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Research paper

The application of ICPA optimization algorithm in multi-objective optimization structural design of prefabricated buildings

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Abstract: With the prefabricated buildings developing, traditional architectural design methods can no longer meet the requirements of efficient, green, and sustainable development. In view of this, based on the analysis of the framework structure of the cyclical parthenogenesis algorithm, the study introduced chaotic optimization algorithm for improvement. And the improved new algorithm was applied to multi-objective problems in the optimization design of prefabricated building structures. Finally, a novel structural design optimization model was proposed. These experiments confirmed that the improved algorithm had the least 160 iterations and 17 optimal solutions, which was an increase of 15 compared to traditional aphid algorithms. Two function solutions of this new structural design optimization model were both between -0.5 and 0.5, with relatively smaller values. In addition, this model could effectively optimize and transform physical buildings, increasing their structural stability by 2.43%, increasing their structural quality coefficient by 4.49%, reducing vibration cycles by 0.06%, and reducing inter story displacement angles by 0.04%. In summary, the improved cyclical parthenogenesis algorithm has good performance in solving multi-objective problems in prefabricated structures, and can quickly and accurately find the global optimal solution. This study aims to provide guidance for the prefabricated building structure design.

Keywords: aphid algorithm, chaotic optimization, assembly, building, structural design

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1. Introduction

Prefabricated Building (PB) is an efficient, energy-saving, and environmentally friendly building model that has received widespread attention in recent years. However, its structural design faces Multi-Objective Optimization Problem (MOP), such as cost, quality, safety, etc. [1]. However, there are interdependent and contradictory relationships between these objective functions, making the problem complex and difficult to solve. In response to these issues, many scholars have explored methods and proposed problem-solving models such as using neural networks and heuristic algorithms [2]. These methods were indeed able to handle MOP in the past. But as public demand continues to increase and PBs structures are constantly being upgraded and updated, these algorithm models are no longer able to meet high requirements for structural design and target optimization. Cyclical Parthenogenesis Algorithm (CPA), as a traditional optimization algorithm, has a unique biological mechanism and optimization process that can simulate the asexual and sexual reproduction process of aphids to find a solution, and this mechanism provides a good global search capability and a high convergence speed. Compared with other optimization algorithms, such as genetic algorithm and particle swarm optimization algorithm, CPA algorithm provides a different search mechanism and biological principle, which provides a new perspective and method for solving the multi-objective optimization problem of assembly building design [3]. In view of this, the research innovatively takes CPA as the framework foundation, analyzes its structure, and improves it by introducing another optimization algorithm. Thus, a new solution is provided for the Multi-Objective Optimization (MOO) structural design of PBs in a targeted manner.

2. Related works

PB refers to a construction method in which prefabricated components are assembled in a factory or on site to complete the overall building. However, in the structural design of PB, multiple conflicting goals are often faced, such as structural strength, material cost, construction period, etc. [4]. Peng et al. found that as buildings became more environmentally friendly, people's demands for engineering project management were increasing. Therefore, a multi-objective genetic algorithm was combined to propose an optimal design strategy. These experiments confirmed that this strategy had certain advantages in solving MOPs designed for PBs [5]. Yao et al. found that traditional heuristic algorithms still had room for improvement in solving MOPs designed for PBs. Therefore, they proposed an improved multi-population constrained genetic algorithm. These experiments confirmed that this algorithm could improve the quality of the optimal solution and shorten the solving time by 75% [6]. Hui et al. proposed a spatial detection algorithm to address spatial conflicts in PBs hoisting construction design after summarizing three types of conflicts. And a MOP model was established through this algorithm that combined minimizing lifting cycle, crane leasing cost, construction cost, and spatial conflict. These experiments confirmed that it could effectively solve spatial conflicts in PB hoisting construction design, thereby optimizing hoisting progress and improving safety performance [7]. Ma and van Ameijde proposed a PB high-density design optimization model to meet the democratization needs of PB, by combining digital modular building systems and MOO methods. These experiments confirmed that the model could balance complex democratic needs and had a high fault tolerance [8].

ICPA is a commonly used MOO algorithm, which is widely used in many MOPs due to its stronger global search ability and convergence speed. Kaveh et al. proposed a novel optimization design strategy by combining ICPA and azalea search algorithm. This could optimize the design of reinforced concrete cantilever retaining walls under static and dynamic load conditions. These experiments confirmed that this hybrid algorithm could adapt to the design of reinforced concrete cantilever retaining walls under complex conditions and had high completion efficiency [9]. Kaveh and Seddighian proposed a hybrid solution optimization algorithm by combining ICPA and water evaporation optimization algorithms to more accurately decompose the domains of continuous two-dimensional and three-dimensional finite element models. These experiments confirmed that the algorithm had high feasibility and robustness in solving the domain of finite element models [10]. Sun et al. found that traditional iterative algorithms couldn't achieve high standards for calculating the initial position of point clouds in complex environments. Therefore, they proposed an optimized prediction method that combined ICPA and curvature features. These experiments confirmed that the prediction error of this method was about 4.72‰, and the iteration speed had been improved by about 42.9‰ [11]. Shen et al. found that existing methods still posed certain challenges in analyzing and detecting the core periphery of complex networks. Therefore, after considering the maximum impact chain and ICPA, they proposed a novel node pairing model. These experiments confirmed that the randomly generated pairing network of the model could efficiently and accurately predict nodes [12].

In summary, many scholars have proposed different approaches and opinions on the multi-objective structural design of PB, and researchers have also achieved corresponding results by applying ICPA to different types of MOP solutions. However, existing research on the application of ICPA to multi-objective structural design optimization of PB mostly focuses on the optimization of prefabricated structural nodes, and there is still relatively little overall optimization of structural design. Therefore, the study attempts to continue in-depth exploration in this direction, aiming to provide an effective solution for PB structural design, improve the efficiency and performance of structural design, and further promote the development of PB.

3. Construction of multi-objective structural design optimization model for prefabricated buildings using ICPA optimization algorithm

The study first introduces CPA. After explaining its structure and drawbacks, it continues to introduce Chaos Optimization Algorithm (COA) for improvement. Secondly, the influencing factors of multi-objective structural optimization design for PBs are analyzed, and a set of MOP functions is established. After joint improvement of CPA, a new optimization model for the design of prefabricated target structure was ultimately obtained.

3.1. CPA algorithm and its improvement

CPA is a heuristic optimization algorithm that simulates the foraging behavior of aphids in nature. It is based on the solving strategy of aphids during the foraging process, with the goal of solving MOP [13]. In CPA, virtual aphid populations are randomly distributed in the solution space of the problem. Each aphid selects the next search location based on the relationship between its current position and the objective function value, guided by pheromones and local experience. The core steps of CPA include parameter initialization, evaluation, reproduction and flight, population update, and termination judgment. By iterating the above steps, CPA gradually converges to the optimal solution of the objective function. Population reproduction includes asexual and sexual reproduction, however, sexual reproduction in CPA involves the sharing of two types of information, while asexual reproduction is a purely maternal transmission of information. If asexual reproduction is carried out for a long time, the population diversity will decrease, leading to lower algorithm convergence. And the random distribution of the initial population will be affected, making the algorithm prone to falling into local optima. Therefore, the study introduces COA for improvement. COA is a heuristic optimization algorithm that can achieve a predetermined state without repetition based on its own motion laws [14]. And the randomness and unpredictability of chaotic sequences are utilized to simulate chaotic phenomena in nature, to find the optimal solution to optimization problems. The chaotic mapping of COA is represented by Equation (3.1).

$$z^{k+1} = \mu z^k (1 - z^k) \tag{3.1}$$

In Equation (3.1), μ represents the control parameter. z^k and z^{k+1} respectively represent the numerical values of chaotic design variables after k iterations. The calculation of the optimization step is represented by Equation (3.2).

$$\begin{cases} k \leq M, \text{ then} \\ f(x^{k+1}) \leq f^*, \text{ then } x^* = x^{k+1}, \ f^* = f(x^{k+1}) \\ k > M, \text{ then stop} \end{cases} \tag{3.2}$$

In Equation (3.2), M represents the maximum number of searches. $f*$ represents the objective function. x^* represents the target variable. By using chaotic mapping for searching, the optimal individual in the aphid population can be attracted, thereby causing CPA to jump out of the local optimal solution. The chaotic search process includes mapping, generating chaotic sequences, reverse reflection, calculating fitness values, and determining information entropy. This process has undergone three optimizations, including information entropy improvement, step size improvement, and stopping accurate measurement improvement. The improvement of information entropy is represented by Equation (3.3).

$$S(t) = -k \sum_{i=1}^{n} p_i(t) \ln p_i(t) \tag{3.3}$$

In Equation (3.3), $P_i(t)$ represents the degree of signal transmission influence between aphid populations. Information entropy is used to achieve adaptive degree representation in

CPA operations, thereby more flexibly grasping the operation situation and rules of CPA. The improvement of step size is represented by Equation (3.4).

$$C(i) = (D_{\max} - D_{\min}) \cdot \frac{J_i - J_{\min}}{J_{\max} - J_i} \cdot \text{rand}\,(0, 1) \tag{3.4}$$

In Equation (3.4), $J_{\max}$ and $J_{\min}$ represent the maximum and minimum fitness of a certain aphid, respectively. J_i denotes the aphid, i of the aphid indicates the adaptation value of the aphid. $D_{\max}$ and $D_{\min}$ represent the maximum and minimum values of distance, respectively. The improved step size calculation will be adjusted according to the iteration speed, thereby improving the accuracy of the algorithm. Before this, the stopping criteria for aphids were based on the maximum number of iterations. When facing complex problems, it is very difficult to accurately determine the number of iterations. Therefore, research has used information entropy as the criterion for judgment, making it more flexible and intuitive. In summary, Figure 1 shows the CPA process improved by COA.

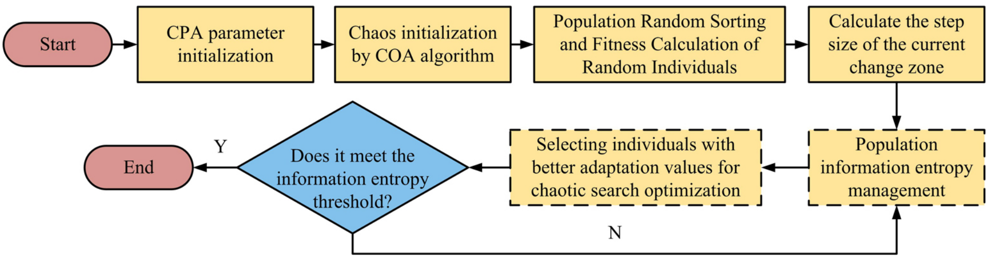

Fig. 1. Schematic flow of the improved CPA

According to Figure 1, the improved CPA includes 8 steps. Firstly, CPA parameter initialization is carried out, such as determining population size, replication frequency, migration probability, etc. Secondly, chaos initialization is performed by COA, followed by population random sorting and fitness calculation of random individuals. Then, the step size of the current change zone is calculated, and population management of aphids is carried out using information entropy to achieve flexible adjustment of adaptability. Individuals with better fitness values are selected for chaos search optimization. Finally, information entropy judgment is performed and the results are output [15, 16].

3.2. Construction of multi-objective structural design optimization model for prefabricated buildings

The optimization of PB structure design generally includes two major directions, namely overall and local optimization. The overall optimization is an improvement of the entire structural scheme. Local optimization is the decision-making and screening of plans related to component structure, size, materials, location, etc. in construction. Due to the numerous influencing factors of architectural structural design, such as environment, safety, economy, and applicability, there are also many fuzzy information coexisting. Therefore, it is necessary to classify and sort the influencing factors, and develop a reasonable descriptive model for the algorithm to perform calculations. Figure 2 shows a description of the influencing factors.

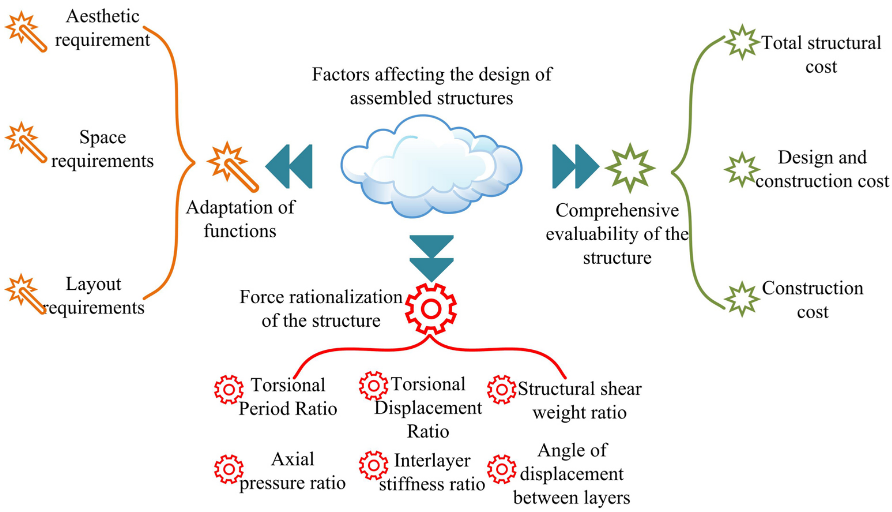

Fig. 2. Description model of influencing factors

According to Figure 2, the research summarizes the influencing factors of PBs structural design optimization into two levels and three major fields. The two major levels include centralized and decentralized criterion layers, which include the adaptability of building functions, the rationality of structural stress, and comprehensive evaluation. The adaptability of building functions can be divided into three categories, namely aesthetic, spatial, and layout requirements. The rationality of structural stress includes torsion cycle ratio, torsion displacement ratio, structural shear weight ratio, axial compression ratio, inter story stiffness ratio, and inter story displacement angle. The comprehensive evaluation includes the total cost of the structure, design cost, and construction cost. The adaptability and evaluation are difficult to quantify. To facilitate the unified operation of subsequent algorithms, the research chooses the rationality of structural stress as the main direction for problem exploration. The non-dimensional normalization method is used in this experiment to handle the force rationality factors on the six structures mentioned above. The calculation of the torsion period ratio after constraint is represented by Equation (3.5).

$$m_1 = T_L \leq RI \cdot T_1 \tag{3.5}$$

In Equation (3.5), RI represents the randomness indicator. T_L and T_1 represent the first natural vibration period of the structure for translational and automatic motion, respectively. The constraint of torsional displacement ratio is represented by Equation (3.6).

$$m_2 = \frac{\Delta u_{\max}}{\Delta u} \leq RI \tag{3.6}$$

In Equation (3.6), Δu represents the average displacement of building floors. $\Delta u_{\max}$ represents the maximum displacement. The constraint of structural shear weight ratio is represented by Equation (3.7).

$$m_3 = V_{Eki} > \lambda \sum_{j=1}^{n} G_j \tag{3.7}$$

In Equation (3.7), λ represents the shear coefficient. G_j represents the gravitational load of the j-th layer. V_{Eki} represents the horizontal floor shear force of the i-th floor. The constraint of axial compression ratio is represented by Equation (3.8).

$$m_4 = \frac{N}{Af_c} \le |U| \tag{3.8}$$

In Equation (3.8), f_c represents the axial compressive strength of the structure. A represents the cross-sectional area of the column. N represents the axial force design value of the column structure. $|U|$ represents the limit value of axial compression ratio. The constraint of interlayer stiffness ratio is represented by Equation (3.9).

$$m_4 = \frac{N}{Af_c} \le |U| \tag{3.9}$$

In Equation (3.9), $|\tau|$ represents the boundary value of displacement stiffness ratio. K_{i+1} and K_{i-1} represent the displacement stiffness of the upper and lower floors of the i-th floor, respectively. The constraint of inter story displacement angle is represented by Equation (3.10).

$$m_6 = \Delta u_c \le |\theta|\, h \tag{3.10}$$

In Equation (3.10), $|\theta|$ represents the boundary value of interlayer displacement angle. h represents the height of the floor. Δu_c represents floor's maximum elastic interlayer displacement. Combined with the above no-gradient quantity processing formulas for the force reasonableness factors, the study integrates these factors with the improved CPA algorithm, and the improved CPA is used to solve these factors. Finally, a new multi-objective optimization model for the design of assembled structures is proposed, and the operation flow of this model is shown in Figure 3.

According to Figure 3, firstly, a structural design optimization model, namely MOP, is established. Secondly, the quantitative scale of each target is determined through the Analytic Hierarchy Process (AHP) to establish evaluation indicators for ICPA. Then, the optimal solution is searched through ICPA, which includes aphid identification, chaotic initialization of population, determination of information entropy threshold, and individual decoding. After obtaining the optimal structural design scheme, an evaluation is conducted. By repeating the above steps, a collection of multiple optimized structural design schemes has been established. Finally, a judgment was made to determine whether the information entropy threshold was reached. If so, the output is terminated. If not, the ICPA is repeated.

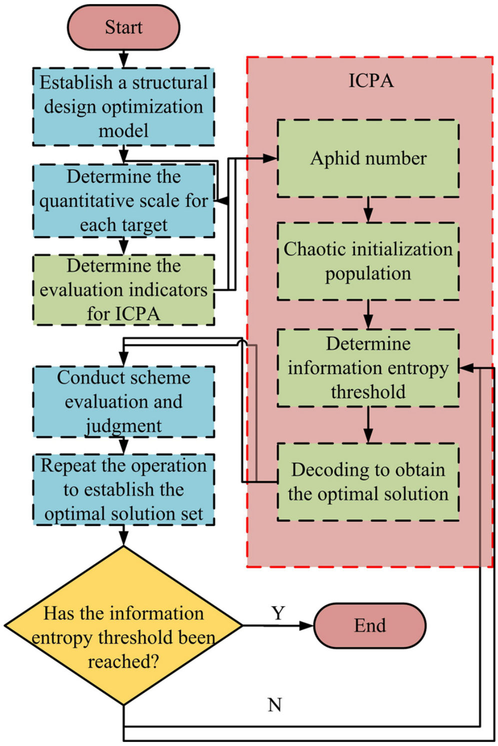

Fig. 3. Process of MOO model for the design of new prefabricated structures

4. Performance testing of multi-objective structural design optimization model for prefabricated buildings using ICPA optimization algorithm

To verify the performance of the proposed new multi-objective structural design optimization model for PBs, the study first conducted performance tests on ICPA, verifying its superiority. Secondly, a suitable biomimetic environment was set up to test the final optimized model, verifying its feasibility.

4.1. Performance testing of improved CPA

The initial population size of this algorithm was set to 300, the population size was 16, the weight coefficient was 0.3, and the information entropy threshold was 0.0004. To fit the data training of MOO algorithms, this study selected two classic examples from the traveling salesman standard problem library, namely Berlin52 and Pcb442. The number of optimal solutions obtained through search was used as a reference indicator to compare three popular

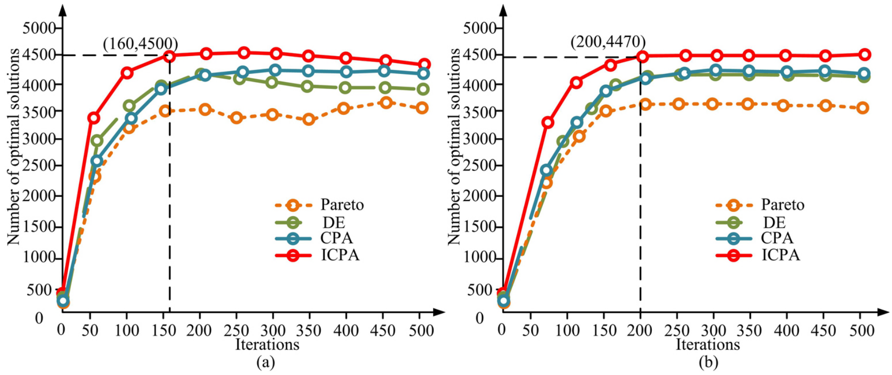

Fig. 4. The performance of four algorithms under different instances; (a) Berlin52, (b) Pcb442

algorithms of the same type. These algorithms included basic CPA, Pareto optimization algorithm, and Differential Evolution (DE) algorithm. Figure 4 shows the test results.

Figure 4(a) shows the results of four algorithms in Berlin52MOP. Figure 4(b) shows the results of four algorithms in Pcb442MOP. According to Figure 4, the minimum number of iterations for ICPA was 160, and the optimal number of solutions was 4500. In Pcb442, the performance of ICPA was still the best, with a minimum of 200 iterations and nearly 4470 optimal solutions. In summary, the proposed new ICPA had better computational power and fewer iterations compared to the other three types of algorithms. In addition, in order to demonstrate the above data effects more graphically and intuitively, and at the same time to enhance the breadth of the test. Taking the number of optimal solutions, the number of worst solutions and the number of convergence times as reference indexes, the study continues to introduce the latest objective optimization algorithms at the current stage, such as Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA) and Fruit Fly Optimization Algorithm, FOA), the test continues and the test results are shown in Table 1.

From Table 1, it can be seen that, under the premise of knowing the number of optimal solutions, among the basic algorithms, the maximum number of optimal solutions for Pareto is 1, the number of optimal solutions for DE is 2, and the number of optimal solutions for CPA is 6. Among the optimization algorithms, the number of optimal solutions of GWO algorithm is 10, the number of optimal solutions of WOA algorithm is 11, the number of optimal solutions of FOA algorithm is 9, and the number of optimal solutions searched by ICPA is 17. Secondly, the iterations of ICPA in these two types of problem solving were 166 and 202, respectively, which were basically consistent with the previous test results. In addition, the performance of ICPA was tested using two different testing functions, including the Sphere unimodal sphere function and the Rastigrin multimodal function. The study set the dimension of the above test functions to 100. Figure 5 shows the test results.

Figure 5(a) shows the Sphere ball function test graph. Figure 5(b) shows the Rastigrin function test graph. According to Figure 5, after testing ICPA, the coordinate concentration points for Sphere sphere function's optimal values were all within −0.5 to 0.5, which was the yellowish part. The Rastigrin function found after testing ICPA that the optimal

Table 1. Quantization results of operational data for four algorithm

Problem Model	**Algorithm**	**Known optimal solution**	**Number of optimal solutions**	**Number of worst solutions**	**Convergence times**
Berlin52	Pareto	3821	3821	2796	246
	DE	4366	4368	15481	210
	CPA	4350	4355	13884	250
	GWO	4321	4429	7763	187
	WOA	4417	4428	6731	169
	FOA	4426	4435	8154	172
	ICPA	4483	4500	7683	166
Pcb442	Pareto	3611	3612	11589	204
	DE	4210	4212	8233	254
	CPA	4251	4257	6078	311
	GWO	4403	4413	7891	253
	WOA	4138	4147	6784	221
	FOA	4411	4419	7986	228
	ICPA	4456	4470	5784	202

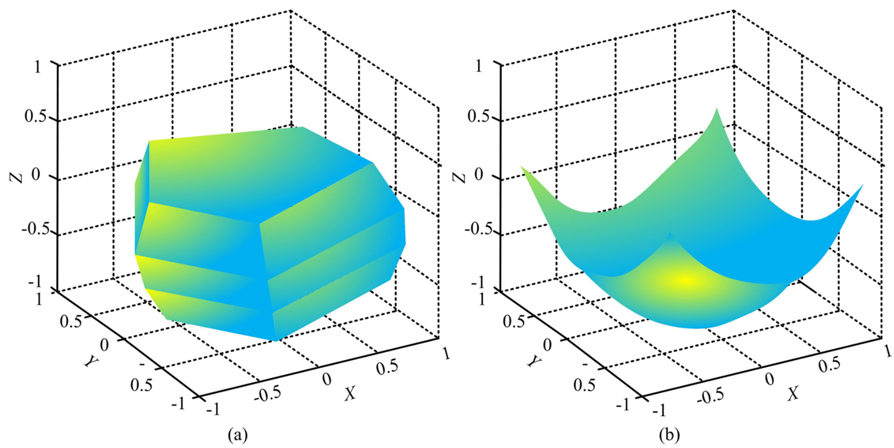

Fig. 5. Test function diagram of ICPA; (a) Sphere, (b) Rastigrin

value at this time was also concentrated in the range of coordinates −0.5 to 0.5. In summary, ICPA is able to find the optimal values of the Sphere sphere function and Rastigrin function, and the required steps for operation are relatively short. This test further confirms that the proposed new ICPA has the characteristics of fast computation and good optimization performance.

4.2. Simulation testing of multi-objective structural design optimization model for prefabricated buildings

A simulation test object was set up for the prefabricated structural design of a 3-story villa, which was composed of prefabricated components such as walls, columns, beams, and slabs. To visually compare the optimization effects of the random building structure design before and after the application of the proposed model, a structural design template before and after the application was drawn in Figure 6.

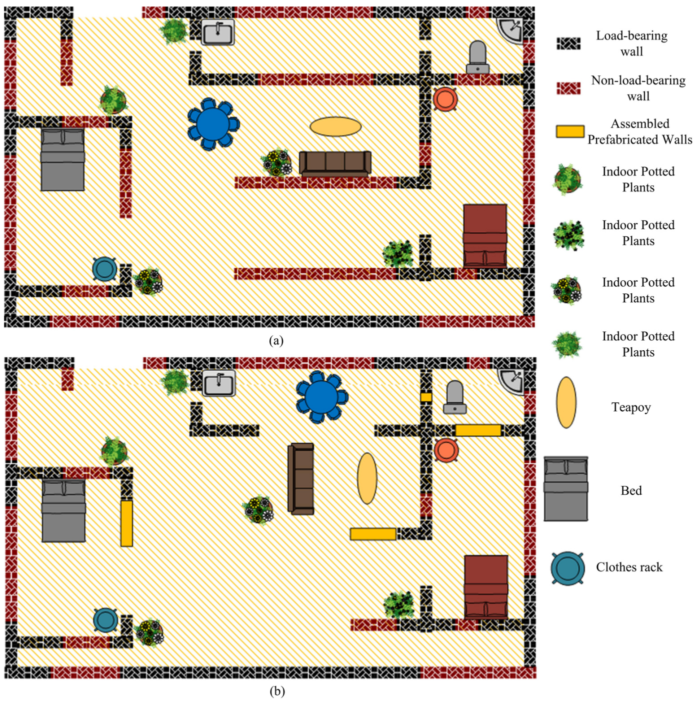

Fig. 6. Wall configuration diagram before (a) and after (b) optimization

Figure 6(a) shows the wall configuration before optimization. Figure 6(b) shows the optimized wall configuration diagram. The black wall is a load-bearing wall, the red wall is a non load-bearing wall, and the yellow rectangle is a prefabricated prefabricated wall. In Figure 6, after optimizing the PBs multi-objective structural design optimization model, most non-load-bearing walls were removed and the layout format was slightly changed. Prefabricated prefabricated walls were added to some necessary wall connection structures, reducing the material and cost of concrete walls, saving time, and improving space utilization. To further test the performance status of the optimized building structure, the study continued to use structural stability, structural quality coefficient, natural vibration period, and inter story displacement angle as reference indicators for testing. Table 2 shows the test results.

Table 2. Index test results after optimization

Index	**Type**	**Before optimization**	**After optimization**
Structural stability	Wind load	22.74	24.39
	Seismic load	7.03	7.81
Structural quality coefficient	X direction	95.70%	97.82%
	Y direction	95.84%	98.21%
Natural vibration period	The first translational period	1.24	1.21
	First torsion period	1.23	1.20
Story drift	Wind load	0.04%	0.02%
	Seismic load	0.06%	0.04%

According to Table 2, all four quantified testing indicators have optimization. The wind load stability in structural stability increased by 1.65 and the seismic load stability increased by 0.78. The quality coefficient of the X-direction structure increased by 2.12%, and the quality coefficient of the Y-direction structure increased by 2.37%. The first translational period decreased by 0.03, and the first torsional period decreased by 0.03. The interlayer displacement angle of wind load decreased by 0.02%, and the interlayer displacement angle of seismic load also decreased by 0.02%. In summary, these data demonstrate that the proposed new model can increase structural stability, improve structural quality coefficient, reduce natural vibration period, and reduce inter story displacement angle.

5. Conclusions

PB, as an advanced architectural concept, has significant advantages in improving building quality, shortening construction cycles, and reducing construction costs. In PB design, MOO structural design is a complex and challenging problem. In view of this, the study introduced CPA and added COA for improvement, proposing an improved CPA, namely ICPA. These experiments confirm that the minimum number of iterations for ICPA under two instances of MOP training is 160, and the optimal number of solutions is 4500. After comparing with similar optimization algorithms, the maximum number of optimal solutions searched by ICPA is 17, and the number of iterations at this time is 166. The coordinate concentration points of the Sphere unimodal spherical function and the Rastigrin multimodal function of ICPA are both within the range of -0.5 to 0.5, with smaller values and better stability. These biomimetic results confirm that the proposed structural design optimization model can effectively complete the optimization and renovation of physical buildings, reducing the material and construction time of concrete walls after optimization. After quantifying the data indicators, the structural stability of this new model increases by 2.43, the structural quality coefficient increases by 4.49%, the vibration period decreases by 0.06, and the interlayer displacement angle decreases by 0.04%. In summary, the application of ICPA in searching for multi-objective solutions exhibits good convergence and global search ability, providing an effective optimization method for PB structure design. However, this study only considers the functionality and structural applicability of CPA optimization. Further research can continue to explore the environment and personnel to enhance the comprehensiveness and feasibility of the study.

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