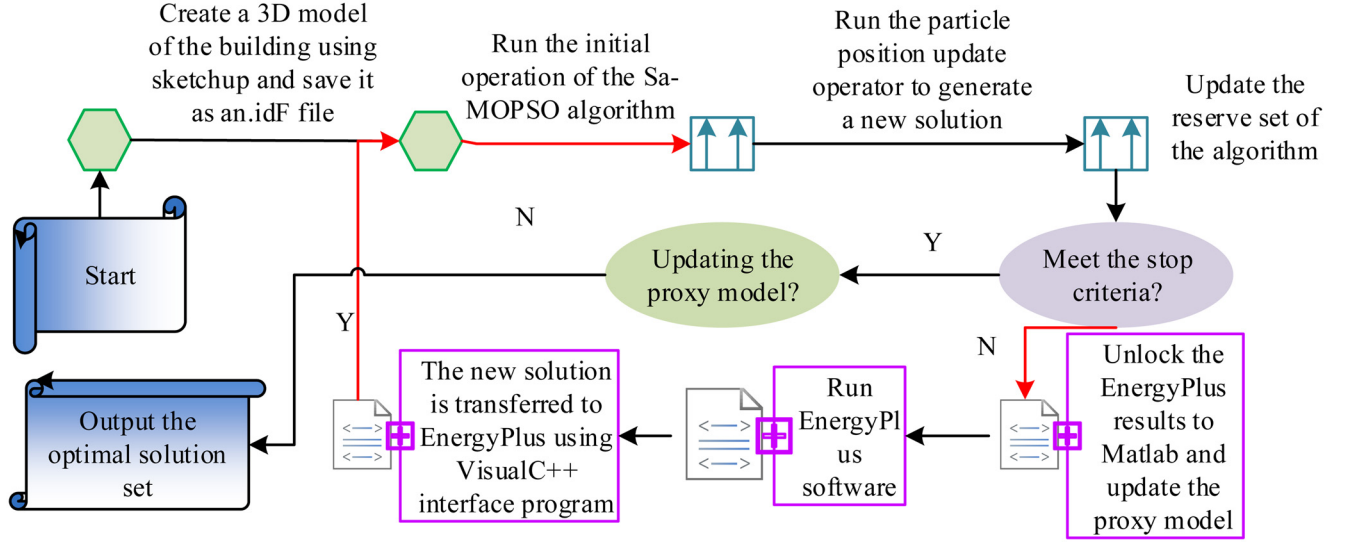


Fig. 5. Implementation framework of the agent model-assisted adaptive multi-objective particle swarm optimization algorithm.

In Figure 5, the execution process of the SA-MOPSO algorithm includes first initializing the algorithm parameters, including the number of particle swarms, dimensions, velocity range and inertia weights. Subsequently, the algorithm is initiated by randomly generating the position and velocity of the initial particle swarm. During the optimization process, an agent model is constructed to assist in deciding the update strategy of particle positions according to the current particle swarm state. For each particle, its fitness value on the objective function is calculated to evaluate its performance in the multi-objective space. With the help of the agent-based model, each particle's position and velocity are updated. Subsequently, non-dominated sorting is performed to classify the individuals in the particle swarm into different frontier tiers. A new particle swarm is formed by selecting the individuals in the frontier tier. The Bare-Bones Particle Swarm Algorithm (BBPSO) can solve the single-objective problem with the particle update as shown in equation (7).

$$x_{i,j}(t+1) = N\left(\frac{pb_{i,j}(t) + gb_j(t)}{2}, |pb_{i,j}(t) - gb_j(t)|\right). \quad (7)$$

In equation (7), N represents the particle swarm size and i denotes the i th particle. $gb_j(t)$ is the global optimal point of i particle, and $pb_i(t)$ the individual optimal point of the i th particle. j represents the dimension, t represents the number of iterations, and $pb_j(t)$ is the j th dimension of the i th individual optimal point in the t th iteration. The study adopted a dual-reserve set co-directed agent model management strategy with variable sample sizes, and in constructing the initial agent model, the study used Latin hypercubes for sampling and used them as samples for constructing the model [24]. The number of samples required for the initial agent model is determined as shown

in equation (8).

$$Q = \frac{(n+1)(n+2)}{2}. \quad (8)$$

In equation (8), n is the randomly selected points. In response to the increased training cost due to the agent model update, the study used the average model prediction error to make a judgment on the timing of the model update. The average error of model prediction for Reserve Set 1 is shown in equation (9).

$$E(f, EP) = \frac{1}{\partial} \sum_{i=1}^{\partial} \sum_{q=1}^{\partial} \frac{|\hat{f}_q(x'_i) - f_q(x'_i)|}{|f_q(x'_i)|}. \quad (9)$$

In equation (9), $\hat{f}_q$ represents the q th objective function value obtained from the fitting of the agent model, and f_q represents the true objective function value calculated by the energy consumption software. EP is the set of endpoints selected from the reserve set 1, ∂ is the number of endpoints, and x_i is the decision variable. The second part is the new sample selection strategy. In order to evaluate the overall similarity between the two datasets, the study uses Hausdorff distance. The Hausdorff distance is calculated as shown in equation (10).

$$H(A, B) = \max(h(A, B), h(B, A)). \quad (10)$$

In equation (10), A and B represent two different datasets, respectively. $h(A, B)$ represents the directed Hausdorff distance from dataset A to B , and $h(B, A)$ represents the reverse Hausdorff distance. The calculation of $h(A, B)$ is shown in equation (11)

$$h(A, B) = \max_{a_\varphi \in A} \min_{b_\gamma \in B} |a_\varphi - b_\gamma|. \quad (11)$$

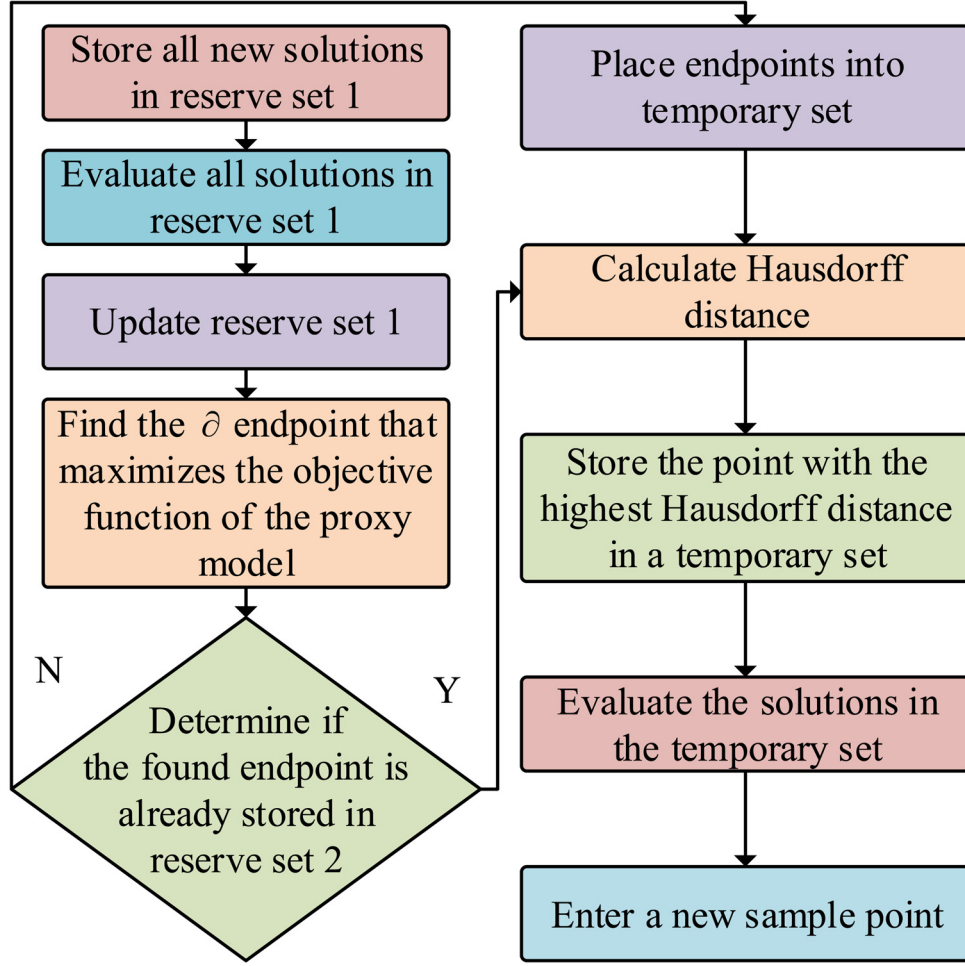


Fig. 6. Specific steps of a new sample selection strategy guided by dual reserve sets.

In equation (11), $|a_\varphi - b_\gamma|$ represents the distance paradigm between point a to point b . a_φ and b_γ are points in data sets A and B , respectively. The calculation of $h(B, A)$ is shown in equation (12).

$$h(B, A) = \max_{a_\varphi \in B} \min_{b_\gamma \in A} |a_\varphi - b_\gamma|. \quad (12)$$

The specific steps of the new sample selection strategy guided by the double reserve set are shown in Figure 6.

In Figure 6, the dual-reserve set-guided new sample selection strategy is an approach for training machine learning models that includes two key sample sets: the core sample set and the edge sample set. The core sample set contains representative samples that have an important impact on the model, while the edge sample set contains samples that are relatively difficult for the model to handle and may lead to performance fluctuations. During the training process, the core and edge sample sets can be dynamically adjusted to improve the model's adaptability and generalization ability for various samples by selecting new samples based on the model's performance on the current core sample set. The third part of

the agent model update strategy is the adaptive adjustment of the new sample size, which is calculated as shown in equation (13).

$$L = l_{\min} + [E[f, EP] \times (l_{\max} - l_{\min})]. \quad (13)$$

In equation (13), $l_{\min}$ represents the minimum sample size, $l_{\max}$ represents the maximum sample size, $E[f, EP]$ is the model prediction error, and $[g]$ represents the upward rounding function. proposed Surrogate-model assisted multi-objective particle swarm algorithm based on decomposition (SMOPSO/D) utilizes the decomposition idea of the decomposition-based MOO algorithm. To generate well-distributed initial particles, the study introduces a congestion-based population initialization strategy. In order to provide a guarantee for the diversity of particle search methods, the study also introduces a decomposition-based particle global and local guide update strategy. The computation of the optimal solution of the aggregation function is shown in equation (14)

$$\min g(x|\lambda_e, z^*) = \max_{1 \leq q \leq R} \left\{ \lambda e^q |f_q(x) - z_q^*| \right\}. \quad (14)$$

Table 1. Parameter settings for validating the performance of Algorithm A and Algorithm B.

Parameter	BBMOPSO-A	SMOPSO/D
Hardware configuration	Intel Core i7-9700 K, 16 GB RAM, NVIDIA GTX 1080	Intel Core i7-9700 K, 16 GB RAM, NVIDIA GTX 1080
Software environment	Windows 10, MATLAB R2020a, Parallel Computing Toolbox	Windows 10, MATLAB R2020a, Parallel Computing Toolbox
Parallel processing	Support, using MATLAB's parallel computing toolbox	Support, using MATLAB's parallel computing toolbox
Maximum iteration number	25	30
Number of particles	60	60
CPU utilization rate	85	70
GPU utilization rate	75	65
Average running time	45 min	35 min

In equation (14), λ_ε represents the ε th weight vector and R is the weight vectors. z^* is the objective function, z_q^* represents the objective function of the agent model, and λ^q is the ε th weight vector of the agent model. Where the objective function z^* is calculated as shown in equation (15).

$$z^* = \min \left\{ \hat{f}_q(x) | x \in \Omega, q \in \{1, 2, \dots, R\} \right\}. \quad (15)$$

In equation (15), Ω represents the range of values of the independent variable x . The fundamental principle of the objective algorithm is to approximate the real objective function using an agent model, which increases the algorithm's speed of convergence and efficacy.

4 Performance validation of MS-M-OEAD with agent modeling assisted MOPSO-based

The study validates the performance of the multi-agent-assisted M-OEAD and the agent model-assisted MOPSO algorithm, selects comparison algorithms and comparison metrics, and sets up the experimental environment and experimental parameters. The experimental hardware configuration is Intel Core i5-12600 K processor, Windows 10 operating system, 16 threads, and 128 GB RAM. The parameter settings for verifying the performance of Algorithm A and Algorithm B are shown in Table 1.

4.1 Differential validation of SMOPSO/D algorithm based on building energy efficiency

In order to validate the performance of the SMOPSO/D algorithm, the BBMOPSO-A algorithm was selected for the study for the comparison of HV, SC measure, coefficient of variation (CV) of mean absolute percent error (MAPE) and root mean square deviation (RMSD). The iterations of the algorithm was set to 30 and the algorithm performance validation was conducted on one bedroom and three bedroom buildings in Tianjin, using EnergyPlus v9.5.0 and MATLAB R2020a software. The experiment was carried out with three replications. One bedroom and three bedroom buildings represent residential design needs

ranging from simple to complex, covering the living space needs of different user groups. A one bedroom apartment usually has a small space and is designed with a focus on efficient use of space and energy conservation; A three bedroom apartment provides more design flexibility, but also brings more complex energy management issues. By testing the algorithm on these two types of residential buildings, it can be verified whether the algorithm can adapt to different design constraints and optimization objectives, and whether it can provide effective energy efficiency solutions for residential buildings of different sizes. The HV comparisons between the BBMOPSO-A algorithm and the SMOPSO/D algorithm for the one-room and the three-bedroom BEEDs are shown in Figure 7.

Figure 7a shows that for a single room building, the HV value of BBMOPSO-a algorithm is compared with the HV values of SMOPSO/D algorithm, algorithms proposed in references [25] and [26]. Different algorithms increase with the increase of iteration times, and the HV value of BBMOPSO-a algorithm is the highest, with a maximum value of 34726, a minimum value of 9171, and an average value of 24892. In contrast, the algorithm proposed in reference [26] has the smallest HV value, with a maximum value of 19491, a minimum value of 8680, and an average value of 14085. Figure 7b shows that as the number of iterations increases, the overall increase in HV value of BBMOPSO-A algorithm is greater than that of SMOPSO/D algorithm, the algorithms proposed in references [25,26]. In the optimization of building energy-saving design, BBMOPSO-A algorithm exhibits better performance than other algorithms. The HV value of BBMOPSO-A algorithm is not only relatively high on average, but also shows a more significant growth trend during the iteration process. This reflects that the algorithm can more effectively explore and utilize new solutions when searching the solution space, thereby finding a solution set closer to the ideal Pareto front in multi-objective optimization problems. The high efficiency and effectiveness of algorithms also mean that they can be applied in the early stages of the design process, providing support for conceptual design and scheme evaluation. This can not only reduce the cost and time of later design modifications, but also help the project team better meet customer expectations and market demand. The comparison

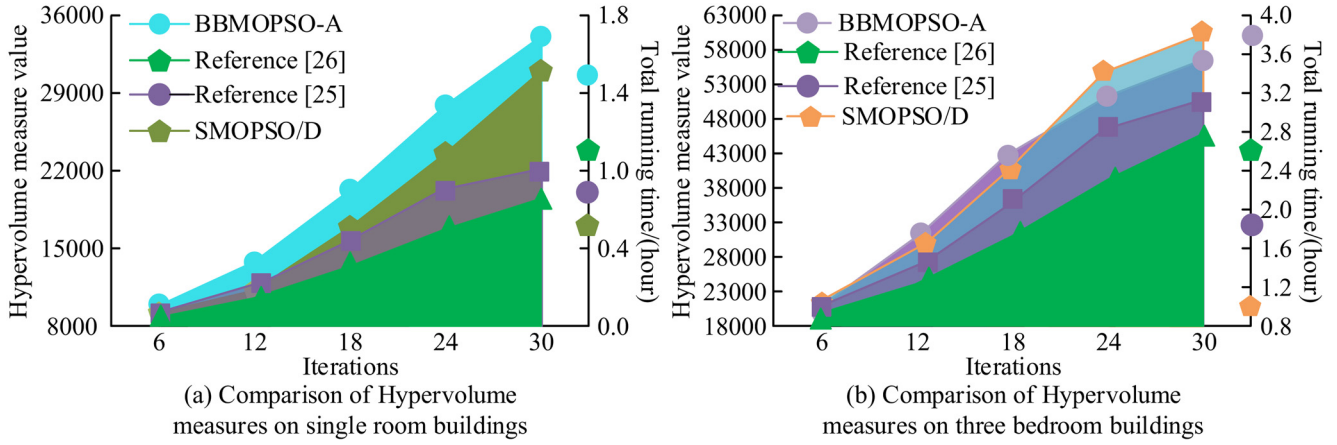


Fig. 7. Comparison of over volume measurement between BBMOPSO-A algorithm and SMOPSO/D algorithm in energy efficiency design of single-room and three-room buildings.

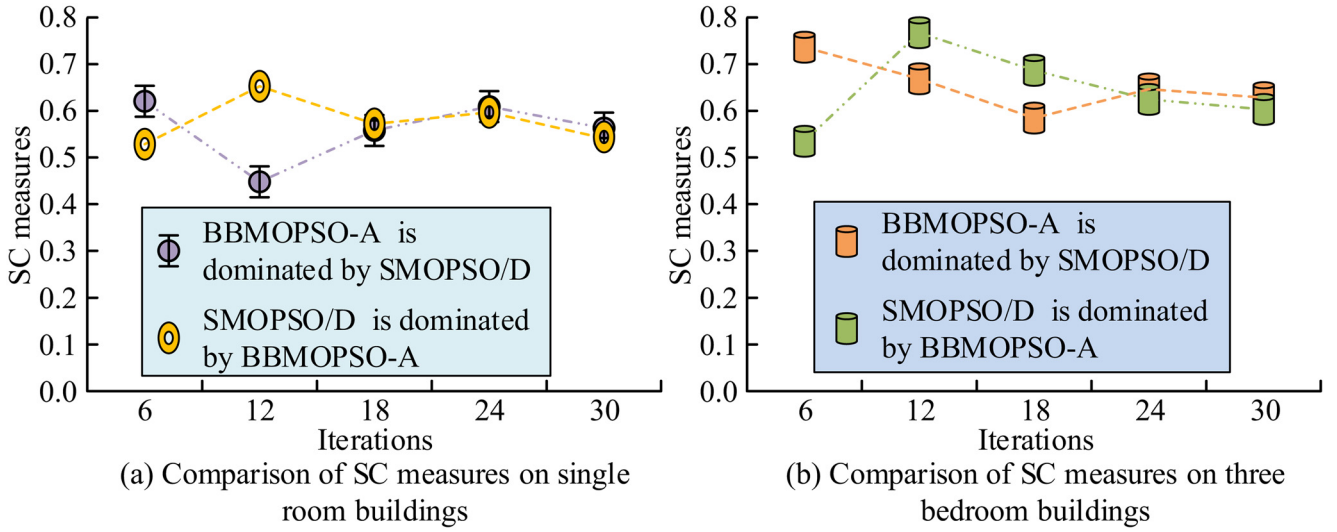


Fig. 8. Comparison of SC measures between BBMOPSO-A algorithm and SMOPSO/D algorithm in energy-saving design of single room and three bedroom buildings.

of SC metrics between BBMOPSO-A algorithm and SMOPSO/D algorithm on one bedroom and three bedroom BEED is shown in Figure 8. Comparison of the SC measures of the BBMOPSO-A algorithm and the SMOPSO/D algorithm on the one-room and three-bedroom BEEDs is shown in Figure 8.

In Figure 8a, as the maximum iterations varies, the proportions of advantage of the BBMOPSO-A algorithm over the SMOPSO/D algorithm are 0.617, 0.463, 0.527, 0.598, and 0.539, respectively. In contrast, the proportions of advantage of the SMOPSO/D algorithm over the BBMOPSO-A algorithm are 0.533, 0.654, 0.554, 0.557 and 0.536. In Figure 8b, the proportions of dominance of the BBMOPSO-A algorithm over the SMOPSO/D algorithm are 0.709, 0.655, 0.594, 0.646, and 0.639, respectively. Meanwhile, the proportions of dominance of the SMOPSO/D algorithm over the BBMOPSO-A algorithm are 0.514, respectively, 0.723, 0.664, 0.631 and 0.623. Comparison of CV and MAPE values of BBMOPSO-A and SMOPSO/D algorithms on one-room and three-bedroom BEEDs are shown in Table 2.

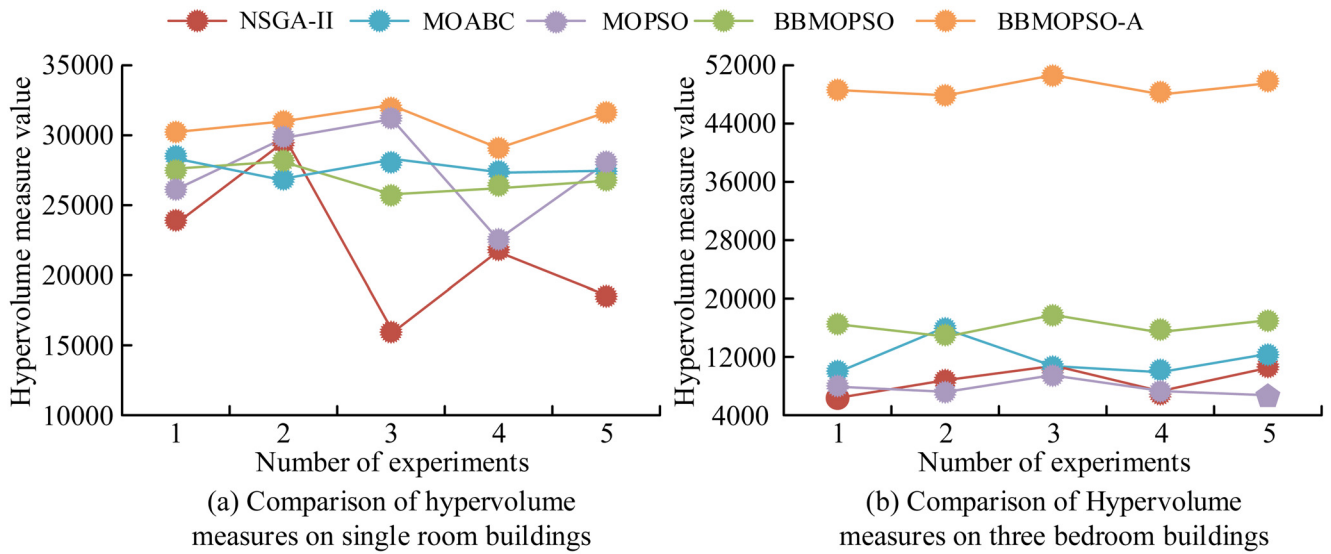
In Table 2, the BBMOPSO-A algorithm has a range of CV values from 0.016 to 0.019 and MAPE values from 0.013 to 0.017 in the energy consumption objective function. The SMOPSO/D algorithm has a better performance in both aspects, with a range of CV values from 0.019 to 0.021 and MAPE values from 0.009 to 0.013.

4.2 Performance validation of multi-objective optimization method based on agent-assisted backbone MOPSO

To validate the performance of the BBMOPSO-A algorithm, it is compared with NSGA-II, MOABC and MOPSO algorithms. With a maximum of 25 iterations and a starting population size of 60, the assessment metrics comprise HV and SC measures. The experiments were selected for energy efficient design of one- and three-bedroom buildings in Tianjin, using EnergyPlus v9.5.0 and MATLAB R2020a software. The experiment was carried out with five replications. The HV comparisons of different algorithms on single and three-bedroom buildings are shown in Figure 9.

Table 2. Comparison of CV and MAPE values between BBMOPSO-A algorithm and SMOPSO/D algorithm in energy-saving design of single room and three bedroom buildings.

Algorithm	Situation	CV			MAPE		
		Number of experiments			Number of experiments		
		1	2	3	1	2	3
BBMOPSO-A	Energy consumption objective function	0.017	0.019	0.016	0.013	0.017	0.009
	Number of uncomfortable hours	0.026	0.023	0.022	0.027	0.031	0.024
SMOPSO/D	Energy consumption objective function	0.012	0.014	0.08	0.007	0.009	0.006
	Number of uncomfortable hours	0.019	0.021	0.020	0.009	0.08	0.013

**Fig. 9.** Comparison of hypervolume measurements using different algorithms in single room and three bedroom buildings.

Analyzing the single room building in Figure 9a, the HV values for the NSGA-II algorithm range from a maximum of 29,765 to a minimum of 15,226 with a mean of 21,677. The reason for the lowest average HV value of the NSGA-II algorithm is that the non-dominant ordering process of NSGA-II becomes computationally intensive on large-scale problems, affecting the efficiency of the algorithm. For the MOABC algorithm, the values range from a maximum of 29,040 to a minimum of 27,461 with a mean of 27,899. Finally, the MOPSO algorithm has values ranging from a maximum of 30,041 to a minimum of 23,194 with a mean of 27,277. The reason why the average HV value of the MOABC algorithm is lower than the BBMOPSO algorithm is very sensitive to parameter settings, and improper parameter selection may lead to a performance degradation. The BBMOPSO algorithm has a range between 25554 and 28489, with a mean value of 27974. The reason for the highest average HV value of the BBMOPSO algorithm is that AAM can help the algorithm to achieve a better balance between global search and local search. By being guided by the AAM, the algorithm can more effectively avoid falling into the local optima, while maintaining the search for the global optimal solution. In Figure 9b, for the three-bedroom building, the HV values of the NSGA-II

algorithm ranges from a maximum value of 10632 to a minimum value of 468 with a mean value of 6169.5. The MOABC algorithm ranges from a maximum value of 12784 to a minimum value of 9087 with a mean value of 9251.9. Comparison of SC measures for different algorithms on single and three-bedroom buildings is shown in Figure 10.

According to Figure 10a, the NSGA-II algorithm is completely dominated by the BBMOPSO-A algorithm in a single room building by a ratio of 1, while the MOABC and MOPSO algorithms are in the range of 0.30 to 0.38 and 0.32 to 0.47, respectively. The BBMOPSO algorithm is in the range of 0.17 to 0.32. According to Figure 10b, the NSGA-II algorithm is completely dominated by the BBMOPSO-A algorithm in the three-bedroom building, with the MOABC and MOPSO algorithms in the ranges of 0.31 to 0.39 and 0.33 to 0.46, and the BBMOPSO algorithm in the range of 0.33 to 0.38. Therefore, the BBMOPSO-A algorithm performs better in terms of performance. A comparison of the Pareto fronts of the different algorithms on single and three-bedroom buildings is shown in Figure 11.

Figure 11 displays a graph with the horizontal axis representing total energy consumption and the vertical axis representing discomfort time. As depicted in Figure 11a, a one-bedroom building experiences a range of discomfort

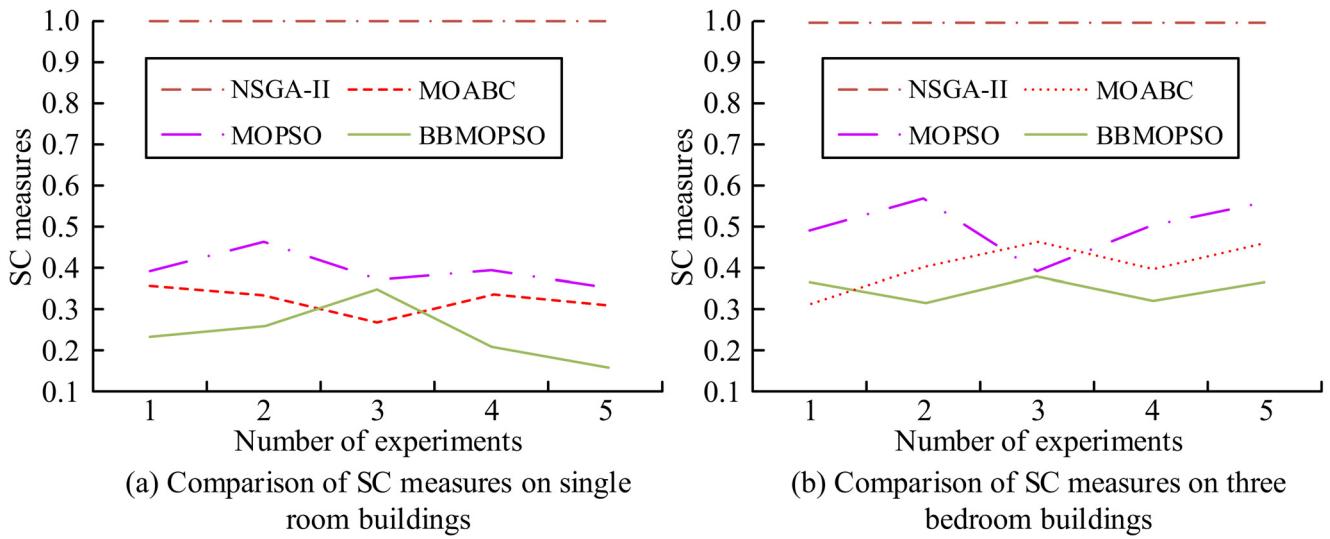


Fig. 10. Comparison of SC measures using different algorithms in single room and three bedroom buildings.

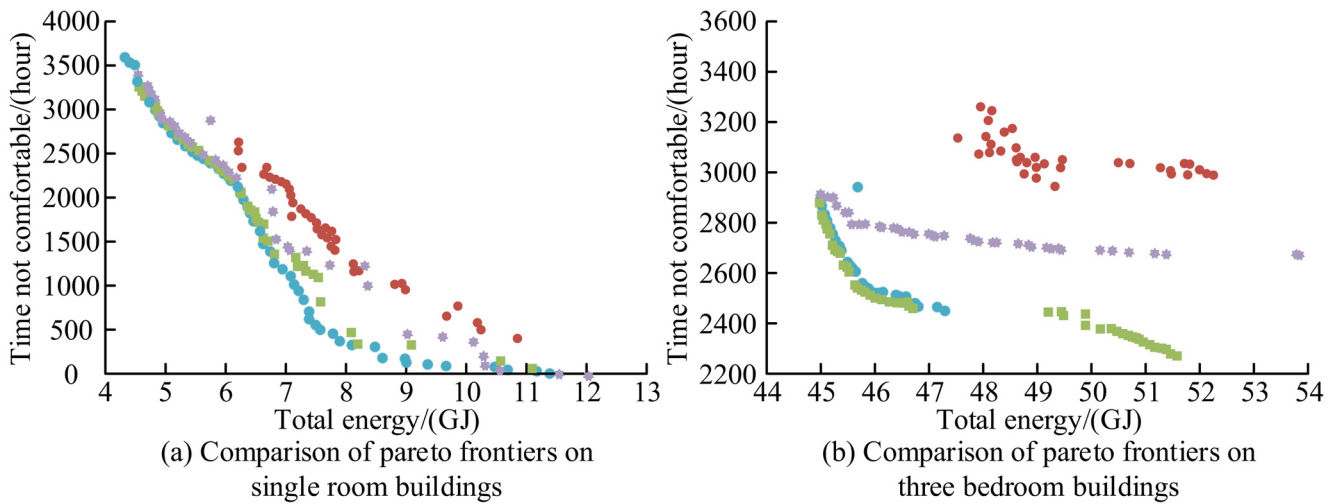


Fig. 11. Comparison of pareto frontiers of different algorithms in single room and three bedroom buildings.

times from 487 to 2632 for the NSGA-II algorithm. The MOPSO algorithm varies from a maximum value of 3448 to a minimum value of 0, whereas the MOABC algorithm goes from a maximum value of 3314 to a minimum value of 13. Furthermore, the BBMOPSO-A algorithm's range extends from a minimum value of 0 to a maximum value of 3601. The BBMOPSO-A algorithm in a three-bedroom apartment is found to be uncomfortable between a maximum value of 2950 and a minimum value of 2430, as shown in Figure 11b.

5 Conclusion

The study presents an enhanced MOO algorithm for green building design. The algorithm combines adaptive perturbation factors with the decomposition-based agent model and particle swarm optimization techniques. The complex BEED problem is decomposed into several sub problems, and the agent model aids in achieving a balanced and comprehensive optimization of multiple objectives. The

research focuses on key metrics in BEED, such as energy consumption, thermal comfort and light intensity. The study findings demonstrated that the HV values were significantly higher for the BBMOPSO-A algorithm in both single and three-bedroom buildings, compared to the other algorithms tested. In single-room buildings, BBMOPSO-A algorithm had a predominance over NSGA-II, MOABC, MOPSO, and BBMOPSO algorithms of 1, 0.3172, 0.3807, and 0.2246, respectively. Similarly, in three-bedroom buildings, the BBMOPSO-A algorithm performed better than the other algorithms, with a predominance of 1, 0.3931, 0.4546, and 0.3553 for NSGA-II, MOABC, MOPSO, and BBMOPSO, respectively. Additionally, the BBMOPSO-A algorithm took 1.5 and 3.8 h to run for the one- and three-bedroom buildings, respectively, while the SMOPSO/D algorithm took 0.8 and 1.1 h, respectively, indicating greater efficiency. The research model, while relatively simple, still faces issues such as parameter sensitivity and poor interpretability. Future research could develop a multi criteria decision support

system to help designers make trade-offs between multiple optimization objectives and provide more intuitive decision support. For large-scale problems, consider applying meta-heuristic algorithms such as genetic algorithms or evolutionary strategies to optimize algorithm parameters, which can effectively find the optimal solution in a large search space.

Funding

This research received no external funding.

Conflicts of interest

The authors declare no conflict of interest.

Data availability statement

All data generated or analysed during this study are included in this published article.

Author contribution statement

This article proposes a method based on big data analysis and cluster analysis to design data analysis techniques for enterprise intelligent manufacturing, and conducts performance testing on the proposed improved algorithm. Chaoqin Bai analyzed the data and Zhuoyue Yang helped with the constructive discussion. Chaoqin Bai and Zhuoyue Yang made great contributions to manuscript preparation. All authors read and approved the final manuscript.

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Cite this article as: C. Bai and Z. Yang: Optimization method of building energy efficiency design based on decomposition multi objective and agent assisted model. *Sust. Build.* **7**, 4 (2024), <https://doi.org/10.1051/sbuild/2024005>