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Optimizing the balance between modularity and personalization of assembled buildings in an intelligent design environment

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Abstract Currently, the construction industry is facing the challenge of balancing modularity and personalization needs, and assembly buildings are promoted by various countries for their high efficiency and environmental advantages. In this study, a comprehensive optimization scheme is proposed for the problem of balancing modularity and customization of assembled buildings in an intelligent design environment. Firstly, a modular design and customization demand balance model is constructed to analyze the relationship between standardization and customization, module flexibility and adaptability, and 3D point cloud data segmentation using BIM technology. Secondly, a multi-objective optimization model of “cost-duration-carbon emission” for the assembly building construction process is constructed based on the Improved Gray Wolf Optimization (IGWO) algorithm, and the dynamic weighting method is introduced to solve the optimization problem under different construction process execution modes. Simulation results show that the optimization accuracy of IGWO algorithm on the test function f1(x) reaches 0.0015, which is more than 95% higher than that of GWO algorithm. It was verified that the optimized assembled component combination reduced the duration by 20%, carbon emission by 12.25%, and cost by 0.56% compared to the all-cast-in-place solution in the baseline scenario. It was found that the optimal range of prefabrication rate for assembled buildings should be controlled in the range of 20%-60%, which is determined according to the specific needs of the project, and should not be pursued as a high prefabrication rate. The method provides a feasible way to achieve a balance between modularity and individualization for assembly buildings in an intelligent design environment.

Index Terms assembly building, modular design, personalized balance, BIM technology, gray wolf optimization algorithm, multi-objective optimization

I. Introduction

With the continuous development of science and technology and society, the construction industry is facing new challenges and opportunities [1]. Traditional construction methods have problems such as low efficiency and high resource waste, which bring a great burden to the environment [2]. And as an emerging construction method, assembly building has received more and more attention and favor by virtue of its high efficiency, sustainability and flexibility [3], [4].

Assembled building refers to the prefabrication and processing of all kinds of components in factories, and then transported to the site for assembly, which finally forms a complete building [5], [6]. Compared with traditional construction, its construction time is shorter, which can significantly improve the construction efficiency [7]. Modularization and personalized design as two core concepts in assembly building, modularization design is based on standardized modules, which achieves the improvement of construction efficiency and quality [8], [9]. Personalized design, on the other hand, pursues uniqueness and adaptability to meet the diverse needs of users [10]. In actual engineering, how to balance modularization and personalized design has become an important issue [11]. The optimization of the balance between the two needs to be considered from the perspectives of technology, economy, environment, design and operation, etc. By reasonably balancing modularization and personalized design, assembly building construction can improve efficiency, reduce costs, and meet the diverse needs of users [12]-[15]. The intelligent design environment provides an optimized solution for the balance of modularity and personalization in assembly buildings, which is based on the integration of technology and the reconstruction of the architectural design process to achieve the balance of modularity and personalization in assembly buildings [16]-[19].

As an important development direction of contemporary construction industry, assembly building is gradually changing the production mode and technical route of traditional construction industry. Traditional building construction is generally characterized by serious waste of resources, environmental pollution, low construction efficiency and other problems, while assembly building can significantly improve construction efficiency, reduce environmental impact and improve construction quality through factory production and on-site assembly. However, in practice, assembly building still faces the contradiction between standardization and individualized demand. Standardization is the basis for achieving scale efficiency and cost control in assembly buildings, but excessive standardization can lead to uniform buildings that fail to meet the diverse aesthetic and functional needs of users. How to maintain the advantages of high efficiency and environmental protection of assembled buildings while meeting the individual needs of customers has become a key challenge in the development of current assembled buildings. Intelligent design environments offer new possibilities for solving this contradiction, and through digital technology and parametric design, it is expected to find a balance between modularity and personalization. The international construction industry has begun to explore the use of BIM technology, artificial intelligence and other means to enhance the design flexibility and construction optimization of assembled buildings, but the relevant research is still in its infancy and lacks systematic optimization methods and evaluation systems. In addition, in the context of peak carbon and carbon neutral targets, the problem of carbon emission in the construction industry has become increasingly obvious, and it has become particularly important to optimize the construction process of assembled buildings in a multi-objective manner, taking into account both economic and environmental benefits. In this study, we firstly establish an equilibrium model by analyzing the modular design principle and customized demand characteristics; secondly, we use BIM technology for 3D point cloud data processing and parametric modeling of assembly buildings; thirdly, we sort out the assembly building construction process and construct a multi-objective optimization model of "cost-duration-carbon emission"; finally, we propose the Improved Gray Wolf Optimization Algorithm (IGWO) to solve the optimization problem and validate the optimization model through simulation experiments and case studies. Finally, the improved gray wolf optimization algorithm (IGWO) is proposed to solve the optimization problem, and the effectiveness of the method is verified through simulation experiments and case studies. This research will provide theoretical support and practical guidance for the design and construction of assembly buildings, and promote the development of the construction industry in the direction of digitalization, intelligence and greening.

II. Balancing modular design with customization requirements

II. A. Modular Design Principles

(1) The relationship between standardization and customization. The balance between standardization and customization is key to achieving successful modular design. Standardization provides an efficient way to reduce costs, increase productivity, and ensure consistent quality by defining common modules. However, in real-world projects, customers often have unique needs, so the relationship between standardization and customization must be handled carefully. Developing clear definitions of standard modules ensures that modules widely used in projects are standardized and generic, providing alternative choices of standardized modules that can be moderately customized when they are needed to meet specific needs without breaking the overall standard.

(2) Flexibility and adaptability of module design. Module design flexibility and adaptability is to ensure that the key to customization needs to be met. Modules must have enough flexibility to adapt to the unique characteristics of different projects and the individual needs of customers. Modules should be designed to be configurable and able to be flexibly combined and adapted according to project needs. Modules should be designed to be extensible so that they can be easily improved if they need to be expanded or upgraded in the future. Integrating some customization options into the module design allows flexibility to respond to individual needs while maintaining standardization.

II. B. Customized Demand Analysis

Customization needs are varied and can encompass all aspects of a building project, and understanding the different types of customization needs is critical to meeting client expectations and ensuring successful design and construction. Exterior customization involves the need to personalize the building's appearance, style and finishes, such as façade design, color choices and architectural elements. Functional customization focuses on the customization of the building's internal functions, including the personalization of space layout, equipment configuration and functional requirements. Technical customization involves the individualization of building systems, material selection and technical specifications, such as special energy efficiency requirements or the integration of intelligent systems. Environmental adaptation customization addresses the need for customization for specific geographic, climatic or environmental conditions, such as seismic design and energy efficiency design. Sustainability customization emphasizes the environmental friendliness and sustainability of the building, including the use of green materials, energy efficiency and eco-friendly design. Client expectations and requirements for a building project have a direct impact on the degree of customization, and the scope of customization is clarified prior to project initiation to ensure that client expectations are aligned with actual delivery. Customization and implementation usually takes more time. In time-critical projects, there is a need to weigh the degree of customization against the project schedule and ensure that the chosen customization solution is technically feasible to avoid unnecessary technical challenges and delays.

II. C.Equilibrium modeling

Establishing the link between module design and customization requirements is a key part of balancing the model. Subdivide the customization requirements into different types such as appearance, functionality and technology, and determine the impact of each type on the module design. Determine the key attributes of the module design, including the degree of standardization, substitutability, flexibility, etc., in order to understand how they correspond to the different types of requirements. Adaptability analysis is performed for each module to determine its level of adaptation to different customization requirements, including its ability to satisfy and what level of modification is required. Constructing a balanced model aims to maximize the benefits of module design while meeting customization requirements, and the model needs to be constructed taking into account a variety of factors to ensure that the balance can be achieved in an actual project. Based on the project requirements and customer expectations, the degree of customization is determined, and a set of trade-offs including time, cost, and technical complexity are developed to assist in decision-making. For each customization requirement, assess the risks it introduces, consider the possible impact of different levels of customization on the successful delivery of the project, establish an effective project management process to ensure that appropriate attention is paid to the management of module design and customization requirements throughout the project lifecycle, and introduce a real-time adjustment mechanism to allow for adjustments to be made as the project progresses to respond to changing requirements.

II. D.Application of BIM technology in assembled buildings

BIM technology [20], assembly building realizes a more refined, efficient and sustainable construction practice. The main application of BIM technology in assembly building construction process lies in the construction of building model before construction. Therefore, the application of BIM will be optimized for the modeling of the walls of the assembled building.

The multi-objective wall 3D reconstruction is the most critical and important goal in the assembly building construction process. The application of wall 3D reconstruction technology can significantly improve the construction accuracy and efficiency. A 3D model of the construction site can be built from the point cloud data captured by the camera or laser scanner. This reduces a lot of manual measurement work. The overall segmentation process of 3D point cloud data segmentation for assembled building walls is shown in Figure 1.

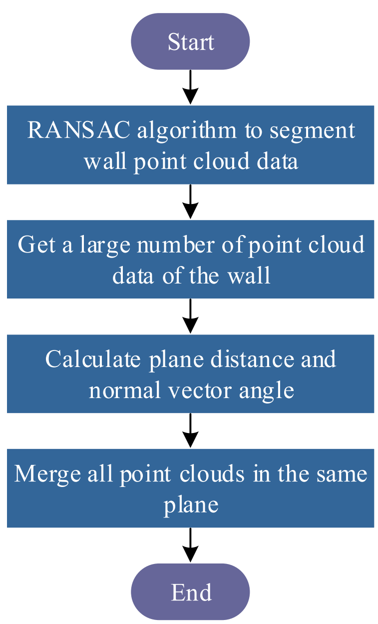

Figure 1: The overall segmentation process of 3d point cloud data

Based on the randomized sampling iterative algorithm (RANSAC), the specific segmentation process of the algorithm is as follows:

Assuming that there are n_o missing points and n_c error points in the 3D point cloud data, the probability that an error point is just a missing point is as in equation (1):

$$P_1 = \frac{W_{er}^3}{W_{(er+os)}^3} \tag{1}$$

In random sampling, a larger number of iterations is set, the minimum number of samples is b, and the probability P_2 that the sampling result is qualified is shown in equation (2):

$$P_2 = 1-(1-\mu)^b \tag{2}$$

In Eq. (2), μ denotes the likelihood of error-free near misses in the point cloud data. Then there is equation (3):

$$b = \frac{\lg(1-P_2)}{\lg(1-\mu^a)} \tag{3}$$

CAD technology (Computer Aided Design) has a wide application base and mature technology system in the construction industry. It can accurately create and edit two-dimensional drawings, providing reliable data support for architectural design. For assembled buildings, CAD technology can help designers accurately draw the plan, elevation and section of wall components, etc., providing detailed size and location information for subsequent 3D model reconstruction.

Revit technology, as one of the core software of BIM technology, is able to realize the precise correlation between components through parametric design. In the 3D model reconstruction of the wall of an assembly building, Revit technology can automatically create a 3D model of the wall according to the dimensional and positional information in the CAD drawings, and maintain consistency with the original design.

The combination of CAD technology and Revit technology can realize the seamless connection of data. Through specific data interfaces or plug-ins, CAD drawings can be imported directly into Revit, avoiding information loss and formatting errors during data conversion. This seamlessness not only improves work efficiency, but also ensures the accuracy and reliability of wall 3D model reconstruction.

By combining CAD technology and Revit technology, the advantages of both can be fully utilized to realize the efficient and accurate reconstruction of the 3D model of the wall. CAD technology provides accurate 2D drawing data, while Revit technology converts this data into an intuitive 3D model, providing comprehensive information support for the design, construction, and operation and maintenance of the assembly building.

II. E. Prefabricated component library and parametric modeling module development

The sharing of assembly building information among projects is realized through the prefabricated component family library, which is mainly used to achieve standardization and normalization for BIM designers in the design process. The prefabricated component library in this paper consists of three functions, namely prefabricated component entry function, prefabricated component preview function, and prefabricated component loading function. Prefabricated components library module technology route: prefabricated components classification → prefabricated components into the library → prefabricated components preview → prefabricated components loading.

In this paper, prefabricated components are divided into structural system and enclosure system according to the system, in which the structural system can be divided into vertical components and horizontal components, and the enclosure system is divided into exterior wall enclosure components and interior wall enclosure components, and the creation process of prefabricated component family can be divided into the following five steps:

(1) Select the corresponding type of family sample;

(2) Modeling according to the design with the commands of stretching, fusing, rotating, releasing, fusing, releasing, fusing, and hollow shape;

(3) Setting the dimensional parameters of the “family” and the spatial logic of the relationship between the parameters;

(4) Setting other attributes of the family;

(5) Load the family into the project for testing.

The parametric modeling program involved in this paper contains five functions: generating axis network, columns, beams, structural beams attached to building walls, and statistical information on building wall loads, which are cumbersome to use separately with the Add-InManager plug-in, and therefore a new “Structural Modeling” tab has been created in Revit, and the above five functions can be set via buttons. Therefore, a new “Structural Modeling” tab is created in Revit, and the above five functions are linked to the program set by buttons.

(1) The designer clicks the “Generate Axis Nets” button, prompts the family type of the axis nets used and the elevation at which the nets are placed, passes the button value to the system, which reads the line information of the walls at the selected elevation and stores it in the collection, passes the command to the transaction, the program traverses all the wall models in the model, and then executes the command to generate the axis nets;

(2) The designer clicks the “Generate Columns” button, prompts the family type of the columns used and the elevation at which the columns are placed, the elevation of the top of the columns is the elevation of the superstructure by default, passes the value of the button to the system, and the program reads all the intersections of the axial network at the elevation and collects them, and then passes the commands to the transaction, and then executes the command of generating the columns;

(3) Identify the axis network in the view, combine the method of beam modeling in Revit, and judge the beam size with the structural design principle, select the modeling elevation and family type, and complete the process of automatic beam generation. The specific process of beam generation is similar to that of columns;

(4) The designer clicks the “wall flush with the bottom of the beam” button, selects the wall that needs to be flush with the bottom of the beam, passes the value of the button to the system, and the system reads the height information of the beam at the elevation and collects it, and subtracts the top elevation of the wall from the height of the beam, and the program passes it to the transaction to execute the command of modifying the elevation;

(5) Revit wall model after the creation of windows and doors the software will automatically calculate the volume of the wall after the opening, proposed to pick up the building wall volume parameters and structural load coefficients combined with the method of exporting line loads, the calculation formula is shown in equation (4).

$$Line\ load\ = wall\ volume / wall\ length \times load\ factor \tag{4}$$

The program collects the volume and length information of the walls, and automatically calculates the line loads of all building walls according to the calculation of the input load coefficients based on the materials of the walls. Specific realization of the process is: the designer clicks on the “line load statistics” button, prompted to enter the line load coefficient, the system collects all the ID, volume, length parameters of the wall, and then passes them to the transaction, and finally executes the calculation commands and sets the path of excel export.

III. Optimizing the balance between modularity and personalization in assembled buildings

III. A. Construction process organization

There are many processes in the building construction site, from the basic engineering construction to the completion and acceptance, in which each sub-project contains many subtle processes. At present, the main forms of building construction include cast-in-place construction and assembly construction. With the continuous development of the construction industry, cast-in-place construction has been difficult to meet the requirements of people's environmental protection, and assembly construction can not only effectively improve the construction efficiency, but also effectively reduce the pollution of the construction process on the environment, therefore, many countries around the world are promoting the development of assembly construction. In this paper, the assembly construction mode process flow is chosen to carry out research, which can not only improve the feasibility of the research, but also comply with the development trend of the construction industry.

From the current practice of assembly construction, the construction process of stacked plate components is more standardized and the construction process is more regulated, so this paper takes the installation of stacked plate components as an example to sort out the process flow of the installation of stacked plate components in assembly buildings, and establishes a multi-objective optimization model on this basis.

III. B. Multi-objective optimization problem

Generally speaking, the installation process of laminated panel components can be sequentially divided into the following processes: entry and inspection of components, erection of equipment support, cleaning of the grass-roots level and construction surface, arrangement of embedded parts, lifting and transportation of laminated panels, installation of laminated panels in place, grouting operations, node protection, site cleaning and other processes. At the same time, through data collection and on-site research, the labor, material and machinery consumption of each process can be obtained, so that the cost and carbon emission of each process can be further calculated.

In general, using the relevant principles of mathematical function conversion, the multi-objective optimization problem can be converted into a mathematical model, as shown in equation (5).

$$\begin{cases} \min Y = (f'(x), f''(x), \cdots), x \in T^m \\ s.t.\ g'(x) \le 0, h'(x) \ge 0 \end{cases} \tag{5}$$

where, $f'(x), f''(x), \cdots$ represents each sub-objective, each sub-objective has the corresponding mathematical function expression; T^m is the feasible solution space, in which each solution can be applied to the original problem, but not all of them are the optimal solution, in general, there are only a few solutions that can make the relative minimization of the objective function; $g'(x)$ and $h'(x)$ are the constraints of the objective function, usually there are more than one constraints. are constraints on the objective function, usually there are more than one constraint.

After establishing the multi-objective optimization model, the next step needs to be solved for the model, because the multi-objective optimization model has certain specificity, so it needs to be processed by using special methods, including the following methods:

(1) Objective planning method. This method is relatively simple and suitable for multi-objective optimization problems with few parameters and few constraints. Firstly, the optimal value of each sub-objective is found, and then the optimal value of each sub-objective is treated as the constraints of the original problem. Finally, the difference between each sub-objective and its corresponding optimal value is reduced, and the final optimal solution is the optimal solution of the original problem.

(2) Fixed weight method. This method utilizes weight coefficients to measure the importance of each sub-objective to the overall objective, and calculates the composite function value through the weight coefficients between 0 and 1 and the sub-objective values, and finally compares the corresponding composite function value of each feasible solution, and if the composite function value is optimal, it means that the corresponding feasible solution is optimal.

(3) Dynamic weighting method. Similar to the fixed weight method, a certain weight is assigned to each sub-objective, but the method adopts dynamic weights, and the weight coefficients change during each calculation, thus enhancing the randomness and global nature of the solution process, which is suitable for the multi-objective optimization problems that are more balanced among the sub-objectives and have no obvious dominance.

The above three methods are the three most widely used methods in the multi-objective optimization solution process, among which, the dynamic weighting method has the following advantages compared with the remaining two methods: firstly, the weighting coefficients are easy to manipulate, which can quickly and reasonably transform the multi-objective optimization problem into a single-objective optimization problem; Secondly, the weight coefficients adopt dynamic change to avoid falling into local optimum in the solution process and improve the scientificity of the optimization results; in addition, the method is used maturely, has certain reference experience, and can achieve good coordination with computer language algorithms. Therefore, in this paper, the dynamic weight method is chosen to solve the multi-objective optimization problem, and the weight coefficients are generated by Eq. (6) in the iterative process.

$$w_i = \frac{a_i}{a_1 + a_2 + a_3} \tag{6}$$

where, w_i is the weight coefficient of the i th sub-objective, and $i = 1, 2, 3$; a_i is a random number between 0 and 1. During each iteration, the algorithm system assigns a value to a_i and then calculates the dynamic weight coefficients, and further uses the sub-objective function values and the weight coefficients to calculate the comprehensive objective function values, realizing the conversion of multi-objective optimization problems to single-objective optimization problems.

III. C. Optimization modeling

In the assembly building construction site, the duration, cost and carbon emission of the laminated panel component installation process depend on the input labor, materials, machinery and other factors. Yi Changsheng et al. found that prefabricated component factory and assembly building construction site processes can be divided into normal mode, rush mode and saving mode for research, and different execution modes correspond to different production resources and consume different costs and durations. On this basis, after considering the carbon emission factor, the on-site installation process of laminated panel components can also be divided into the above three modes, and the same process in different execution modes corresponds to different costs, durations, and carbon emissions, and the search for the optimal combination of multi-objective execution modes of the process can provide guidance for the optimization of on-site construction.

The optimization objective of this paper is the multi-objective optimization of "Cost C -Duration T -Carbon Emission E ", and the optimization model is established according to the execution modes of different processes as shown in Equation (7).

$$\begin{cases} \min C = \sum_{i=1}^{m}\sum_{j=1}^{q_i} C_{ij} \\ \min T = \sum_{i=1}^{m}\sum_{j=1}^{q_i} T_{ij} D_{ij} \\ \min E = \sum_{i=1}^{m}\sum_{j=1}^{q_i} E_{ij} D_{ij} \\ s.t. \sum_{j=1}^{q_i} D_{ij} = 1 \end{cases} \tag{7}$$

where, m is the number of construction processes; q_i is the number of execution modes possessed by the i th process; D_{ij} is a decision variable that takes the value of 0 or 1, and the value of 1 when the j th execution mode is used in the i th process, and 0 otherwise.

III. D. Model solving based on the gray wolf optimization algorithm

Gray wolf optimization algorithm (GWO) is a new type of swarm intelligence optimization algorithm. Based on the Gray Wolf Optimization Algorithm, this study designs a random key coding mechanism, converts continuous coding into discrete coding and combines the crossover and mutation operations in the genetic algorithm to improve the global search capability of the discrete Gray Wolf Algorithm, which is capable of solving the prefabricated component production scheduling model. In order to distinguish it from the improved Gray Wolf optimization algorithm, the Gray Wolf optimization algorithm is referred to as the basic Gray Wolf optimization algorithm in this study.

III. D. 1) Basic Gray Wolf Optimization Algorithm

There is a strict hierarchy within the gray wolf pack, which is divided into α , β , δ and ω according to the social rank, from the largest to the smallest in terms of power, and the distribution of the social rank is shown in Figure 2. Gray wolf packs are usually led by a small number of head wolves leading a group of gray wolves toward prey, i.e., gray wolf packs will hunt collectively under the leadership of α . Predation in gray wolf packs is divided into 3 steps: encirclement, hunting and attacking prey.

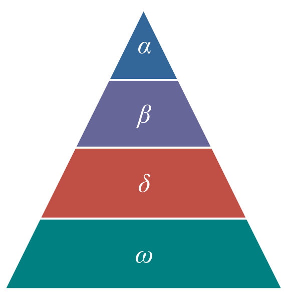

Figure 2: The social hierarchy of the grey Wolf

In the basic gray wolf optimization algorithm [21], assuming that the location of the prey is provided by the best solution in the search space, the solution can be used to find a better solution, and continuously iterative optimization, and ultimately get the optimal solution.

Eq. (8) to Eq. (12) represent the process of gray wolf packs encircling the prey, and its mathematical model is described as:

$$\vec{D} = \left|\vec{C}\cdot\vec{X}_p(t) - \vec{X}(t)\right| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}\cdot\vec{D} \tag{9}$$

$$\vec{A} = 2\vec{a}\cdot\vec{r}_1 - \vec{a} \tag{10}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{11}$$

$$\vec{a} = 2 - t \cdot \left(\frac{2}{t_{\max}} \right) \tag{12}$$

Eqs. (13) to (15) represent the hunting process of the gray wolf, and its mathematical model is described as:

$$\begin{cases} \vec{D}_\alpha = \left| \vec{C}_1 \vec{X}_\alpha(t) - \vec{X}(t) \right| \\ \vec{D}_\beta = \left| \vec{C}_2 \vec{X}_\beta(t) - \vec{X}(t) \right| \\ \vec{D}_\delta = \left| \vec{C}_3 \vec{X}_\delta(t) - \vec{X}(t) \right| \end{cases} \tag{13}$$

$$\begin{cases} \vec{X}_1 = \vec{X}_\alpha(t) - \vec{A}_1 \cdot \vec{D}_\alpha \\ \vec{X}_2 = \vec{X}_\beta(t) - \vec{A}_2 \cdot \vec{D}_\beta \\ \vec{X}_3 = \vec{X}_\delta(t) - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \tag{14}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{15}$$

where, X_α , X_β and X_δ are the current positions of α , β and δ respectively; C_1 , C_2 and C_3 are random vectors; X_1, X_2 and X_3 are the updated positions of α , β and δ respectively.

Where Eq. (14) denotes the distance between α , β and δ and other individuals, Eq. (15) denotes the step length and direction of orientation of ω individuals from α , β and δ in the wolf pack.

Although the basic gray wolf optimization algorithm has certain advantages in solving the scheduling problem, it has two shortcomings: first, the global search ability of the basic gray wolf algorithm is unstable, and it is easy to fall into the local optimum dilemma; Secondly, the basic Grey Wolf optimization algorithm was initially proposed to solve the continuous problem, but the assembly prefabricated component production scheduling problem is a discrete problem, so the basic Grey Wolf optimization algorithm cannot be used directly to solve the problem. Therefore, it is necessary to improve the above two deficiencies of the basic Gray Wolf optimization algorithm to make it more suitable for solving the precast component production scheduling problem.

III. D. 2) Steps to Improve the Gray Wolf Optimization Algorithm

(1) Coding

The maximum order value rule (LOV) based on random key encoding can be used to realize the conversion of the gray wolf position coordinates from continuous to discrete values. The maximum order value rule of random key encoding is as follows: firstly, the position element X_{ik} is assigned a random number between $[0,1]$, secondly, the intermediate sequence φ_{ik} is obtained by arranging them in non-ascending order, and finally, the processing order of the components $(\pi_{i,\varphi_{ik}} = k)$ is calculated.

(2) Decoding

The decoding process, i.e., the process of generating a specific scheduling scheme. In the decoding process, it is necessary to initialize the start time and end time of each component, and update the time matrix in the scheduling process. It should be noted that the start time of each component in each process depends on the completion time of the previous process and the maximum value of the completion time of the previous component in the process, and the start time of the maintenance process is equal to the end time of the pouring process. Labor constraints, process constraints, and buffer constraints also need to be taken into account when generating the specific scheduling plan. Finally, the scheduling time schedule of all component production is updated according to the specific scheduling scheme.

(3) Population initialization

According to the encoding method, each solution (gray wolf) is a prefabricated component production scheduling sequence. randperm function can randomly disrupt a numerical sequence, in order to improve the efficiency of the program operation, the use of random generation method for the population initialization, the use of randperm function to generate a set of non-repeating random integer data, in order to indicate the production and processing sequence of the components.

(4) Adaptation function

The determination of the fitness function [22] depends on the objective function of the model, and the fitness value is the probability of survival and reproduction of individuals under certain environmental conditions. The objective of the model in this study is to minimize the maximum completion time, and the smaller the maximum completion time is, the larger its fitness value is, so the inverse of the objective function in the model is set to be the fitness function of the population, and the top three individuals are defined as α , β , and δ according to the magnitude of fitness value of the solution.

(5) Head wolf selection mechanism

An important step in the basic gray wolf optimization algorithm is to select the top three individuals in terms of fitness value as the head wolf. This selection operation reduces the loss of effective solutions and increases the probability that high-performance individuals are retained, which in turn improves global convergence and solution efficiency. In this study, a roulette strategy is used to select the α wolf, β wolf, and δ wolf with the highest fitness.

(6) Crossover and mutation operations

Since the basic gray wolf optimization algorithm completes the updating of individual positions based only on the three solutions with the best individual fitness during the evolutionary process, the algorithm is prone to fall into the local optimality dilemma. Therefore, the basic gray wolf optimization algorithm is improved by combining the crossover and mutation operations of the genetic algorithm with the basic gray wolf optimization algorithm, so as to improve the global search ability of the gray wolf optimization algorithm. In the specific optimization scheduling operation, two-point crossover operation and reverse order mutation operation are used for the optimal individual.

(7) Individual position update

The basic gray wolf optimization algorithm adopts the elite retention strategy in the process of gray wolf population evolutionary update, and retains the optimal adaptive individuals (α , β and δ) directly to the next generation. Then, based on the basic principles of the basic gray wolf optimization algorithm, the location information of gray wolves is updated by using tracking, encircling and attacking prey, so as to carry out the individual location update of the whole population.

(8) Specific steps

The specific steps of the improved gray wolf optimization algorithm are as follows:

a) Set the parameters, set the population size as wolf, the maximum number of iterations as maxiter, and the dimension of the independent variable as dim;

b) Randomly initialize the population;

c) Perform GWO algorithm search, calculate the value of population fitness, and use roulette strategy to determine the top three individuals and their locations in terms of fitness, i.e., determine α wolf, β wolf, and δ wolf;

d) Perform crossover and mutation operations on the optimal individuals with a certain probability, and then update the α wolves, β wolves and δ wolves according to the value of the adaptation degree from the largest to the smallest;

e) Update the individual information of the population according to the information of the optimal individual;

f) Recalculate the individual fitness based on the updated individual information of the population, if the updated individual fitness is better than the original individual, it becomes the new α wolf, β wolf and δ wolf, and continue to perform the search operation in a loop;

g) If the original individual is always better than the updated individual or reaches the maximum number of iterations, then end the search operation and output the optimal solution.

IV. Simulation experiments and analysis

In order to verify the superiority of the improved IGWO, this paper utilizes three benchmark test functions to compare and simulate the improved IGWO with the GWO algorithm, GRO algorithm, and GRO-GWO algorithm, and the 3D surface plots of the three functions are shown in Fig. 3-Fig. 5, respectively. In order to facilitate a better comparison of the results, this paper sets the maximum number of iterations of each algorithm as 2000, 400 and 200, respectively, in addition, this paper sets the population size of the four algorithms as N=150.Finally, the above four algorithms are run independently for 30 times, and the respective optimal solutions are taken for side-by-side comparisons, and the results obtained from the simulation are shown in Table 1.

The optimization accuracy of the improved IGWO in the three test functions is significantly better than the other three algorithms in the three different functions, and the results obtained are closer to the real value, and the error of this paper's algorithm is only 0.0015 in the *f1(x)* function, which indicates that the IGWO algorithm proposed in this chapter has a better balance between the global search and the local search, and it fully proves that the improvement strategy of this paper is effectiveness of the improved strategy in this paper.

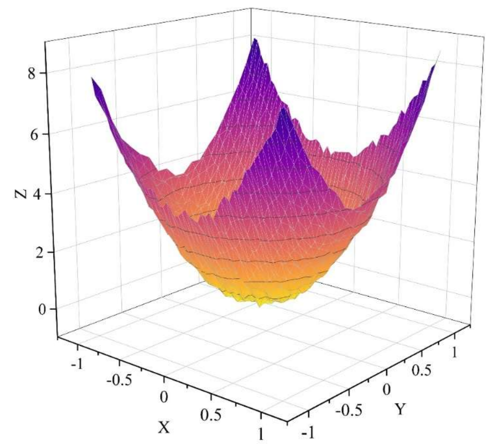

Figure 3 The three-dimensional graph of *f1(x)*

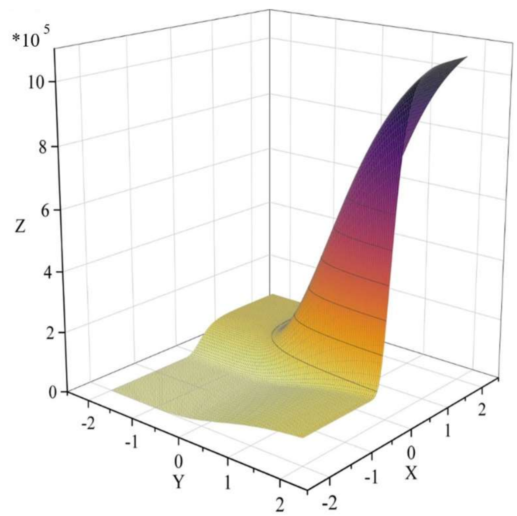

Figure 4 The three-dimensional graph of *f2(x)*

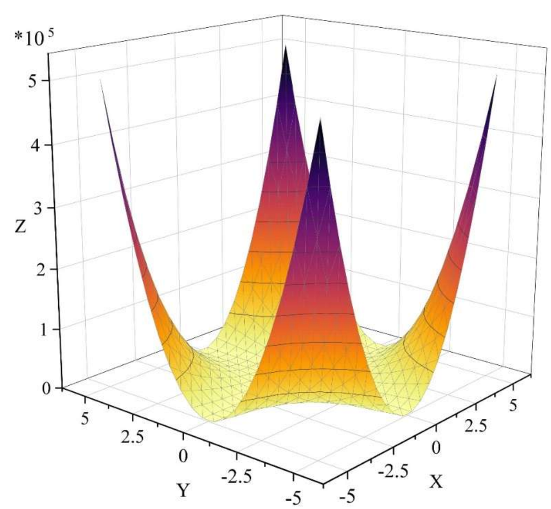

Figure 5 The three-dimensional graph of *f3(x)*

Table 1: Comparison of algorithm results

Function	Minimum value	IGWO	GWO	GRO	GRO-GW
f1(x)	0	0.0015	0.0654	18.5461	0.0561
f2(x)	0.0002	3.4811e-04	0.0259	0.0056	0.0019
f3(x)	2	2.0000	4.1561	4.3151	2.0000

V. Case scenario analysis

The results of multi-objective optimization of prefabricated component assemblies using the IGWO algorithm are mainly determined by the magnitude of the weights of the sub-objectives and the range of prefabrication rates. The weight coefficient is an assessment of the degree of importance of each sub-objective, which indicates the requirement or urgency of the sub-objective in an engineering project. The level of prefabrication rate represents the degree of industrialization of the building, and the evaluation standards of each province and city have clear requirements for the prefabrication rate of assembled buildings. Therefore, in order to explore the influence of the range of weight coefficients and prefabrication rate on the combination of prefabricated components, this paper conducts a scenario analysis.

V. A. Analysis of Pareto chart results

The prefabricated component assemblies for different scenarios are obtained by solving using Matlab tools, the number of optimal solutions varies according to the range of prefabrication rates and weights, and the number of Pareto solution sets obtained by running different scenarios is shown in Fig. 6.

In terms of the number of optimal solutions, the number of optimal solutions in the cost-focused scenario decreases as the assembly rate increases, and the schedule-focused scenario increases as the assembly rate increases. This is mainly because the cost-focused scenario will favor the selection of cast-in-place components, and in the low precast rate range do not have to think about the precast components must be selected to meet the precast rate requirements, so the cast-in-place components have a larger range of choices, while the schedule-focused scenario will favor the selection of precast components, and the schedule-focused scenarios have a larger selection of precast components in the high precast rate range, thus making the weights of the different weights in the different precast rate range differences in the number of pareto solution sets.

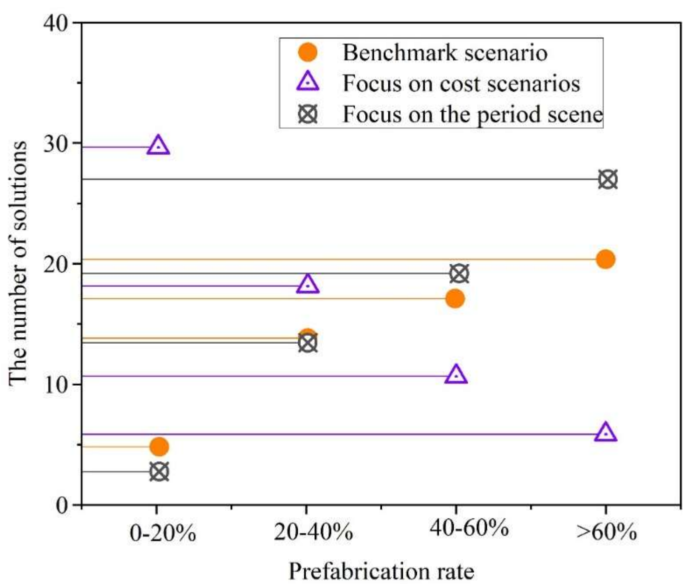

Figure 6: The pareto solution set number

In order to better investigate the impact of different scenarios on the prefabricated component combination selection results as well as the cost and duration of the component selection results, this paper plots the Pareto frontier plots of the component combination optimization results, the results of which are shown in Figures 7-Figures 9. Fig. 7-Fig. 9 represent the pareto frontier plots for the baseline scenario, the cost-focused scenario, and the duration-focused scenario, respectively, and the range of prefabrication rates is represented by different colors in the plots. The pareto frontier plots for different scenarios are analyzed as follows.

The effect of weighting factors on the pareto frontier plot is analyzed by observing the position of scatter points in the plot. The weights of each sub-objective are the same in the baseline scenario, and the selection of optimal solutions is relatively balanced in terms of cost and duration, and the optimal value in the baseline scenario is achieved through the overall reduction of each sub-objective to minimize the overall target value, so the optimal solutions in the pareto solution set are mainly distributed more evenly and concentrated in the middle part of the three-dimensional three-dimensional graph. In the cost-oriented scenario, the weight of cost is higher, and the change of unit cost has a greater impact on the target value than the change of unit duration. In the cost-oriented scenario, the optimal value is achieved by choosing cast-in-place components to directly reduce more cost to minimize the comprehensive target value, i.e., choosing cast-in-place components, so the pareto solution set is concentrated in the upper right corner of the 3D graph where the cost is lower.

The weight of duration is higher in the duration-focused scenario, and the change of unit duration compared with unit cost has a larger impact on the target value. In the duration-focused scenario, the integrated target value is minimized mainly by lowering more duration, i.e., prefabricated components are chosen, and thus the pareto solution set is mainly concentrated in the part of the three-dimensional drawing with a lower duration.

In summary, by analyzing the pareto solution set under different scenarios, we can conclude that the number of prefabricated component combinations and the construction process of the assembled building are affected by the prefabrication rate and the weights of the cost and duration sub-objectives. The weights of the sub-objectives affect the cost and duration of the project by influencing the selection of the component construction process, which determines “how to select” the component construction process. The prefabrication rate affects the cost and duration of the project by influencing the number of components to be selected under the construction process, which determines “how much” of the component construction process to be selected.

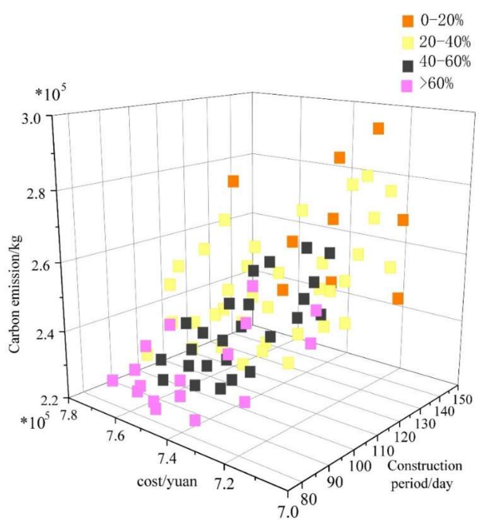

Figure 7: Benchmark scenario

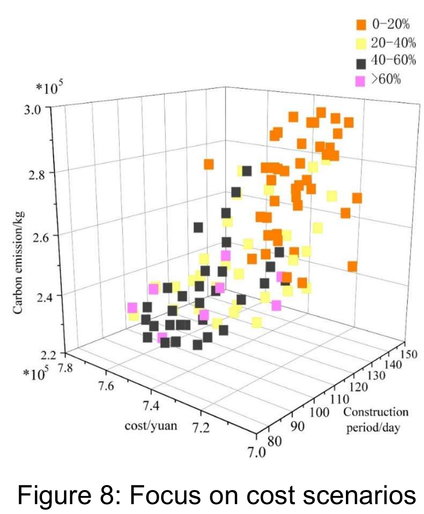

Figure 8: Focus on cost scenarios

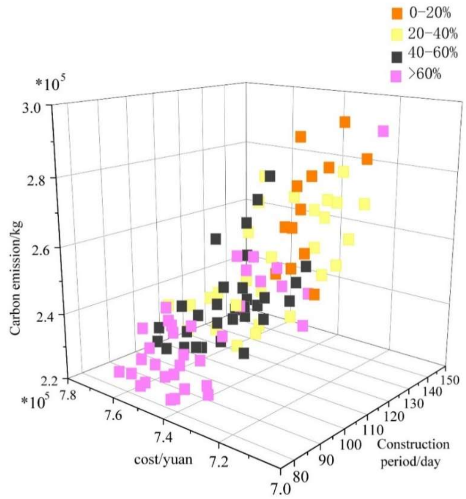

Figure 9: Focus on the period

V. B. Optimization effect analysis

In order to have a more intuitive understanding of the degree of optimization, this paper selects the prefabricated component combinations with the smallest integrated objective weight values under different scenarios and applies the optimization rate to analyze them, and the results are shown in Table 2.

The table describes the results of the selection of prefabricated components of the optimal solution under different scenarios, as well as the cost, duration and carbon emissions of the corresponding projects. Taking the baseline scenario as an example, the weights of cost, duration and carbon emission are taken as 1:1:1, and the construction process of the optimal program is: (first floor) precast columns - cast-in-place beams - precast slabs - precast walls - precast stairs (second floor) cast-in-place columns - cast-in-place beams - precast slabs - cast-in-place walls - cast-in-place stairs (third floor) cast-in-place columns - cast-in-place beams - cast-in-place slabs - cast-in-place walls, with prefabrication rate of 25.145, cost of 7.12×10^5 yuan, duration of 116 days, and carbon emission of 265 t. Other scenarios are modeled in the same way.

Table 2: Optimization effect analysis table

	Layer number	Current building	Assembly building		
Different scene	-	Full current scenario	Benchmark scenario	Cost attention	Construction period
Target weight	-	-	C: T:E=1:1:1	C: T:E=4:1:1	C: T:E=1:4:1
Prefabricated rate (%)	-	0	25.145	27.235	32.156
Pillar beam	First layer	Current casting	Precast	Current casting	Current casting
	Second layer	Current casting	Current casting	Current casting	Current casting
	Third layer	Current casting	Current casting	Current casting	Current casting
	First layer	Current casting	Current casting	Precast	Precast
	Second layer	Current casting	Precast	Precast	Precast
	Third layer	Current casting	Current casting	Current casting	Current casting
Wall	First layer	Current casting	Precast	Precast	Precast
	Second layer	Current casting	Precast	Precast	Precast
	Third layer	Current casting	Current casting	Current casting	Precast
	First layer	Current casting	Precast	Precast	Precast
	Second layer	Current casting	Current casting	Current casting	Current casting
	Third layer	Current casting	Current casting	Current casting	Current casting
Stair	First layer	Current casting	Precast	Precast	Precast
	Second layer	Current casting	Current casting	Precast	Precast
Cost (yuan)*10^5	-	7.16	7.12	7.07	7.13
Period (day)	-	145	116	111	104
Carbon emissions (t)	-	302	265	261	250

(1) The optimal solution in the baseline scenario reduces the cost by 0.56%, the duration by 20.00%, and the carbon emission by 12.25% compared to the all-cast-in-place building. This indicates that the prefabricated component portfolio obtained by applying the methodology of this paper is optimized in terms of cost, duration and carbon emission, which can effectively save the cost and duration of the project while minimizing the carbon emission of the building.

(2) The weight coefficients reflect the degree of preference of stakeholders for different objectives, while the degree of optimization of objectives in multi-objective optimization mainly depends on the size of weights.

(3) The prefabrication rate range of the optimal combination of prefabricated components scheme mainly focuses on the range of 20%-60%, which indicates that for assembled buildings, we should not pursue a high prefabrication rate, but should determine the optimal prefabrication rate according to the needs and requirements of specific projects. An appropriate prefabrication rate range can achieve the best balance in terms of cost, schedule, and carbon emission, and realize the most optimized results.

VI. Conclusion

The research on the balance between modularization and personalization of assembled buildings in intelligent design environment has achieved remarkable results. The relationship between standardization and personalization is clarified through the establishment of a modular design and customization demand balance model, which provides a theoretical basis for engineering practice. The Improved Gray Wolf Optimization (IGWO) algorithm achieves an accuracy of 3.4811e-04 on the test function f2(x), which is 93.8% higher than the GRO algorithm. The case study shows that the multi-objective optimization model for assembled buildings based on the IGWO algorithm has an excellent performance and achieves excellent results in different scenarios. The optimal prefabrication rate for assembled buildings should be controlled in the range of 20%-60% rather than blindly pursuing a high prefabrication rate. Focusing on the duration scenario, the prefabricated component combination solution can reduce the duration to 104 days, which is 28.3% less than the all-cast-in-place solution. The optimization results show that the selection of prefabricated components is not only affected by the prefabrication rate, but also by the weighting coefficient, which determines “how to select” the component construction process, while the prefabrication rate determines “how much to select” the component construction process. The application of BIM technology and parametric modeling enables the assembly building to realize precise control and efficient collaboration in the design and construction phases, which provides intelligent solutions and promotes the construction industry to move towards green solutions, and also provides the building industry to move towards green construction. The application of BIM technology and parametric modeling enables precise control and efficient collaboration in the design and construction phases of assembled buildings, providing intelligent solutions for the assembled building industry and promoting the transformation of the construction industry to green and digitalization.

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