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Research paper

Efficiency multi-agent model assisted Moea/D algorithm for optimization design for building taking into account annual energy consumption and annual user discomfort hours

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Abstract: Recently, with the continuous consumption of energy, building energy conservation has been popular in the energy field. In response to the high computational cost, slow convergence speed, and low accuracy of existing optimization design methods for building energy efficiency, this study first built a multi-objective optimization model for building energy efficiency on the ground of the annual energy consumption of buildings and the quantity of uncomfortable hours for users. Then it introduces a multi-agent model auxiliary mechanism to improve the decomposition based multi-objective evolutionary optimization algorithm, and then solves the multi-objective optimization model for building energy efficiency. In order to select the optimal decision variable of the algorithm, the decision parameters were analyzed and found that the performance was optimal when the number of samples, aggregation number and base model were set to 25.3 and 20. The improved multi-objective evolutionary optimization algorithm on the ground of decomposition has average supervolume and running time values of 32416.13 and 1774.58 seconds under office buildings, and 7899.13 and 3616.96 seconds under residential buildings, respectively. In addition, the annual user discomfort time of office buildings is 555.28h, which is lower than other comparison algorithms. In summary, the optimal performance of the algorithm when the decision variable is set to 25.3 and 20. The algorithm proposed by the research institute has superior performance and has certain application value in selecting the optimal solution for building energy-saving design.

Keywords: multi-agent model, multi-objective optimization evolutionary algorithm based on decomposition, energy efficiency, annual energy consumption, annual user discomfort hours

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1. Introduction

Energy is the cornerstone of the operation of modern society, and the national economy, people's livelihood and national security are crucial to improving people's well-being and promoting economic and social development [1, 2]. The energy consumption of the construction industry is the main component of the global energy consumption. However, with the increasing shortage of energy resources and the increasing aggravation of environmental pollution, building energy conservation has become the focus of people's attention. In order to realize sustainable development, building energy conservation has become one of the important policy directions of various governments [3, 4]. However, due to the complexity of building energy consumption, building structure, system design and other factors, the traditional single-target optimization method often can not solve the problem of building energy conservation. Multi-objective Optimization Evolutionary Algorithm Based On Decomposition (MOEA/D) is an evolutionary algorithm used to solve multi-objective optimization problems [5]. MOEA/D handles by splitting the multi-objective optimization problem into a set of sub-problems. Each subproblem focuses on only one aspect of the optimization objective, and the global optimal solution is found through interactions between the subproblems [6]. Such a decomposition approach can significantly reduce the complexity of the multi-objective optimization problem. Therefore, the MOEA/D algorithm can comprehensively consider the energy consumption, living comfort, environmental impact and economic benefits of energy-saving buildings, and help designers to make correct decisions. However, because the MOEA/D algorithm also has the problem of high computational cost. Multi-agent Model Assistance (MMA) mechanism is an auxiliary mechanism for multi-objective decision problems in the optimization algorithm. This mechanism assists the master optimization algorithm by introducing multiple agent models to improve the quality of the search efficiency and reconciliation of the algorithm [7]. In the MODEA/D algorithm, the MMA mechanism can accelerate the search process through parallel computing, and with the assistance of multiple agent models, it can provide a more comprehensive collection of solutions. Therefore, the study proposes to improve the MOEA/D algorithm based on the MMA mechanism, and here to improve the MOEA/D algorithm to build a multi-objective optimization model of building energy saving. This study aims to provide an innovative approach for the field of BEE to achieve sustainable, efficient, and environmentally friendly building design, thereby addressing increasingly serious energy and environmental challenges. There are two main innovative research points. The first point is to construct a MOO model for BEE on the ground of the contradictory performance indicators of BEC and user discomfort. The second point is the introduction of the MMA mechanism, which autonomously determines the basic proxy model that needs to be updated on the ground of the degree of change in the optimal solution on each reference weight vector. The research structure contains four. The first summarizes relevant research outcomes. The second is the optimization of building energy-saving design (BESD) on the ground of MOEA/D. The third is to verify the feasibility of the presented algorithm. The final is a summary of the relevant results.

2. Related works

BEE refers to the design that reduces BEC and improves its efficiency while ensuring the basic functions and requirements of the building. Many scholars have conducted in-depth discussions on how to carry out energy-saving design work in buildings. Ostadijafari and Dubey proposed a pipeline based model predictive controller to minimize the net energy cost of building air conditioning systems while satisfying the comfort of building occupants. The research results indicate that the controller has low computational complexity and performs well in achieving the economic goal of cost minimization [8]. The Wen team took Nanjing Metro Station as an example and proposed new measures to improve ventilation efficiency from the perspective of architectural design. This includes increasing the atrium space, increasing atrium vents, and funnel shaped exits, and using dynamic grid based computational fluid dynamics methods to simulate ventilation performance under piston effect. The research results found that the optimized building design can significantly improve the airflow environment and ventilation efficiency, and decrease BEC [9]. Zeng et al. discussed the impact of adjusting the evaporative cooling system of variable air volume fan coil on temperature and humidity for optimizing the EC of the evaporative cooling system. Simulation experiments have shown that higher fan frequencies have more intensive EC during the cooling process compared to lower fan frequencies, so fan frequencies should be reduced within a reasonable range [10].

Optimization of BESD is a typical MOO problem. This usually involves balancing and optimizing multiple objectives such as energy efficiency and indoor comfort. Shao et al. focused on rural single story independent residential buildings and used the conflicting indicators of BEC, thermal comfort, and economy as objective functions. They proposed a BESD algorithm that combines EnergyPlus simulation software and multi-objective Bayesian optimization. The simulation findings confirm the feasibility of the energy-saving design algorithm for the building [11]. The Le Gia team used the Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm. It is combined with building simulation, to study the trade-off between investment cost and EC optimization to improve BEE, reduce carbon dioxide emissions, and minimize life cycle costs. The research results found that the optimal solution of the NSGA-II algorithm presents a trade-off between EC and capital cost in the form of Pareto frontier [12]. Liu and Guo first elaborated on the relevant methods affecting green building materials (GBM) to explore the impact of green materials on BEE optimization, and provided intervals and standards for quantitative evaluation. Then relevant researchers constructed a GBM optimization selection model and proposed a multi-objective energy-saving optimization algorithm. The simulation experimental results provide scores for the green level and environmental impact factors of several candidate GBM, verifying the effectiveness of the relevant optimization algorithm [13].

At the same time, there are more and more research on target optimization and classification. Delgarm et al. proposed to build a multi-objective optimization method for building energy efficiency and indoor thermal comfort based on the multi-objective artificial bee swarm (MOABC) optimization algorithm and EnergyPlus building energy simulation tool, studied the effectiveness of the development and found that the method is more better than the traditional single-objective optimization method. Chegari et al [14]. To improve the indoor thermal comfort and energy performance of residential buildings, proposed to construct an efficient multi-objective optimization method based on multi-objective genetic algorithm, analyzed the effectiveness of this method, and found that its maximum expected performance was better than other comparison methods [15]. In order to develop a versatile energy consumption method, Khan et al. proposed to build a multi-objective optimization method using genetic algorithm, Rhinoceros 3D software and Grasshopper plug-in simulation optimization process to verify the effectiveness of the method and found its increase by 34.84% compared with the traditional method [16].

3. Multi-objective decision-making optimization for BEE on the ground of MMA-MOEA/D algorithm

In the optimization of BESD, BEC and user discomfort are contradictory performance indicators. In response to the above issues, this study constructed a MOO model for BEE and solved it using the MOEA/D algorithm.

3.1. Construction of MOEA/D algorithm for MOO of BEE

BESD is the utilization of reasonable design strategies and technical means for optimizing the energy utilization of buildings, such as heat, light, and gas, while meeting the basic functions and requirements of buildings. It aims to minimize BEC, improve energy utilization efficiency, and achieve sustainable utilization and protection of environmental resources [17]. In the optimization of BEE design, Annual Energy Consumption (AEC) and Annual User Discomfort Hours (AUDH) are two main criteria. AEC refers to the total EC of a building within a year, used to evaluate the energy efficiency and energy-saving status of the building. AUDH refers to the total time that uncomfortable conditions occur inside a building within a year, which is used to evaluate the comfort level of the indoor environment of the building. However, there is a conflict and constraint between the building's annual energy consumption and the annual user uncomfortable hours, that is, improving one target may harm other targets. Therefore, the research goal is to obtain a set of optimal solutions by finding a balance point between the two goals. The reduction of AEC usually leads to an increase in AUDH. For enhancing BEE design, this study constructs a MOO model for BEE on the ground of this, as showcased in Eq. (3.1).

$$\left\{ \begin{array}{l} \min F = (\mathrm{AEC}\,(X), \mathrm{AUDH}\,(X)) \\ \mathrm{s.t.} X = \begin{pmatrix} x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, \\ x_{12}, x_{13}, x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19} \end{pmatrix} \end{array} \right. \tag{3.1}$$

In Eq. (3.1), the determination of X depends on the orientation of the room x_1, thermal conductivity of wall insulation material x_2, the solar absorption rate x_3 of the external wall, the heat transfer coefficient x_4 of the window, the solar heat gain coefficient x_5 of the window, the length x_6 of the living room window, the width x_7 of the living room window, the length x_8 of the bedroom window, the width x_9 of the bedroom window, the length x_{10} of the kitchen window, the width x_{11} of the kitchen window, the length x_{12} of the bathroom window, and the width x_{13}

of the bathroom window. X also depends on decision variables such as living room lighting density x_{14}, bedroom lighting density x_{15}, kitchen lighting density x_{16}, bathroom lighting density x_{17}, air conditioning system heating setting temperature x_{18}, and air conditioning system cooling setting temperature x_{19}. The range of decision variables is determined on the ground of BEE design standards. The decision variables are constrained by building materials, building structure, building equipment, building layout and building peripheral environment. For example, in terms of building materials and structures, the materials with high thermal insulation performance are selected to optimize the heat insulation performance of the building and reduce the energy loss. To solve the MOO model for BEE, this study proposes a BEE design method on the ground of MOEA/D. The MOEA/D algorithm decomposes MOO problems into some single objective sub optimization issues, and utilizes a certain number of individual information from adjacent problems to independently solve each sub problem through evolutionary mechanisms. By comprehensively considering all sub problem solution sets, the overall Pareto optimal solution set is obtained [18]. The study chose the Chebyshev method for solving. The objective function aggregation form of the Chebyshev method is shown in Eq. (3.2).

$$\min g^{tche}\left(X|\lambda, Z^*\right) = \max_{1\le i\le M}\left\{\lambda|f_i\left(X\right) - Z_i^*\right\} \tag{3.2}$$

In Eq. (3.2), λ is the reference weight vector. Z^* is the reference point. The 1 determination of Z^* is shown in Eq. (3.3).

$$Z^* = \min\left\{f_i\left(X\right)|X \in \Omega\right\}, \quad i \in \{1, 2, \cdots, M\} \tag{3.3}$$

In Eq. (3.3), Ω is the decision space. M serves as the quantity of targets. This study is on the ground of the MOEA/D algorithm, which first utilizes decomposition method for spliting the problem into multiple sub optimization problems, as well as uses the information of adjacent sub problems to update individual positions. This is for avoiding the population dropping into local optima, so the steps of the BESD method on the ground of MOEA/D are shown in Fig. 1.

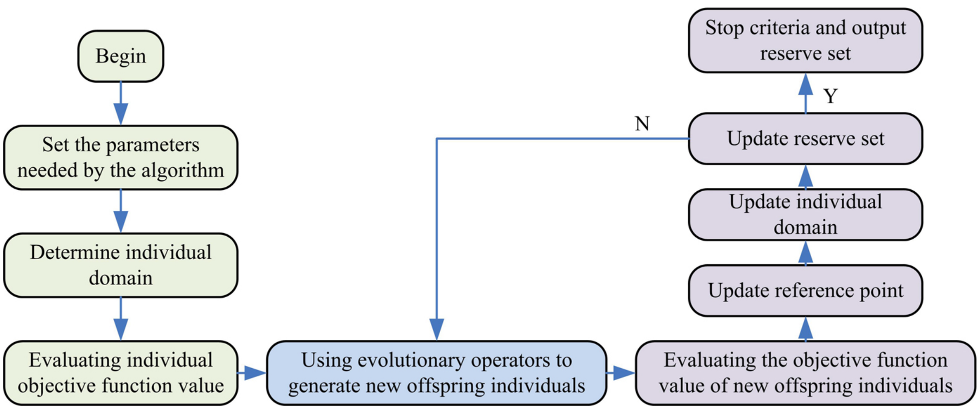

Fig. 1. Methods and steps of BESD on the ground of MOEA/D

The steps in Fig. 1 are as follows: first, set the required parameters and reserve set for the algorithm, and then determine the domain of each individual for evaluating the objective function values of each independent individual. Then, the study uses evolutionary operators to generate new offspring individuals and continues to evaluate their objective function values. It updates reference points and individual domains, thereby updating the reserve set. If the stop condition is satisfied, the reserve set is output. If not, the method continuously produces new offspring individuals through the calculation operator. According to the proposed BESD method, this study could get a set of Pareto optimal solutions that are not mutually dominant. Meanwhile, the BESD method on the ground of MOEA/D also provides a compromise solution selection strategy on the ground of fuzzy decision technology, which can select the most suitable solution from many Pareto optimal solutions. The study randomly select an individual a1 and a2 from the Pareto optimal solution. We can obtain an evolutionary operator a3, which is the first target value of the decision maker. Fuzzy decision technology defines the satisfaction level χ_i^k of the decision-maker with the second objective value as Eq. (3.4).

$$\chi_i^k = \begin{cases} 1, & f_i(X_k) \leq f_i^{\min} \\ \dfrac{f_i^{\max} - f_i(X_k)}{f_i^{\max} - f_i^{\min}}, & f_i^{\min} < f_i(X_k) < f_i^{\max} \\ 0, & f_i(X_k) \geq f_i^{\max} \end{cases} \tag{3.4}$$

In Eq. (3.4), $f_i^{\min}$ and $f_i^{\max}$ represent the mini and max values of the i-th objective function. The definition of the normalized membership function χ^k corresponding to X_k is shown in Eq. (3.5).

$$\chi^k = \sum_{i=1}^{M} \chi_i^k \Bigg/ \sum_{k=1}^{|SET|} \sum_{i=1}^{M} \chi_i^k \tag{3.5}$$

In Eq. (3.5), $|SET|$ serves as the quantity of elements in the set SET. The compromise solution strategy on the ground of fuzzy decision technology is the solution with the maximum χ^k value in SET.

3.2. Improvement of MOEA/D algorithm combining MMA mechanism

During the solving process, the BEE design method on the ground of MOEA/D requires repeated evaluation of individual fitness values, which is costly to execute and does not satisfy the needs of BEE design. In response to the above issues, this study introduced the MMA mechanism to improve the MOEA/D algorithm, resulting in the MMA-MOEA/D algorithm. The MMA-MOEA/D algorithm mainly consists of four modules: construction and management of multi-agent models, population update on the ground of MOEA/D, individual evaluation on the ground of adjacent agent aggregation, and update of reference points. The construction and management module of the multi-agent model contains two: the construction and update of the multi-agent model, and the generation of filled samples. The construction update of a multi-agent model refers to generating an initial basic agent model for each objective function on λ to evaluate the optimal solution of the sub optimization problem determined by λ. λ represents the weight vector, where multiple objective functions can be linearly combined into a single integrated objective function. By optimizing on different weight vectors, a solution set for multiple targets. If the proxy model used is not accurate, it is essential for updating the proxy model until the accuracy of the proxy model is optimal. The prerequisite for updating the proxy model is that the basic proxy model corresponding to a weight vector will only be updated when the optimal solution of the weight vector remains unchanged for multiple generations. For individual X, its uncertainty level is shown in Eq. (3.6).

$$u(X) = \frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{\zeta+1}\sqrt{\frac{\left(\widehat{f}_i^j(X) - \overline{f}_i(X)\right)^2}{\zeta+1}} \tag{3.6}$$

In Eq. (3.6), $\widehat{f}_i^j(X)$ and ζ respectively represent the proxy model evaluation value and domain size of individual X. $\overline{f}_i(X)$ refers to the average approximate value of solution X on the i th target. When training the proxy model, it is required that the input samples have the same dimension and length. Therefore, it is essential for filling in the generated samples for satisfying the needs of the model input. The individual evaluation on the ground of adjacent agent aggregation is mainly utilized for evaluating the objective function values of individuals in the predicted population. By aggregating $\zeta + 1$ evaluation results, the final objective value of X_i is obtained, as shown in Eq. (3.7).

$$\widehat{f}_m(X_i) = \sum_{j=0}^{\zeta} w_j \times \widehat{f}_m\left(X_i|SM - \lambda_i^j\right), \quad m = 1, 2, \cdots, M \tag{3.7}$$

In Eq. (3.7), $SM - \lambda_i^j$ is the $\zeta + 1$ basic proxy model corresponding to the $\zeta + 1$ reference weight vectors. $\widehat{f}_m\left(X_i|SM - \lambda_i^j\right)$ is the set of individual target values for $\zeta + 1$ pair of the basic proxy model. w_j serves as the weight of $SM - \lambda_i^j$, which determines the accuracy of individual evaluation values, as shown in Eq. (3.8).

$$w_j = 0.5\frac{\left|\lambda_i^0 - \lambda_i^j\right|^{-1}}{\sum_{q=1}^{\zeta}\left|\lambda_i^0 - \lambda_i^q\right|^{-1}} \tag{3.8}$$

In Eq. (3.8), $\left|\lambda_i^0 - \lambda_i^j\right|^{-1}$ is the reciprocal of the distance between λ_i^0 and λ_i^j. The larger the $\left|\lambda_i^0 - \lambda_i^j\right|^{-1}$ value, the greater the weight of $SM - \lambda_i^j$. The quality of reference point Z^* is related to the distribution and convergence of the obtained Pareto front-end. The study determines a new reference point Z_m^* on the ground of the actual target value and predicted target value, as shown in Eq. (3.9).

$$Z_m^* = \begin{cases} f_m^{\min}, & f_m^{\min} < \widehat{f}_m^{\min} \\ \frac{t}{T_{\max}} \times f_m^{\min} + \left(1 - \frac{t}{T_{\max}} \times \widehat{f}_m^{\min}\right), & \text{otherwise} \end{cases} \tag{3.9}$$

In Eq. (3.9), t and $T_{\max}$ serve as the number of iterations and the maximum of updates to the proxy model. $f_m^{\min}$ is the minimum value of the t objective functions saved in the m-th iteration. $\widehat{f}_m^{\min}$ is the minimum value of m objective functions stored in the solution set evaluated by the proxy model. When $f_m^{\min} < \widehat{f}_m^{\min}$, $f_m^{\min}$ is chosen as a new reference point to expand the population search range. When $f_m^{\min} > \widehat{f}_m^{\min}$, directly selecting $\widehat{f}_m^{\min}$ as the new reference point may result in invalid target areas. To implement the MMA-MOEA/D algorithm proposed in the study, the EnergyPlus software was used to simulate the energy behavior of buildings, as shown in Fig. 2.

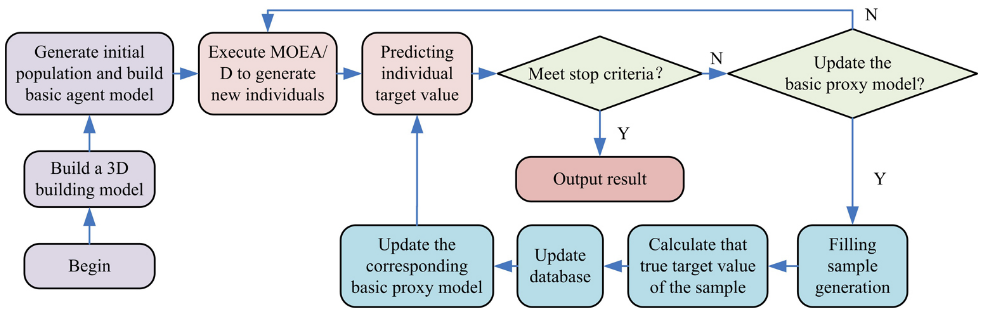

Fig. 2. Execution flow of MMA-MOEA/D algorithm

In Fig. 2, the study first drew the desired optimized 3D model of the building to generate an initial population and construct N basic proxy models. On this basis, MOEA/D is used to generate new individuals to predict individual target values. Then it determines whether the basic proxy model needs to be updated. If it needs to be updated, use EnergyPlus software to output the AEC and AUDH objective function values, and retrain the basic proxy model that needs to be updated. If not required, continue running the MMA-MOEA/D algorithm until the algorithm satisies the termination condition. For the MOO model of BEE, the computational complexity of the algorithm is also a key issue that needs paying attention to, as shown in Eq. (3.10).

$$C = RFEs \times C_F + C_s + C_g + t_{\max} \times C_{\text{other}} \tag{3.10}$$

In Eq. (3.10), $RFEs$ is the actual number of individuals evaluated by EnergyPlus. $t_{\max}$ serves as the total of algorithm iterations. C_F, C_s, C_g, and C_{other} represent the actual target value evaluation, proxy model construction update, sample generation filling, and other computational costs required to update the population, respectively. The calculation of C_s is shown in Eq. (3.11).

$$C_s = (2N + T_s) \cdot O\left(\zeta^3\right) \tag{3.11}$$

In Eq. (3.11), T_s is the number of updates to the proxy model, and $O\left(\zeta^3\right)$ is the computational complexity of training the radial basis function model. Due to C_F's greatest contribution to the computational complexity of the algorithm and its relatively high computational cost, the final computational complexity expression of the MMA-MOEA/D algorithm is showcased in Eq. (3.12).

$$C \approx RFEs \times C_F + (2N + T_s) \cdot O\left(\zeta^3\right) \tag{3.12}$$

4. Analysis of multi-objective decision-making optimization effect for BEE on the ground of MMA-MOEA/D

For testing feasibility of the proposed algorithm, this study takes a class of residential and office buildings in a certain city area as application objects, and sets up multiple control groups.

4.1. Effectiveness analysis of MOEA/D algorithm

This study takes a class of office buildings and residential buildings in a certain city area as application objects for verifying the effectiveness of the algorithm. The total area of office buildings is 31.68 square meters, and the total area of residential buildings is 110 square meters. The length and width of windows in residential buildings are determined by the size of the building model room, and the remaining variable values are determined according to the BESD standards. The length, width and height of the office building are set as 8.8, 3.6, 3.9 m respectively, and the personnel density and lighting density are set as 3.5 m^2/person and 9 w/m^2 respectively. The return air volume coefficient, radiation coefficient and visible light coefficient of residential buildings are 0.37 and 0.18, respectively. The coefficient of heat transfer of the light to the area air is 0.40. 10 parameters such as the building orientation, the length and width of Windows in each heat area, the window heat transfer coefficient and the solar heat coefficient, the thermal conductivity of wall insulation material are considered as the decision variables of this model. Their values are shown in Table 1.

Table 1. Value of the decision variables

Decision variable	**Unit**	**Reference value**	**Decision variable**	**Unit**	**Reference value**	**Decision variable**	**Unit**	**Reference value**
Building orientation	◦	0	The heat factor of the sun	/	0.65	Toilet Lighting density	w/m^2	7
Thermal conductiv-ity	m	0.043	Kitchen lighting density	w/m^2	5.5	Set temperature	◦	25
Solar absorption rate	/	0.6	Bedroom lighting density	w/m^2	6	Set the heating temperature	◦	20

This study selected the Strength Pareto Evolutionary Algorithm (SPEA), S-Metric Selection Evolutionary Multiobjective Optimization Algorithm (SMSEMOA) and NSGA-II algorithms against the MOEA/D algorithm. The experimental platform is MATLAB software and EnergyPlus. The experiment was conducted on a personal computer with an Intel(R)Core i7 i7-7700k S R338@3.60.GHz. The performance indicators are Hyper Volume (HV), AEC, and AUDH, where the larger the HV value, the more excellent the algorithm convergence.

Table 2 showcases the HV values obtained from two algorithms used for office and residential buildings. For office buildings, the max, mini, and average HV values of the MOEA/D algorithm are 32835.47, 7372.54, and 19691.24, respectively, which are higher than the NSGA-II algorithm's 16718.45, 5563.72, and 12743.13. For residential buildings, the maximum HV values of MOEA/D and NSGA-II algorithms are 6556.45 and 3844.47 respectively, the minimum HV values are 928.38 and 902.25 respectively, and the average HV values are 5648.62 and 3212.84 respectively.

Table 2. HV value results of two algorithms

Building type	**Algorithm category**	**Maximum**	**Minimum**	**Average**
Office buildings	MOEA/D	32835.47	7372.54	19691.24
	NSGA-II	16718.45	5563.72	12743.13
	SPEA	14632.33	5321.22	10724.03
	SMSEMOA	15734.71	5039.25	9843.99
Residential buildings	MOEA/D	6556.45	928.38	5648.62
	NSGA-II	3844.47	902.25	3212.84
	SPEA	3057.45	701.28	2839.55
	SMSEMOA	2987.65	864.85	2127.12

Fig. 3(a) denotes the Pareto frontier from two algorithms for office buildings. The AUDH and AEC of the MOEA/D algorithm are 555.28h and 7.56, which are below the 895.45h and 8.87 of the NSGA-II algorithm. Fig. 3(b) shows the Pareto frontier obtained by two algorithms for residential buildings, with an AUDH of 2835.12 hours and an AEC of 45.98 for the MOEA/D algorithm. The AUDH of the NSGA-II algorithm reaches 2875.23h, and the AEC is 45.72. On the ground of the relevant outcomes, it demonstrates that the MOEA/D algorithm has significant advantages in convergence and distribution.

4.2. Analysis of the application effect of MMA-MOEA/D algorithm

To verify the feasibility of the MMA-MOEA/D algorithm, this study used NSGA-II, MOEA/D, MOABC, and Multi Objective Particle Swarm Optimization (MOPSO) algorithms as control groups for experiments. The population size and maximum iteration times of each algorithm were set to 20 and 50 epochs, respectively. The first results of the HV values of office buildings and residential buildings are shown in Fig. 4.

Fig. 4(a) denotes the HV values of different algorithms for office buildings. The MMA-MOEA/D algorithm has a HV maximum, minimum and mean of 72796.45,20447.46 and 32416.13, which are better than the other algorithms. Fig. 4(b) shows the HV values of residential buildings using different algorithms. The HV maximum, minimum and mean values of MMA-MOEA/D were 10982.23,5708.89 and 7899.13, which were better than the other algorithms.

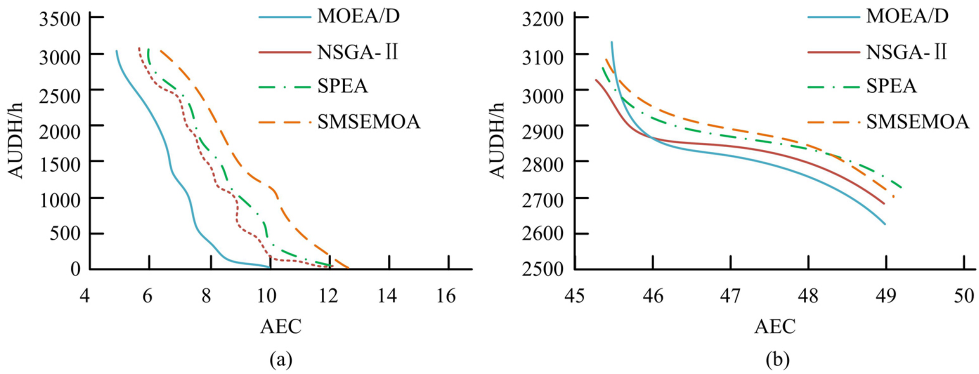

Fig. 3. Pareto frontier obtained by two algorithms: (a) The Pareto frontier of two algorithms in office buildings, (b) The Pareto frontier of the two algorithms in residential buildings

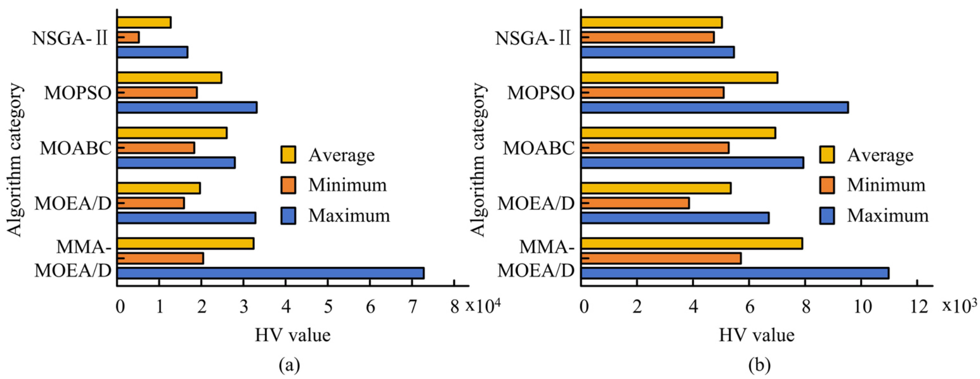

Fig. 4. HV value results of different algorithms: (a) HV values of office buildings with different algorithms, (b) Different algorithms are used HV values of residential buildings

Fig. 5(a) showcases the running time of various algorithms for office buildings. The maximum running times of MMA-MOEA/D, MOABC, and MOPSO algorithms are 2203.68 seconds, 3908.09 seconds, and 3868.59 seconds. The average running time of the MMA-MOEA/D algorithm reaches 1774.58 seconds, which is lower than the 3425.23 seconds and 3415.31 seconds of the MOABC and MOPSO algorithms. The minimum running time of MMA-MOEA/D, MOABC, and MOPSO algorithms is 1666.33 seconds, 3043.71 seconds, and 3.99.57 seconds. Fig. 5(b) shows the running time of various algorithms for residential buildings. The maximum, average, and minimum running times of the MMA-MOEA/D algorithm are 3784.15 s, 3616.96 s, and 3485.20 s, respectively. The maximum, average, and minimum running times of the MOABC algorithm are 6825.56 seconds, 6471.28 seconds, and 6039.18 seconds, respectively. The maximum, average, and minimum running times of the MOPSO algorithm are 7191.59 s, 6735.34 s, and 6422.66 s, respectively. The results in Figs 4 and 5 indicate that the MMA-MOEA/D algorithm possesses the fastest running time and significantly outperforms other algorithms in terms of performance, demonstrating superior performance in MOO problems for BEE.

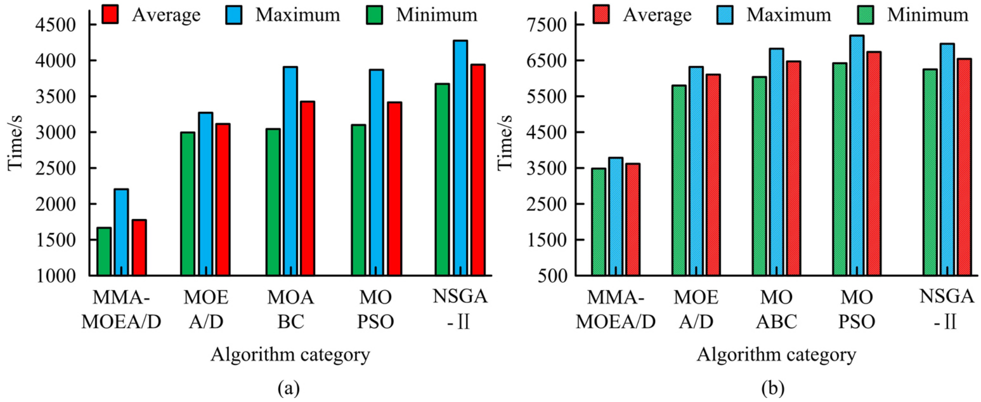

Fig. 5. Running time of different algorithms: (a) The average running time of different algorithms for office buildings, (b) The average running time of different algorithms for residential buildings

5. Conclusions

With the rise of evolutionary optimization based BEE design methods, the field of BEE is also facing new challenges and opportunities. Most BESD methods not only require the use of expensive third-party software to evaluate individual fitness, but also have shortcomings such as long running time, slow convergence speed, and easy local convergence, which are not conducive to achieving building energy-saving goals. In response to the above issues, this study first constructed a MOO model for BEE, and introduced the MMA mechanism to obtain the MMA-MOEA/D algorithm on the ground of the MOEA/D algorithm. Then, the MOO model was solved. The research results show that the AUDH and AEC of the MOEA/D algorithm for office buildings are 555.28 hours and 7.56 hours, respectively, which is 340.17 hours and 1.31 hours less than the NSGA-II algorithm. Compared to the NSGA-II algorithm, the MOEA/D algorithm reduces discomfort time by 1.40% while only increasing EC by 5.69% for residential buildings. For office buildings, the average HV value of the MMA-MOEA/D algorithm is 32416.13, which is higher than the 26031.88 of the MOABC algorithm. The average running time of the MMA-MOEA/D algorithm reaches 1774.58 seconds, which is 1650.65 seconds less than the MOABC algorithm. For residential buildings, the average HV and running time of the MMA-MOEA/D algorithm are 7899.13 and 3616.96 seconds, respectively, which are better than the 6937.54 and 6471.28 seconds of the MOABC algorithm. In summary, the MMA-MOEA/D algorithm possesses robust performance and performs well in the field of BEE. However, there are still shortcomings in the research. Due to the simplicity of the office and residential building models used in the research, they were not designed on the ground of actual building drawings. Further discussion will be conducted on the selection of building model construction in future work.

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