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International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Optimization Strategies of Intelligent Construction Processes and Enhancement of Living Experience in High-Quality Houses Driven by Lean Construction Theory

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SUMMARY: *Based on lean construction theory, this paper divides the total goal of high-quality residential intelligent construction work into four sub-goals: schedule, cost, quality and greenness, and establishes a multi-objective balanced optimization schedule model. The cost model is constructed by work decomposition method, the quality model is established based on construction reliability theory, and the greenness evaluation index system and model are established by synthesizing authoritative green building and assembly building evaluation system. On this basis, the crossover and mutation mechanisms in the immune genetic algorithm are introduced into the particle swarm algorithm to form the immune particle swarm genetic algorithm. Then the immune particle swarm genetic algorithm is used to solve the optimization model. The solution results show that the optimal equilibrium solution optimizes 12.12%, 16.55%, 5.56%, 5.00% in the level of schedule, cost, quality and environment, respectively, which effectively promotes the improvement of the overall construction objectives. The multi-objective modeling and optimization method proposed in this paper provides a reference for the management and decision-making of high-quality residential intelligent construction projects.*

KEYWORDS: *Multi-objective optimization; Immune particle swarm genetic algorithm; Residential experience enhancement; Greenness evaluation index system; High-quality residential construction*

1 Introduction

In recent years, the demand for high-quality housing has been expanded, and the construction process and living experience have been highly scrutinized by architects and residents. The traditional residential construction process presents a linear model, and each link mostly operates independently, which leads to problems such as wasted resources in the construction process, increased communication costs, reduced quality of residential living, and prolonged construction period [1-3]. With the continuous development of intelligent construction of residential buildings, the intelligent construction process has attracted much attention. The multi-level technology assurance system including integrated building information modeling, Internet of Things, artificial intelligence, 5G communication, cloud technology and digital twin, refining the four core principles of data leadership, human-machine collaboration, dynamic improvement and modularization standards, and implementing strategies from three specific levels of intelligent planning, intelligent construction and intelligent supervision have promoted the upgrading of the construction process efficiency and the residential living experience [4-8]. However, there are challenges in the integration and application between these intelligent

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https://doi.org/10.65102/is2026317 Published: 30 April, 2026

technologies, resulting in insufficient data application of the intelligent construction process, poor resource allocation in the construction process leading to waste of resources, limited process optimization, and insignificant effect of the improvement of the living experience [9-12].

Lean construction theory is a very important ideological foundation in the manufacturing system, extended to the construction industry, mainly using systematic thinking to identify and remove various resource waste phenomena, such as redundant output, useless waiting and unnecessary material handling, in order to optimize resource allocation [13-16]. At the same time, intelligent technology, with accurate data collection and analysis capabilities, can achieve optimal deployment of materials, equipment and manpower, thus greatly improving the level of project execution, not only improving construction efficiency and quality, but also promoting the development of comfortable and intelligent buildings [17, 18]. It can be seen that the rational application of lean construction theory helps to optimize the residential intelligent construction process and living experience. However, at present, the application of lean construction theory in the residential field is superficial, focusing more on the construction process design and less on intelligent building construction.

In this paper, the total goal of high-quality residential intelligent construction is decomposed into four dimensions: schedule, cost, quality, and greenness, and corresponding sub-models are established respectively. Combining the Delphi method and OWA operator assignment method to construct the evaluation system and model of the greenness of high-quality residential construction, it overcomes the subjectivity of the determination of the weight coefficients of the evaluation indexes. According to the excellent learning ability of the particle swarm algorithm, the crossover and mutation mechanism of the immunogenetic algorithm is introduced into the particle swarm algorithm, which maintains the diversity of the population and at the same time makes the algorithm able to jump out of the local optimum and search for the optimum quickly, and provides a method for the solution of the multi-objective optimization model of the construction process. The experimental design is carried out through actual engineering cases to verify the effectiveness of the proposed model and method in terms of the distribution of the algorithm's solution set, the solution effect and other dimensions.

2 Multi-objective equilibrium optimization model for intelligent construction of high-quality houses

Building Information Modeling (BIM), a cutting-edge technology, not only provides powerful tools in the design and construction phases, but also brings greater efficiency, precision, and collaborative capabilities to urban spatial planning.

BIM technology provides planners and designers with precise, visualization tools in the design phase of urban spatial planning. Through BIM models, the effects of different planning schemes are simulated, their feasibility is quickly assessed, and data support is provided for decision-making.

In the building construction phase, BIM technology assists in planning the construction process and optimizing resource allocation, thus improving building efficiency and quality. At the same time, BIM models can plan a reasonable construction sequence, reduce conflicts and errors, solve potential problems in advance, and reduce changes and repetitive work.

BIM models can continuously update information about buildings and urban facilities for maintenance and management. From equipment maintenance to energy consumption monitoring, BIM technology enables city managers to operate and maintain urban facilities more efficiently.

2.1 Multi-objective optimization model for high quality residential construction process

Based on the research and understanding of the process of the whole life cycle of high-quality residential intelligent construction, this study concludes that the whole life cycle of high-quality residential intelligent construction can be divided into four phases decision-making phase, research and development phase, general assembly phase, and operation phase.

2.1.1 Duration model

In the actual construction process, such as operational errors, poor resource allocation, force majeure and other probabilistic events can be directly caused by the rework of the process. We regard N_1 and N_2 as two consecutive work processes, and if we manage them as serial work, N_2 work needs to start after N_1 work is completely finished. When there is rework, the N_2 job group will have additional waiting period and the total duration will increase accordingly. It is assumed that the portion of the increased duration of N_1 rework that impacts N_2 is T_1^{re}, and this portion of the impacted rework will be counted in the total duration.

$$T_i = t_i^{normal} + t_i^{re} - t_i^{ce} \tag{1}$$

This formula considers that the excess duration generated by the rework of the process, the impact on the duration of its subsequent process is consistent with the process, but this impact will not continue to pass backwards, that it can be resolved in the process and the subsequent process in the continuous process.

High-quality residential intelligent construction construction process, the total duration is composed of the sum of the duration of each process, which needs to be combined with the actual, together with the consideration of parallel and rework operation length. High-quality residential intelligent construction construction period is:

$$T = \sum_{i=1}^{n} t_i^{normal} - \sum_{i=2}^{n} t_i^{ce} + \sum_{i=1}^{n} t_i^{re} \tag{2}$$

where t_i^{normal} is the normal working hours without parallelism and rework of process i, t_i^{ce} is the working hours that overlap with the previous process in parallel when working in parallel engineering, and t_i^{re} is the working hours where rework occurs and has a real impact on the subsequent work. t_i^{ce} is only possible from the second process, so here i is taken from 2.

2.1.2 Cost modeling

The cost content of this study, formulated for the characteristics of high-quality housing, includes component unit costs. This model determines that the total cost of the project is the sum of direct and indirect costs, and taxes and so on are not considered in the calculation of the cost. The cost components of intelligent construction of high-quality residential buildings are shown in Figure 1.

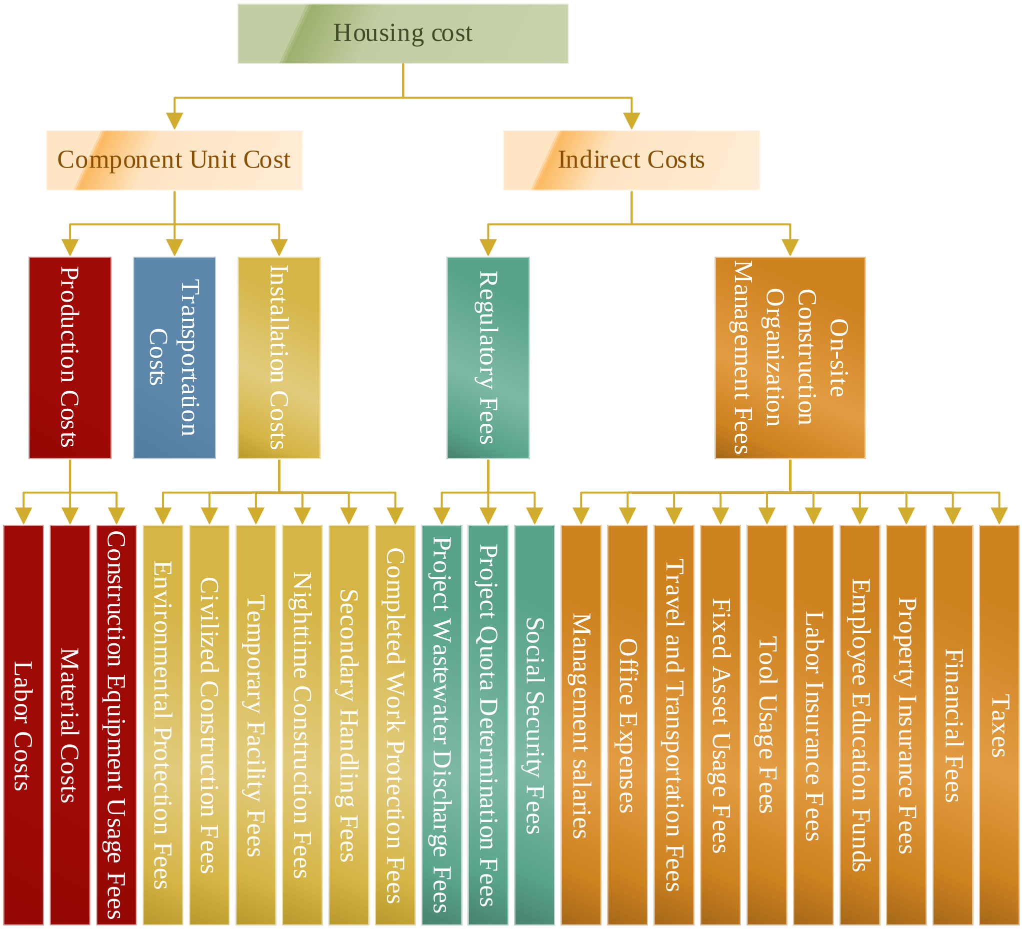


Figure 1: High quality housing construction cost composition

As the object of study is the component unit and the corresponding process in the WBS work decomposition, all the data of direct cost are collected by the contract amount signed by the supplier of the component unit.

High-quality residential intelligent construction projects, with industrialized attributes, in the construction of the project cost model in the direct cost is only considered in the work unit spent on manufacturing and assembly costs, indirect costs arising from each product work unit, the cost is included in the contract signed by the supplier of components and contractors in the price of the project, in principle, the indirect cost of the site is mainly the management fee, which consists of the indirect cost per day times the total duration of the work to obtain. The total number of work periods is obtained, and the specific cost mathematical model is:

$$C = \left(\sum_{i=1,k=1}^{i=n,k=r_i} DC_{ik} + \sum_{i=1,k=1}^{i=n,k=r_i} t_{ik} \times IC \right) \cdot D_{ik} \tag{3}$$

$$s.t. \sum_{k=1}^{r_i} D_{ik} = 1 \tag{4}$$

$$IC = \frac{C_P \eta}{T_P} \tag{5}$$

where DC_{ik} is the cost of manufacturing and assembling parts for performing the k operation mode selected for the i th construction process, i.e., the direct cost, and IC is the daily indirect cost incurred by selecting different operation modes.

2.1.3 Quality models

The process quality level Q_i is expressed as a continuous value from 0 to 1, with larger values indicating higher quality levels. The Q_{is} represents the process quality level at the shortest process time and Q_{il} represents the process quality level corresponding to the longest process time.

The quality level Q_{ik} of a single process i under k working mode is modeled as:

$$Q_{ik} = \ln\left(a_{ik} t_{ik} + b_{ik}\right) \tag{6}$$

$$ts_{ik} \le t_{ik} \le tl_{ik} \tag{7}$$

$$a_{ik} = \frac{e - e^{q_{ik}}}{tl_{ik} - ts_{ik}}, b_{ik} = \frac{e^{q_{ik}} \times tl_{ik} - e \times ts_{ik}}{tl_{ik} - ts_{ik}} \tag{8}$$

where t_{ik} is the time required for the i th process in the k th way of operation, e is a natural constant, ts_{ik} is the shortest duration of the work, and tl_{ik} is the longest duration of the work; and q_{ik} is the quality level of the i th process in the k th way of operation.

In any project, the quality of the work is expressed as a result of the transfer of quality between the processes because of the transfer correlation between the processes.

The final quality level Q of the construction assembly stage can be decomposed into the quality level Q_i of each process cumulatively obtained, combined with the construction reliability theory, the quality level model is:

$$Q = \underset{i=0}{\overset{n}{G}} Q_i \tag{9}$$

Each node i located in the network graph, upon its completion, can be obtained as a result of the quality level:

$$Q_i^{out} = \left[1 - \prod_{j=1}^{n}\left(1 - Q_j^{in}\right) \times Q_i\right] \tag{10}$$

where: Q_j^{in} , Q_j^{out} corresponds to the quality level results generated by the immediate preceding and following work of job i, respectively; $i = 1$, $Q_i^{in} = 0$.

Among the whole segment of the construction assembly stage, the first process serves as the initial input, Q^{in} that is Q_0^{in}, and the quality output of the last process n is the quality result obtained at the end of the construction assembly stage, that is:

$$Q = \underset{i=0}{\overset{n}{G}} Q_i = Q_n^{out} \tag{11}$$

$$Q_i \in [0,1] \tag{12}$$

where Q_n^{out} is the number of quality levels of work immediately after work n.

In order to make the study simpler, the quality level is quantified in this study. It is expressed by the quality level index, which is represented by a value from 0 to 1, with a high quality level for a large value. For the quality level of the project as a whole, all Q of the reference are between 0 and 1.

2.1.4 Greenness model

In the choice of methodology for the establishment of greenness indicators, this study was conducted using the Delphi method. The Delphi method is a simple and easy decision-making method. The initial screening indicators were summarized and categorized into a total of 2 target layers and 5 evaluation layers. Energy saving and environmental protection A: energy saving level $A1$, carbon emission $A2$; assembly management B: assembly of construction process $B1$, construction management $B2$, and labor productivity $B3$.

For the calculation of carbon emission replacement A_2, according to the calculation standard in the "Construction Carbon Emission Calculation Standard" GB/T 51366-2019, combined with the research conclusions in the establishment of the index system in the previous section, we get equation (13):

$$C_e = \sum_{i=1,k=1}^{i=n,k=r_i} \left(K_e^{1k} \times E + t_{ik} \times L \right) \Big/ A \tag{13}$$

In the established evaluation system for the greenness level of high-quality housing, the five indicators have different scales and cannot be directly weighted using data in the calculation. Therefore, it is necessary to normalize the indicators before the final calculation of the greenness level. Among the above selected greenness evaluation indicators, assembly of construction process B_1, construction management B_2 and labor productivity B_3 are positive indicators, while energy consumption level A_1 and carbon emission placement A_2 are negative indicators. After normalization, the values of all five indicators are between 0 and 1, and the calculation formula is as follows.

$$\text{Positive indicators:} \frac{x_i - \min}{\max - \min} \tag{14}$$

$$\text{Negative indicators:} \frac{\max - x_i}{\max - \min} \tag{15}$$

Combining the above, the greenness evaluation model can be completed and constructed as follows:

$$G = \sum_{p=1}^{u} \left(\omega_p \cdot \sum_{i=1,k=1}^{i=n,k=r_i} G_p^{ik} \right) \cdot D_{ik} \tag{16}$$

$$s.t.\ \sum_{k=1}^{r_i} D_{ik} = 1 \tag{17}$$

Weights were set for each evaluation indicator. In the expert interview session, this was handled here by experts through questionnaire scoring. The weights of the greenness evaluation indicators were calculated by the OWA operator assignment method, and the weight values obtained by *A*1, A2, B1, B2, and B3 were seen to be 0.166, 0.195, 0.215, 0.218, and 0.206, respectively.

2.1.5 Multi-objective equilibrium optimization model

The above single-objective model is combined to achieve the optimization objectives of lowest cost, shortest duration, best quality and highest level of greenness. The overall multi-attribute utility function model is:

$$\begin{cases} \min T = \sum_{i=1}^{n} t_{ik}^{normal} + \left(\sum_{i=1}^{n} t_{ik}^{re} - \sum_{i=2}^{n} t_{ik}^{ce} \right) \cdot D_{ik} \\ \min C = \left(\sum_{i=1,k=1}^{i=n,k=r_i} DC_{ik} + \sum_{i=1,k=1}^{i=n,k=r_i} t_{ik} \cdot IC \right) \cdot D_{ik} \\ \max Q = Q_n^{out} \\ \max G = \sum_{p=1}^{u} \left(\omega_p \cdot \sum_{i=1,k=1}^{i=n,k=r_i} G_p^{ik} \right) \cdot D_{ik} \end{cases} \tag{18}$$

$$\begin{aligned} & T \le T_p \\ & C \le C_p \\ & Q_{\min} \le Q \\ & G_{\min} \le G \end{aligned} \tag{19}$$

Establishing an overall balanced optimization model for high quality residential intelligent construction schedule, cost, quality and greenness as:

$$\begin{aligned} u(T,C,Q,G) = K_T \times & \left[\sum t_{ik}^{normal} + \left(\sum t_{ik}^{re} - \sum t_{ik}^{ce} \right) \right] \cdot D_{ik} \\ & + K_C \times \left(\sum DC_{ik} + \sum t_{ik} \cdot IC \right) \cdot D_{ik} + K_Q \times Q_n^{out} \\ & + K_G \times \sum_{p=1}^{u} \left(\omega_p \cdot \sum G_p^{ik} \right) \cdot D_{ik} \end{aligned} \tag{20}$$

$$K_T, K_C, K_Q, K_G > 0,\ K_T + K_C + K_Q + K_G = 1 \tag{21}$$

2.2 Multi-objective equilibrium optimization model solution algorithm

2.2.1 Immunogenetic algorithms

The evolutionary algorithm represented by genetic algorithm is an iterative search algorithm that imitates the biological evolution mechanism, which uses crossover and mutation operators to realize the information interaction and local search between individuals in the population, providing optimization opportunities for each individual, and guiding the population to evolve in a better direction through the competitive selection mechanism of the survival of the fittest. However, since the two genetic operators of crossover and mutation are realized based on a certain probability, they have greater randomness and blindness.

In order to compensate for the shortcomings of the genetic algorithm, a biological immune mechanism is introduced on the basis of the genetic algorithm (GA), which utilizes a priori knowledge to construct an immune seedling, and draws on the ability of the immune system to produce and maintain a diversity of antibodies, as well as the ability of self-regulation, and introduces the immune mechanism on the overall framework of the genetic algorithm, resulting in the formation of the immune genetic algorithm. Here, the objective function of the solution problem corresponds to the antigen of the invading organism, and the candidate solution of the problem corresponds to the antibody (i.e., the individual to be evolved), and the degree of approximation of the feasible solution to the optimal solution is described by the affinity between the antigen and the antibody. By integrating the mechanism of artificial immune system and evolutionary algorithm both, the immunogenetic algorithm formed adds vaccination operator, immune detection operator, immune balance operator, etc., and has great improvement in individual updating, selection operator, and maintenance of diversity compared with evolutionary algorithm.

After adopting crossover and mutation operators in traditional genetic algorithms, the immunogenetic algorithm utilizes prior knowledge and introduces vaccination operator. Thus, the individuals are approximated to the optimal solution, which accelerates the convergence of the algorithm and realizes the process of individual renewal.

And in the immunogenetic algorithm, after the crossover, mutation, and vaccination operators, the newly generated individuals need to be operated by the vaccine detection operator, i.e., to determine whether their fitness is better than that of the parent individuals, and if degradation occurs, the newly generated individuals are replaced with the parent individuals. Then, using the selection probability jointly determined by the fitness and concentration values of the antibody, it participates in the roulette wheel selection operation, and finally selects the new generation of the population.

In the immunogenetic algorithm, in addition to the fitness of the antibody, the immune balance operator is also introduced to participate in the selection of the antibody. The immune balance operator inhibits the antibody with high concentration and conversely promotes the antibody with lower concentration.

2.2.2 Particle Swarm Optimization

Particle swarm optimization algorithms are characterized by evolutionary computation and swarm intelligence. Similar to other evolutionary algorithms, the particle swarm algorithm also realizes the search of optimal solutions in the complex space through collaboration and competition among individuals.

In the particle swarm algorithm, the solution of each optimization problem is regarded as a bird, i.e. “particle” in the search space. The initial population is first generated, i.e., a group of particles are randomly initialized in the solution space, each particle is a feasible solution to the optimization problem, for which a fitness value is determined by the objective function. Each particle will move in the solution space and its flight direction and distance will be determined by the speed of movement. Usually the particle will follow the current optimal particle to search in the solution space. In each iteration, it will update itself according to two “extremes”, one is the optimal solution found by the particle itself, and the other is the optimal solution found by the whole population, which is the global extreme value.

The particle swarm algorithm can be described as follows: Let a swarm of particles search in an n -dimensional space, consisting of m particles to form a population $Z=\{Z_1,Z_2,\cdots,Z_m\}$, in which the position $Z=\{z_{i1},z_{i2},\cdots,z_{im}\}$ of each particle denotes a solution of the problem. The particles search for a new solution by constantly adjusting their position Z_i. Each particle remembers the optimal solution it searched for, denoted as P_{id}, as well as the best position experienced by the entire swarm, i.e., the currently searched optimal solution, denoted as P_{gd} . In addition each particle has a velocity, denoted as $V_i=\{v_{i1},v_{i2},\cdots,v_{im}\}$, and when both optimal solutions have been found, each particle updates its own velocity according to equation (22).

$$v_{id}(t+1)=wv_{id}(t)+\eta_1\text{rand}()(p_{id}-z_{id}(t))+\eta_2\text{rand}()(p_{gd}-z_{id}(t)) \tag{22}$$

$$z_{id}(t+1)=z_{id}(t)+v_{id}(t+1) \tag{23}$$

where: $v_{id}(t+1)$ - the velocity of the i th particle in the d th dimension in the $t+1$ th iteration;

w - inertia weights;

η_1,η_2 - acceleration constants;

$rand()$ - for a random number between 0 and 1.

2.2.3 Immunogenetic particle swarm algorithm

As a stochastic search algorithm that simulates the behavior of natural organisms, the particle swarm algorithm has the potential to achieve a globally optimal search, but at the same time there are cases of premature convergence. In the algorithm, the interaction between individual particles is mainly reflected in two points: one is the interaction between itself and its own history record, each individual can use its own cognition to adjust itself according to its own experience of the optimal position, which has the ability of “self” learning and improvement; the second is the interaction between the global record and itself, which updates its information according to the gap of the best position experienced by the whole group, which has the ability of “self” learning and improvement. The second is a global record of interactions with itself, updating its own information according to gaps in the best positions traversed by the group as a whole, with the advantage of learning from “others”. This kind of behavior to find out the gap between itself and its own history and learn from the best individuals is the instinct of biological evolution, and also the motivation of individual progress, which is exactly the most worthy of particle swarm algorithms, and this kind of idea can be embedded in many other intelligent algorithms.

In this paper, we introduce the crossover and mutation mechanisms of the immunogenetic algorithm into the particle swarm algorithm, and combine them with the immune memory mechanism to maintain the diversity of the population, and this new algorithm is called the Immunogenetic Particle Swarm Algorithm (IGPSO), which is capable of avoiding the “premature maturity”, jumping out of the local optimum, and converging to the globally optimal solution quickly.

According to the principle described above, the specific flow chart of IGPSO algorithm is designed as follows:

(1) Set the initial position and velocity of particles, i.e., initialize the particle swarm.

(2) Calculate the fitness value of each particle.

(3) Judge whether the termination condition of the algorithm is satisfied, if the condition is

satisfied, output the optimal solution and stop the operation. Otherwise, continue the optimization operation.

(4) Immune detection, according to which the memory bank is updated.

(5) Judge "early maturity".

(6) Genetic operation and updating the velocity and position of particles.

(7) Population update, determine whether to meet the termination conditions of the algorithm, if so, output the optimal solution, otherwise go to step 2 and continue the optimization operation.

The flow schematic is shown in Fig. 2.

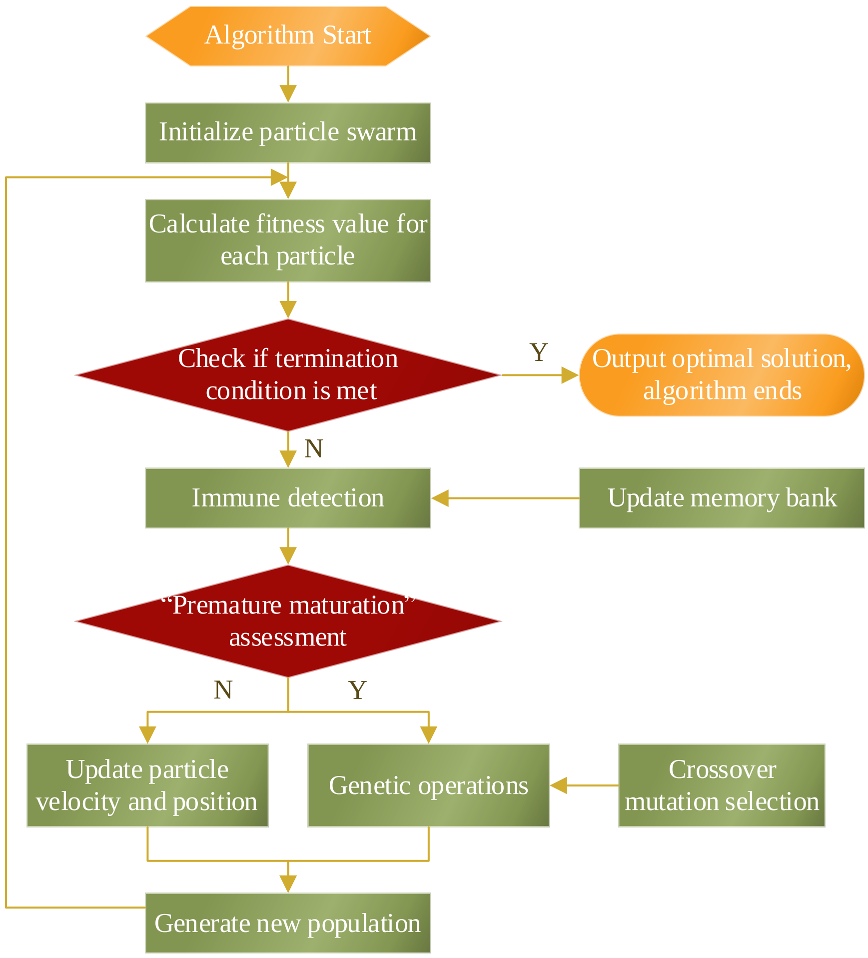


Figure 2: IGPSP algorithm flowchart

3 Calculation and analysis of an example of multi-objective optimization for high-quality residential construction

3.1 Description of instances

This project aims at the development of a high-quality residential district contracted by an engineering and construction construction enterprise, which covers a total area of 63,500 square meters, selecting eight major activities in the construction phase of the building, and the project has a contractual planned duration of 685 days, a contractual cost of 623.3 million yuan, a quality level of not less than 0.9, and a green level value of not less than 0.8.

This green construction project has set strict quantitative targets for environment, energy, land, materials and quality in accordance with relevant documents and management regulations, and realized the smooth progress of the project through scientific construction management and construction technology. Green construction techniques are adopted in the architectural design stage, the structural construction of the building and the later stage of electromechanical installation to minimize environmental pollution and improve construction safety and building quality.

3.2 Analysis of the algorithm for solving the multi-objective equilibrium optimization model

3.2.1 Test Functions

In order to be able to determine whether the algorithms used are effective in dealing with multi-objective optimization problems, several test functions are usually used to measure them. The test results can determine whether the algorithm used is effective or not, and can also be compared with other algorithms. In this paper, we choose three common test functions: ZDT-1 function, ZDT-2 function and ZDT-3 function to determine whether the immunogenetic particle swarm algorithm in this paper can effectively deal with multi-objective optimization problems, and compare it with NSGA-II algorithm.

3.2.2 Algorithm Setup

In this paper, Matlab programming is used to test the ZDT-1 function, ZDT-2 function, and ZDT-3 function using the Immunogenetic Particle Swarm algorithm and NSGA-II algorithm, respectively. During the test, the species size of the NSGA-II algorithm was set to 120, the crossover probability was set to 0.9, and the tournament selection method was used for the operation, and the variance probability was set to 1/L, where L is the number of decision variables. The initial number of particles of the immunogenetic particle swarm algorithm is set to 90, and the condition for the end of the algorithm loop is to reach the maximum number of iterations, and here the maximum number of iterations is taken to be 300.The results of the operation of the three functions of ZDT-1, ZDT-2, and ZDT-3 are shown in Fig. 3 to Fig. 5, respectively.

The GD and S values of these two algorithms with respect to the three functions are shown in Table 1 and Table 2 respectively.

Both algorithms can converge to the real Pareto front, and it can be seen that the S value and GD value of the function of the improved immunogenetic particle swarm algorithm are closer to 0. Although the performance of the S value of the NSGA-II function is partially better than that of the improved immunogenetic particle swarm algorithm in the ZDT2 function, it seems that in general, the improved immunogenetic particle swarm algorithm can cover the whole Pareto front, and has a better convergence and GD value compared to the NSGA-II function with better convergence and diversity. The S-value and GD-value of the immunogenetic particle swarm algorithm have strong diversity and convergence than NSGA-II algorithm, and the improved immunogenetic particle swarm algorithm has better results.

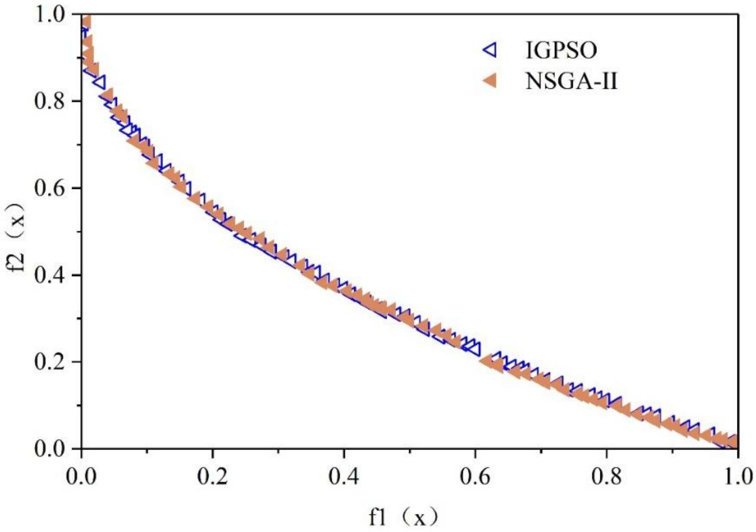


Figure 3: ZDT1 The results

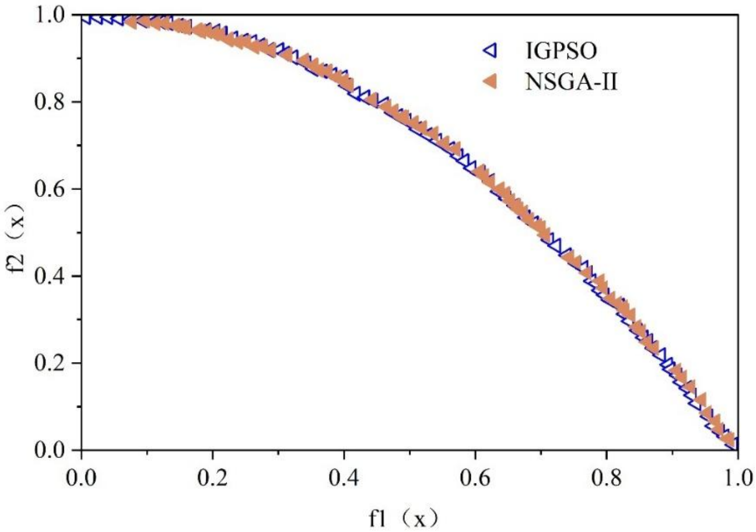


Figure 4: ZDT2 The results

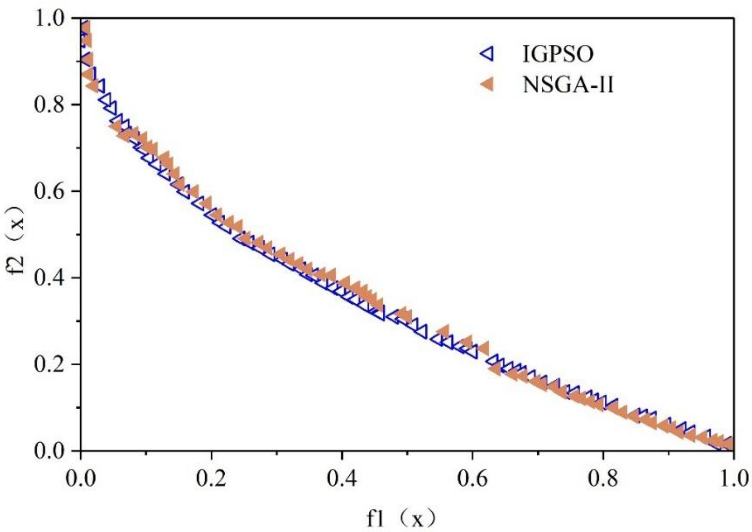


Figure 5: ZDT3 The results

Table 1: The GD value of the ZDT function

Function	GD	IGPSO	NSGA-II
ZDT1	Optimal value	1.544E-4	0.0014082
	Worst value	1.271E-4	8.823E-4
	Mean	1.388E-4	0.0011022
	Median value	1.321E-4	9.852E-4
	Standard value	7.13814E-6	1.664E-4
ZDT2	Optimal value	0.0011553	1.531E-4
	Worst value	9.277E-4	1.498E-4
	Mean	0.0010992	1.376E-4
	Median value	0.0011141	1.341E-4
	Standard value	7.29728E-5	1.447E-4
ZDT3	Optimal value	0.0018404	3.491E-4
	Worst value	0.0012523	3.165E-4
	Mean	0.0014756	3.295E-4
	Median value	0.0014303	3.282E-4
	Standard value	0.0016233	3.397E-4

Table 2: The S value of the ZDT function

Function	S	IGPSO	NSGA-II
ZDT1	Optimal value	4.63E-05	0.0007814
	Worst value	1.17E-05	0.0001365
	Mean	1.93778E-05	0.0003201
	Median value	3.55888E-05	0.0002761
	Standard value	2.97045E-05	0.0004645
ZDT2	Optimal value	0.0004027	9.84E-06
	Worst value	0.0001773	1.03E-05
	Mean	0.0002805	1.8832E-05
	Median value	0.0005515	3.26425E-05
	Standard value	0.0006235	4.35516E-05
ZDT3	Optimal value	0.0008393	9.78E-05
	Worst value	0.0010128	0.0001002
	Mean	0.0006511	8.50838E-05
	Median value	0.0011515	0.0001671
	Standard value	0.0014761	0.0001785

3.2.3 Multi-objective equilibrium optimization algorithm setup

MATLAB is used for the optimization solution of this project, the duration of the process is used as the decision vector x. There are 4 processes in this project, so the decision vector x is a 4-dimensional column vector, and the position vector and velocity vector of a particle are both 12-dimensional. Generally speaking, the value of the population size is usually between 20-40, and usually 10 particles can lead to the optimal solution for simpler problems. In view of the greater complexity of the construction project, the initial size of the particle population is set to 200 in this paper.The traditional Pareto front is shown in Fig. 6.

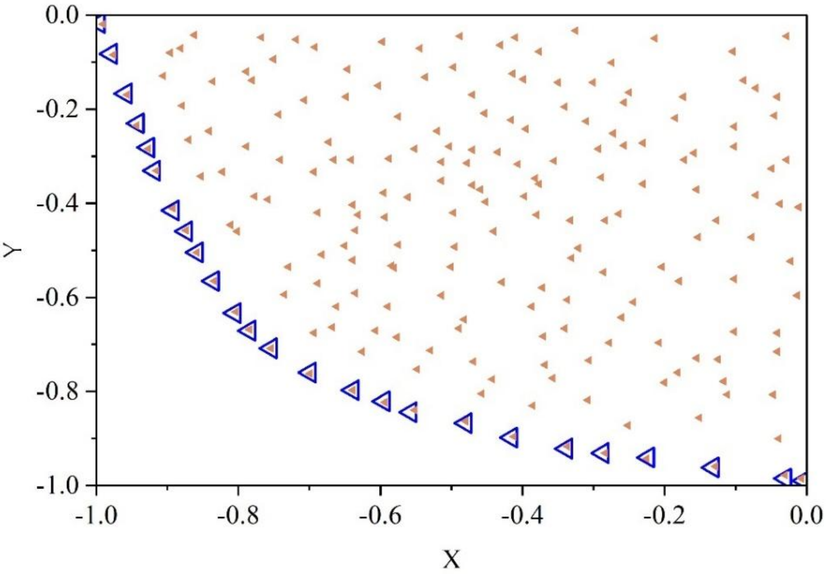


Figure 6: The traditional pareto front

3.3 Multi-objective equilibrium optimization model solution results

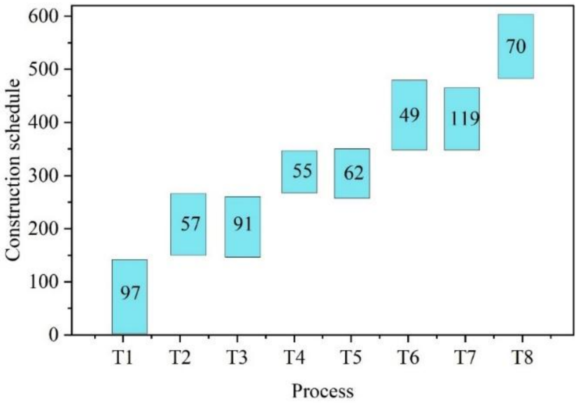
3.3.1 Analysis of solution results

After solving this multi-objective construction problem by immunogenetic particle swarm algorithm, a series of feasible and effective solutions are obtained, and Table 3 shows the better solutions of the multi-objective part of the construction project, and each group of solutions can be used as alternatives. The project decision maker can choose the solution according to the need to realize the reasonable allocation of resources in the construction process of each process.

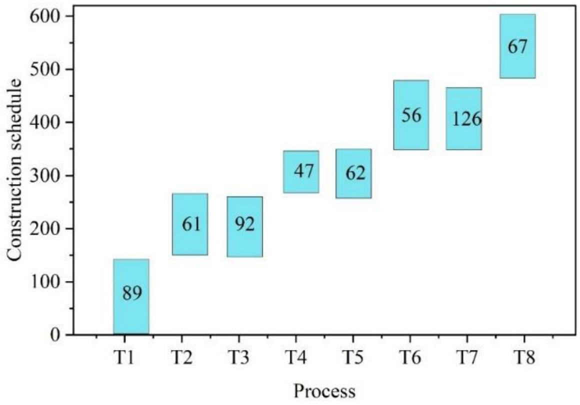
Table 3: Multi-objective partial solution of construction project

Scheme	T	C	Q	E	T1	T2	T3	T4	T5	T6	T7	T8
1	600	50895	0.94	0.83	97	57	91	55	62	49	119	70
2	600	53125	0.95	0.83	89	61	92	47	62	56	126	67
3	602	52017	0.95	0.84	98	59	94	48	62	51	128	62
4	613	52986	0.94	0.85	95	60	94	46	62	51	135	70
5	597	55193	0.95	0.82	95	57	97	47	60	52	126	63
6	613	55211	0.94	0.86	98	55	94	52	53	57	123	81

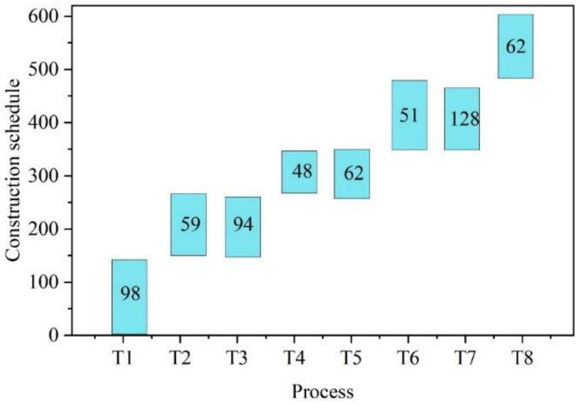
The alternatives in Table 3 are represented by Gantt charts, and the scheme Gantt charts are shown in Fig. 7, Figs. (a) to (f) are the Gantt charts of Scenarios 1 to 6, respectively, which allow for a more intuitive observation of the characteristics of each alternative.



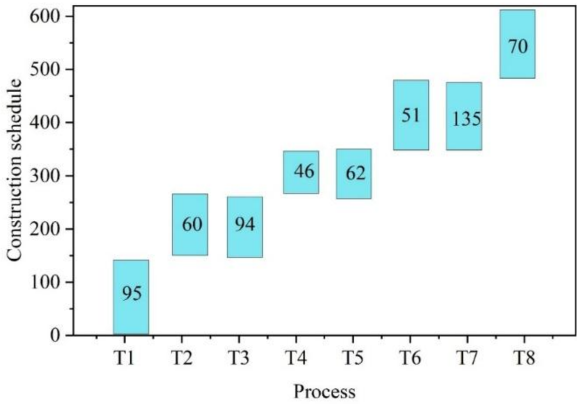
(a) Plan 1 gantt chart



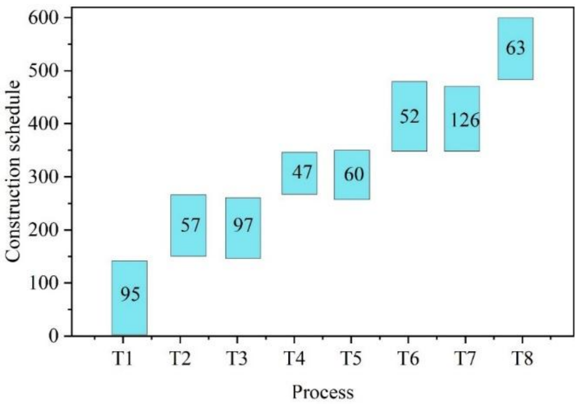
(b) Plan 2 gantt chart



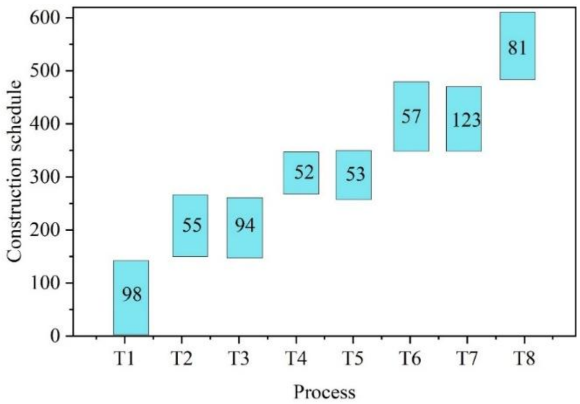
(c) Plan 3 gantt chart



(d) Plan 4 gantt chart



(e) Plan 5 gantt chart



(f) Plan 6 gantt chart

Figure 7: Plan 1~ 6 gantt chart

In order to make the project decision makers understand the distribution of the Pareto solution obtained by the immune genetic particle swarm algorithm for this high-quality residential construction project, a three-dimensional diagram of “T-C-QE mean” is drawn, and the three-dimensional diagram of “T-C-QE mean” is shown in Figure 8. The equilibrium optimization solution obtained by the immunogenetic particle swarm algorithm, the construction project duration is mainly distributed in [560,660], the cost is mainly distributed in [56400,57600], the distribution of the solution set is reasonable, and the solution result is effective.

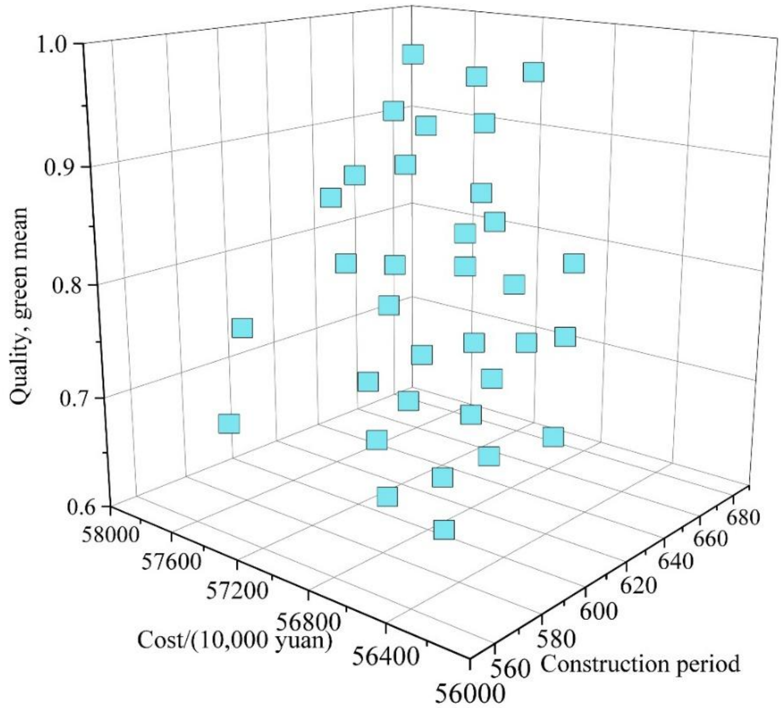


Figure 8: Three-dimensional diagram of "T-C-Q, E mean"

The solution to the objective model of this construction case using PSO is shown in Table 4.PSO also shows some ability to solve the multi-objective optimization problem of this construction project, and can optimize each main control objective to different degrees. The optimization degree of the two algorithms can be calculated by comparing the better solutions obtained by using the Immunogenetic Particle Swarm Algorithm and PSO for solving the high-quality residential construction case model, and the optimization effect of the two algorithms can be compared as shown in Table 5.

Comparing the minimum basic requirements of the construction project, both algorithms, IGPSO and PSO, can obtain effective optimization solutions by solving the optimization model, which gives the duration of the specific construction process, and can optimize the project objectives such as schedule, cost, quality, etc., to a certain extent, and it can be clearly seen that the IGPSO proposed in this paper has better optimization effect, and Scheme 1 has the best optimization effect in cost, as high as 18.35%, and the best optimization effect in cost. Optimization effect is the best, as high as 18.35%; while Scheme 5 performs the best in the objective of schedule level, with an optimization effect of 12.85%. It can be clearly seen that Scheme 3 embodies advantages in terms of duration, cost and quality level, and is the current optimal balanced scheme.

Intelligent building systems, as a product of modern technology, are gradually changing the face of urban space planning and residential building design. These systems provide occupants with a more comfortable, convenient and sustainable living environment by integrating advanced information technology, automated control and data analysis.

Table 4: Project optimization scheme of PSO solution

T	C	Q	E	T1	T2	T3	T4	T5	T6	T7	T8
625	57230	0.92	0.81	96	62	99	60	64	52	127	78

Table 5: Comparison of optimization effects between the two algorithms

Algorithm	Scheme	Duration optimization (%)	Cost optimization (%)	Quality optimization (%)	Green optimization (%)
IGPSO	1	12.41%	18.35%	4.44%	3.75%
	2	12.41%	14.77%	5.56%	3.75%
	3	12.12%	16.55%	5.56%	5.00%
	4	10.51%	14.99%	4.44%	6.25%
	5	12.85%	11.45%	5.56%	2.50%
	6	10.51%	11.42%	4.44%	7.50%
PSO		8.76%	8.18%	2.22%	1.25%

3.3.2 Multi-objective decision-making research for business decision support

With the gradual enhancement of modern management technology and the continuous improvement of intelligent algorithms, intelligent computing provides decision makers of engineering projects with a more convenient and quicker way of thinking to solve multi-objective problems, which can produce more diversified and better decision-making solutions, and can select suitable alternatives for their own characteristics and needs. Inspired by the multi-objective decision-making of green construction projects, this section establishes a multi-objective decision-making evaluation model based on the types of social organizations, which provides decision-making solutions for the objective needs of various types of organizations.

For the vast majority of enterprises, the pursuit of maximizing economic benefits is the biggest goal for the survival and development of enterprises, in which the most central benefit provider is profit, which is very critical for for-profit enterprises. The most prominent enterprise goal pursued by for-profit enterprises is economic efficiency, hoping to maximize economic profit through very small payment, in this case, enterprises tend to choose the plan with the optimal cost objective, and do not pay too much attention to the optimization of other objectives.

In order to protect people's livelihood and serve the public, there are a number of social responsibility undertaking enterprises in the society, which are usually closely related to government departments, such as undertaking the construction of municipal projects and infrastructure construction and so on.

Under the current mode of economic development, many enterprises have started to pursue the common development of economic benefits and social benefits, because to a large extent, the higher the degree of corporate social responsibility, the higher the social benefits, and the social benefits will, in turn, play a role in the economic benefits. More and more large-scale for-profit enterprises are taking a longer view of their social responsibility, taking into account the interests of other recipients, and choosing among the many decision-making options the one that balances economic and social objectives.

For different interest-seeking organizations or enterprises, project decision makers should choose the appropriate personalized targeting options according to their own interests. With the advancement of modern management technology and the development of intelligent computing, the multi-objective optimization strategy based on intelligent algorithms can provide diversified solutions for the enterprise's project decision-making, and it can also be used in other fields of management.

4 Conclusion

Driven by the lean construction theory, this study centers on the intelligent construction of high-quality housing and the improvement of residents' living experience. Currently, more and more construction companies are not only concerned about economic benefits, but also focus on social responsibility, which is specifically reflected in the emphasis on the schedule, cost, quality and environmental protection of high-quality residential construction projects. These four goals are rich in connotation and are the embodiment of social interests. This paper links the multi-objective research practice of high-quality residential construction projects with modern management system, and establishes a multi-objective optimization schedule model for high-quality residential intelligent construction.

The algorithm performance test results show that IGPSO has better convergence and diversity in the ZDT series of functions, and the GD and S values of the IGPSO algorithm are closer to 0 on the whole, and the algorithm is able to more closely approximate the real Pareto frontier, provide more scientific decision-making for the multi-objective construction of high-quality residential intelligence, and is able to bring substantial improvements to the residents' living experience.

In the immune genetic particle swarm algorithm for high-quality residential intelligent construction multi-objective optimization schedule model, the immune genetic particle swarm algorithm and particle swarm algorithm, compared with the better optimization effect, so that the four objectives to achieve the overall optimal under the conditions of the qualification, the optimal equilibrium solution of the immune genetic particle swarm algorithm, compared with the PSO algorithm, the four objectives of the schedule, cost, quality and environmental protection were The four objectives of schedule, cost, quality and environmental protection are improved by 3.36%, 8.37%, 3.34% and 3.75%, respectively, compared with the solution of PSO algorithm.

Through the combination of lean construction theory and intelligent technology, this study realizes the multidimensional enhancement of construction objectives, and brings a feasible technical path for the improvement of residents' living experience. Technological innovation makes the residents' living experience more convenient, intelligent and comfortable. Intelligent transportation systems make travel more convenient, and intelligent energy management and smart home systems provide a personalized home control experience. The application of technological innovations helps to improve the sustainability of communities. Through the application of intelligent energy management systems and renewable energy, energy consumption is reduced and carbon emissions are lowered, which contributes to the protection of the urban environment. Emerging communities gain a better urban image due to their technological innovations and become demonstration areas that lead the way in technological development, attracting more people to live and invest in them.

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