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Research on multi-objective combinatorial optimization algorithm and its spatial layout application for environmental art design of smart city

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Abstract Smart city is developing at a rapid speed, which will make a huge change in the production mode and industry, and “smart” design and construction in environmental art design will be the future development trend. This paper takes the construction of park green space as a research case, establishes a multi-objective optimization model based on genetic algorithm by combining the characteristics of the research area, and plans 33 candidate park green spaces in the area with low level of park green space service by combining the information of urban land use planning. In view of the shortcomings of traditional genetic algorithm, which is easy to fall into local optimization, simulated annealing algorithm is introduced to improve the standard genetic algorithm by composing hybrid genetic-simulated annealing (GA-SA) algorithm. The results show that the convergence speed of the hybrid genetic-simulated annealing algorithm is significantly improved, which is stronger than the simple genetic algorithm. The optimization model can ensure the goal of planning the minimum green area of the park, and the spatial distribution separation is kept in the range of 0.577 to 0.596, which has a better design. The research method of this paper is of reference and guidance to the environmental design and planning of the smart city.

Index Terms smart city, genetic algorithm, simulated annealing algorithm, multi-objective optimization

I. Introduction

Cities are an important symbol of human civilization and an important place for people to live, work and communicate [1]. In recent years, with the rapid development of science and technology and the acceleration of urbanization, smart cities have gradually emerged globally [2]-[4]. Smart city is a modern city supported by information technology, aiming to optimize the allocation of resources, improve the level of urban management and provide convenient services, and realize the sustainable development of economy, society and environment [5], [6]. In the process of smart city development, spatial planning and optimization play a key role [7].

In the current urban development, spatial layout exists problems such as unreasonable urban functional zoning, unbalanced distribution of urban public facilities, and imperfect urban transportation system [8], [9]. Spatial planning is an essential part of smart city construction, which can maximize the functionality and sustainability of the city through reasonable land use and urban layout [10]-[12]. In the process of smart city development, the goal of spatial planning and optimization is to establish a fully functional, synergistic and efficient urban environment that is pleasant to live and work in [13], [14]. First, spatial planning needs to clarify the main functional areas and development priorities of the city. For example, the planning of different functional zones, such as commercial, industrial, and residential zones, needs to fully consider the spatial distribution and resource allocation of the city [15]-[17]. Secondly, spatial optimization needs to improve the operational efficiency and functionality of the city through technical means and management measures. For example, intelligent scheduling and monitoring of urban resources are realized through the application of intelligent systems and sensor networks [18]-[20]. In addition, spatial planning and optimization need to pay attention to the social and environmental sustainable development of the city. For example, the planning and construction of urban green space should be strengthened to enhance the ecological environment quality of the city [21]-[23].

The study established a multi-objective optimization model for urban environmental art space layout, and selected 33 candidate points for urban parks to be built through comparison. Genetic algorithm tools are used to introduce the optimization objectives, and the multi-objective optimization of urban environmental space layout is finally completed through computer reasoning algorithm. Based on the advantages and disadvantages of simulated annealing algorithm and genetic algorithm, the algorithm is synthesized and proposed based on genetic-simulated annealing algorithm, which is mainly improved by combining the advantages of simulated annealing algorithm that can generate a certain probability of accepting the poor solution to avoid the genetic algorithm falling into the local optimal solution. Through the establishment of the spatial layout optimization model for candidate points for multi-objective optimization, screening out the location of the park green space to be built in line with the objective function, to achieve the optimal design of the spatial layout of urban environmental art.

II. Multi-objective optimization model of urban environmental art design space layout

II. A. Model construction of urban environmental art design layout optimization

II. A. 1) Screening of candidate sites for planning environmental art spaces to be designed

The screening of candidate sites for planning parks to be built is a collection of candidate urban parks to be constructed within the study area in order to supplement the shortcomings of the current status quo of urban parks within the study area, maximize the value of urban parks, and enhance the overall service level of urban parks and green spaces. The selection of candidate sites needs to be analyzed and evaluated according to the urban land use status quo, urban land use planning, urban master plan and the service capacity of the current urban park green space. The main selection principles are: economic principle, operability principle, scientific principle, and people-oriented principle. The guiding program for the proposed candidate sites in this paper is as follows:

(1) Urban park green space service blind areas are prioritized for selection, and candidate points are added in the vicinity of settlements without park service.

(2) Candidate points are prioritized for selection in areas where the service load of urban park green space is too high.

(3) Prioritize undeveloped land as candidate points in combination with urban land use planning as well as the current situation.

(4) Add candidate sites without increasing demolition costs.

(5) Commercial, warehousing, transportation, military, residential, basic farmland and other land can not be used as candidate sites.

In this paper, a total of 33 candidate sites for urban parks are obtained through comparison, and the intersection of each candidate site with the nearest road is taken as the entrance of the park to be built.

II. A. 2) Multi-objective optimization model for urban environmental art space layout

The construction of urban park green space is generally transformed under the existing ecological environment or selected by comprehensively considering the state of land cover as well as the location, and the construction of park green space needs to spend a lot of manpower, material and financial resources, therefore, this paper proposes to explore and study the optimal layout of the regional urban park green space without changing the status quo park location from the perspectives of environmental protection and economic savings. In order to ensure the fairness and efficiency of urban park green space services and the economy of park construction, therefore, this model starts from the three objectives of the highest service efficiency of the new park green space (the new park per unit area serves the largest population in the surrounding area), the best accessibility (the shortest per capita walking time from the residents in the service area of the new park to the park), and the smallest total area of the new park to build a model based on the enhancement of the overall service capacity. Layout optimization model. The genetic algorithm of Matlab is used to solve the Pareto optimization solution set, which results in the optimal siting plan for the layout of urban parks and green spaces.

The objective function is defined as follows:

Objective 1: New parks have the highest service efficiency (new parks serve the most neighboring population per unit area)

$$ServiceEff = \max\left(\sum_{i=1}^{m}\chi_i\sum_{j=1}^{n}a_{ij}\frac{P_j}{A_i}\right) \tag{1}$$

Goal 2: Best accessibility (shortest walking time per capita from settlement to neighborhood park)

$$Travel\,\mathrm{Cos}\,t = \min\left(\sum_{i=1}^{m}\chi_i\frac{\sum_{j=1}^{n}a_{ij}C_{ij}P_j}{\sum_{j=1}^{n}a_{ij}P_j}\right) \tag{2}$$

Goal 3: Minimize the total area of new parks

$$Area = \min\left(\sum_{i=1}^{m}\chi_i A_i\right) \tag{3}$$

Constraint: the service area of the new park to be built covers all “unserved” neighborhoods.

Equation (1) describes the population objective of the service, which seeks to add new parks to serve more people, i denotes the number of the park to be built, j denotes the number of each neighborhood, and P_j the population size of the neighborhood. a_{ij} denotes the decision variable for the allocation of the service point i

and the demand point j, when the demand point is located within the radius of the service time of the park i, $a_{ij} = 1$, otherwise $a_{ij} = 0, A_i$, and A_i denotes the park to be built i's footprint.

Equation (2) describes the accessibility objective, which pursues the shortest walking time per capita from the residential points within the service area of the additional park to that additional park, C_{ij} is the time cost from demand point j to service point i, and a_{ij} denotes the decision variable for the allocation of the service point i $ to the demand point j; when the demand point is located in the park i's $a_{ij} = 1$ when the service time radius is within i, otherwise $a_{ij} = 0, P_j$ and P_j the population size of the settlement. In order to facilitate the convergence of the function, the average value is represented in the algorithm.

Equation (3) describes the economic intensification objective, which seeks to achieve the highest service efficiency with the least amount of additional park area. Where A_i denotes the area of this additional park.

II. B.Establishment of Combinatorial Optimization Algorithm

II. B. 1) Genetic algorithms

Genetic Algorithms (GA) are a class of stochastic search algorithms evolved by drawing on the evolutionary laws of biology - survival of the fittest, survival of the fittest, and survival of the fittest mechanisms [24].

Genetic algorithms deal not with the parameters themselves, but with individuals after encoding the set of parameters. Due to the application of coding technology, the resultant object can be operated directly without the qualification of derivation and function continuity, so it is suitable for all kinds of optimization problems; Genetic algorithm has inherent hidden parallelism, and compared with other optimization algorithms, it has a better ability to search for the global optimization; Using the probabilistic method of searching for the optimization, it can automatically obtain and guide the optimization of the search space, and adaptively adjust the direction of the search, and it does not need a definite It doesn't need to determine the rules.

Genetic algorithm has the advantages that other methods do not have, at the same time, because genetic algorithm adopts the selection mechanism that decides whether the individual is copied or not according to the size of the fitness value, so that it is prone to the situation that individuals originating from the same population are reproduced in large quantities, forming the inbreeding, resulting in the local search of the algorithm and the premature convergence, which leads to the failure of the global optimization process, especially for the multi-peak function is prone to such a phenomenon.

II. B. 2) Simulated annealing algorithm

The Simulated Annealing Algorithm (SA) is a stochastic optimization search algorithm based on the Mente Carlo iterative solution strategy, whose starting point is based on the similarity between the annealing process of solid matter in physics and general combinatorial optimization problems [25]. Simulated annealing algorithm in a certain initial temperature, along with the continuous decline of the temperature parameters, combined with probabilistic jump characteristics in the solution space to randomly find the global optimal solution of the objective function, that is, the local optimal solution can be probabilistically jumped out of and ultimately converge to the global optimum.

The basic principle of simulated annealing algorithm is as follows:

(1) Given an initial temperature T_0, and an initial point, compute the function value $f(x)$ for that point.

(2) Randomly generate a perturbation Δx, obtain a new point $x = x + \Delta x$, calculate the function value $f(x')$ for the new point, and the difference in function values $\Delta f = f(x') - f(x)$.

(3) If $\Delta f \leq 0$, the new point is accepted as the initial point for the next simulation.

(4) If $\Delta f > 0$, calculate the acceptance probability of the new point, $P(\Delta f) = \exp(-\Delta f \cdot K \cdot T)$, to generate a uniformly distributed pseudo-random number r on the interval $[0,1]$ if $P(Deltaf) \geq r$, then the new point is accepted as the initial point for the next simulation, otherwise the new point is discarded and the original point is still taken as the initial point for the next simulation.

However, the simulated annealing algorithm does not know much about the condition of the whole search space, which does not make it easy to make the search process enter the most promising search region, thus making the simulated annealing algorithm computationally inefficient.

II. B. 3) Hybrid GA-SA algorithm

1. Coding

Genetic algorithm is to be solved for coding and then operate on the chromosome, rather than directly for the solution to be solved, and selection, crossover and mutation are for the chromosome, so the coding of the algorithm has a great impact on the algorithm's search performance and convergence speed. Currently there are many kinds of coding forms, commonly used binary coding and real number system coding, the two specific coding forms are as follows:

1) Binary coding

In the genetic algorithm, the use of binary coding is the most common form, this form of coding is mainly composed of a string of numbers consisting of 0 and 1's, so that the required space to be solved is converted to a binary space. The chromosome length is calculated by equation (4), if the upper and lower limits of the variable $[X_{\min}, X_{\max}]$ are certain, the higher the value of the precision is taken, the longer the chromosome length will be.

$$L = \log_2\left(\frac{X_{\min} - X_{\max}}{\delta} + 1\right) \tag{4}$$

Where, $X_{\max}$ is the upper limit of the variable, $X_{\min}$ is the lower limit of the variable, δ is the precision.

2) Real Number Encoding

Because real number coding does not need to reconvert the system, so the use of real number coding than binary coding produces much more accurate results, and in the same coding accuracy requirements, the length of the chromosome out of the real number coding is also more streamlined can be effective in reducing the space of computer storage, real number coding is not only the accuracy of the improvement in the speed of computation, computation time and so on, there is a certain degree of improvement, so real number Coding application in complex networks, large data and other cases have obvious effects.

2. Population initialization

The composition of the population is composed of multiple individuals, the more individuals, the larger the population, and the larger the population, the larger the search range also increases, and the search range is too large, which directly affects the calculation speed and calculation time; if the population size is too small, it will lead to the algorithm's search space is reduced, so that the algorithm falls into the local optimal solution.

3. Adaptation Calculation

Individual excellence and fitness, fitness is mainly based on the objective function to judge the individual, but also for the continuous evolution of the genetic algorithm to provide a basis, it can be seen that the fitness of this is not only the direction of individual evolution is also an important reference standard for the selection of the operation.

The fitness function formula is shown in (5):

$$fitness = \begin{cases} \dfrac{1}{F} & F_{\min} > 0 \\ F_{\max} + \delta - F & F_{\min} < 0 \end{cases} \tag{5}$$

where: $fitness$ is the fitness function, F is the objective function of equation (5) of this paper, $F_{\min}$ is the minimum value of the objective function, $F_{\max}$ is the maximum value of the objective function, δ is any integer.

4. Selection Operation

Selection operation is the process of retaining the good individuals, as more and more good individuals are retained, it will also make more and more good individuals in the population, by adopting the principle of elimination of the fittest and survival of the fittest for individuals, it can make the adaptive degree of the population also evolve in the direction of more and more, and improve the adaptive ability. Different selection methods will have different effects on the optimization of the population, this paper adopts the expected value method to perform the selection operation of the genetic algorithm.

The expected value method is characterized by the fact that the number of individuals inherited to the next generation is mainly based on the individual fitness value to determine, in the implementation of the operation is generally divided into two steps, the specific formula is shown in (6).

1) Calculate the individual fitness value and the sum of all individual fitnesses separately, and divide the two equations to obtain the ratio of the two;

2) Multiply the proportion obtained in step (1) with the population size to obtain an integer, and then the number of this individual in the next generation of individuals can be obtained.

$$N_i = round\left(P_i * N\right) \tag{6}$$

where N_i is the retained number of the i th individual in the next generation, P_i is the proportion of the i th individual of the contemporary generation in the total individuals, N is the total number of individuals.

5. Crossover operation

Binary encoding and real number encoding will produce some differences in cross operation, the form used in this paper is as follows:

1) Binary encoding-single point crossover

The form of crossover in this way is to use a randomized mechanism for the individual, select a point on the individual, and swap the data at the two original individuals corresponding to the crossover point and re-generate the individual. As shown in equation (7).

$$\begin{cases} S_v^k = 0110010001 \\ S_w^k = 1001101010 \end{cases} \rightarrow \begin{cases} S_v^{k+1} = 01100|01010 \\ S_w^{k+1} = 10011|10001 \end{cases} \tag{7}$$

2) Real coding a uniform arithmetic crossover

Uniform arithmetic crossover in the crossover operation is not required to determine the individual crossover point, directly make the two original individuals weighted to generate a new individual can be. As shown in equation (8).

$$\begin{cases} S_i^{k+1} = \alpha \cdot S_i^k + (1-\alpha) \cdot S_j^k \\ S_j^{k+1} = \alpha \cdot S_j^k + (1-\alpha) \cdot S_i^k \end{cases} \tag{8}$$

6. Mutation operation

Mutation operation has a certain degree of randomness, the use of random mechanisms, the individual to select a certain point, the content of the individual on this point to replace, through this way you can get a new individual, for different means of encoding, the use of the mutation method also varies, this paper will use the binary encoding and real number encoding method is shown below:

1) Binary encoding

Variation operation in the adoption of binary coding, only in the random mechanism of the selected point at the "1" will become "0", the selected point at the value of "0" will become "1", while maintaining the same value as before in places other than the selected point, as shown in equation (9):

$$S_v^k = 01100\boxed{1}0001 \rightarrow S_v^{k+1} = 01100\boxed{0}0001 \tag{9}$$

2) Real encoding

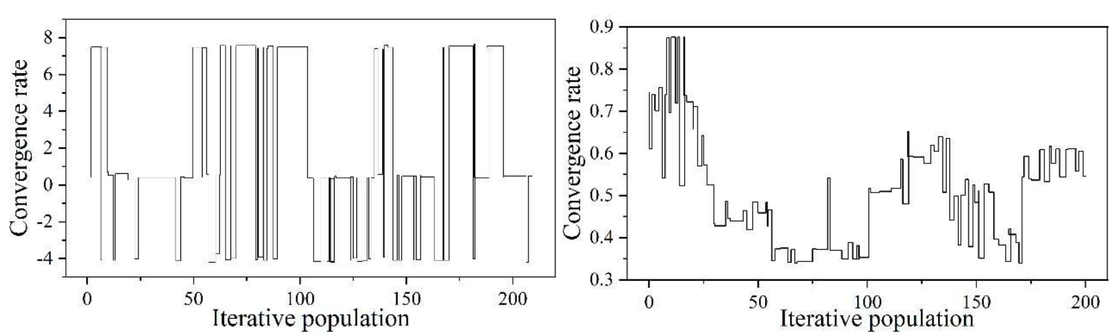
Real number coding, like binary coding, also uses a random mechanism to select the location of the mutation, but in comparison real number coding is a little more complex and determines the upper and lower limits of the variable (a_m, b_m) that needs to be performed for the mutation operation, which allows for the creation of a new gene and the formation of an entirely new chromosome , the specific form of which is shown in equation (10):

$$S_i^k = (v_1 \cdots v_n) \rightarrow S_i^{k+1} = (v_1 \cdots, v_m' \cdots v_n) \tag{10}$$

For the form of v_m' determined by using uniform variation, uniform variation in the variable variables from the variable interval obtained at random, need to satisfy $v_m' \in (a_m, b_m)$, can be obtained through the $v_m' = round\left(rand \cdot (b_m - a_m) + a_m\right)$.

II. B. 4) Simulated annealing operation with GSA validation

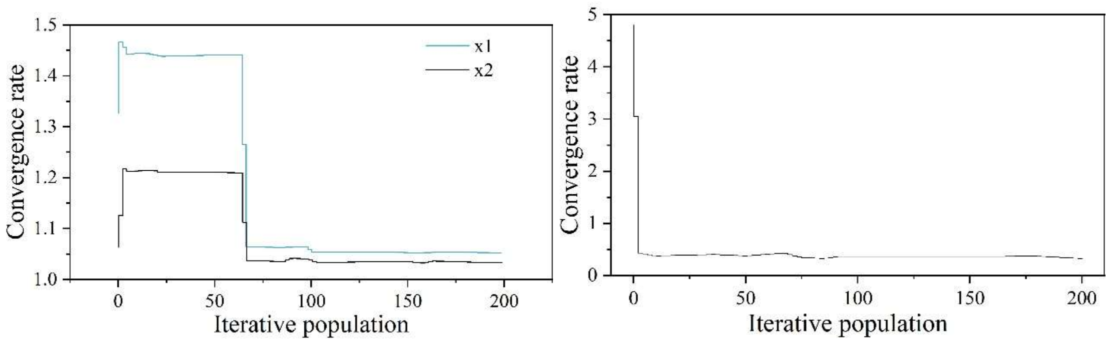
This paper integrates the simple genetic algorithm with the simulated annealing algorithm to improve its optimization effect and enhance its optimization efficiency in view of the mid-term precocity phenomenon and the slow convergence speed in the later stage of the simple genetic algorithm. For the practical application of the hybrid genetic algorithm, this paper adopts the Rosenbrock's valley function, which is a non-convex function used to test the evolutionary algorithm, and its curve is roughly parabolic, and the variables have strong coupling and are extremely difficult to minimize. The strong coupling between its variables is extremely difficult to minimize, which causes great difficulties in the optimization of evolutionary algorithms, and is now commonly used to test the execution ability of algorithms. The range of the independent variables is chosen as [-5.5], the minimum value of the whole domain is 0, and the optimal value of both independent variables is 1. The optimization results of the simple genetic algorithm and GSA for the Rosenbrock's valley function are shown in Figures 1 and 2.



(a) Optimization 1 (b) Optimization 2

Figure 1: Simple genetic algorithm optimization results

The results show that the simple genetic algorithm falls into the “trap” of local optimization at the beginning of the evolution, and there is a continuous oscillation phenomenon, and it cannot continue to converge; while the GSA proposed in this paper has converged to the global optimal solution around the 5th generation, and the optimization variables are converged around the 70th generation, which is the optimal solution for the Rosenbrock's valley function. The GSA proposed in this paper has converged to the global optimal solution around the 5th generation, and the optimization variables have converged to the global optimal solution around the 70th generation, which shows the better optimization ability of the GSA.



(a) Optimization 1 (b) Optimization 2

Figure 2: Optimization results of the genetic simulated annealing algorithm

II. C.Multi-objective optimization model solution

This model starts from the three objectives of new parks with the highest service efficiency, best accessibility, and the smallest footprint, and establishes a layout optimization model based on the best service capacity with the constraint of covering all the current status quo unserviced settlements.The genetic algorithm tool in the Matlab software is used to find the solution from the 33 parks to be constructed in the plan. According to the objectives of the function model, the model site selection results are shown in Fig. 3, each point on the Pareto curve indicates an optimal site selection scheme, and after obtaining the Pareto solution set, the final decision selection can be made among these site selection schemes.

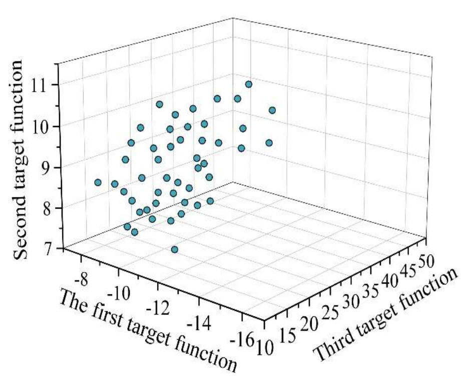


Figure 3: optimal solution set diagram of the optimization model

III. Multi-objective optimization results and analysis

III. A. Site selection multi-objective optimization results

This model starts from the two objectives of the park green space serving the largest total population in the surrounding area and the best accessibility, and establishes the layout optimization model based on the best accessibility. The genetic algorithm tool in Matlab software is used to solve the optimal layout of park green space from 33 planned parks to be built under the condition that all residents can reach the nearest park within 30 minutes. According to the objective of the model, the model site selection results are shown in Fig. 4, and each solution point on the Pareto curve indicates an optimal site selection scheme. After obtaining the Pareto solution set, the decision maker can make the final decision choice among these site selection options according to his/her preference.

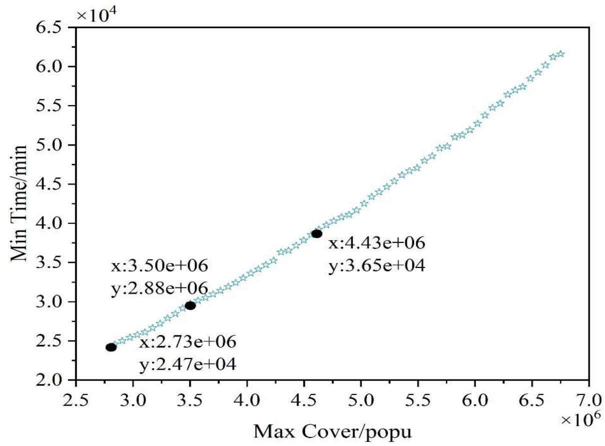


Figure 4: The three solution locations of the optimal solution in the model

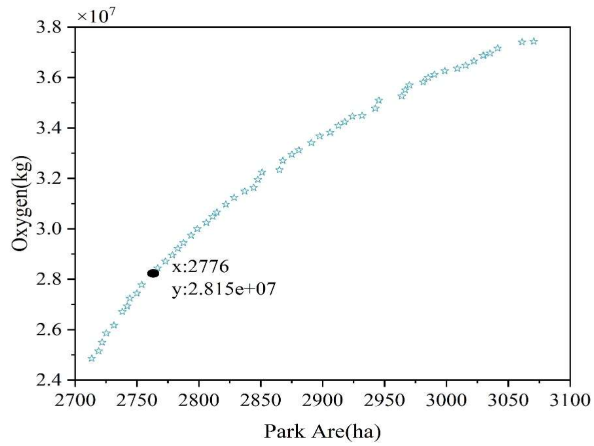
In order to show the results of the model optimal site selection, the optimal site selection of the spatial layout of the park green space with the total number of parks of 37, 43 and 48 were selected and compared and analyzed with the status quo parks in the three components of the service coverage, and the number of population served and the total time spent walking (a) to the nearest park by each residential place, as shown in Table 1. According to the results of the table calculations, it shows that the increase of candidate parks in the study area based on the best model solution of accessibility is significantly better than the status quo parks in terms of the number of people served and the total time spent on walking (a) from each residential place to the nearest park.

Table 1: Compare the optimization results of multi-target configuration model

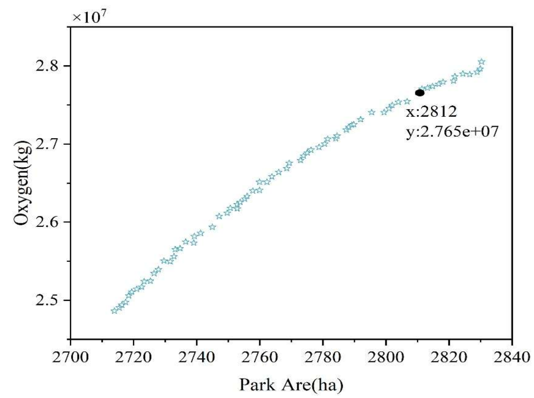
	Solution 1	Solution 2	Solution 3	Park green status
Park number(Present situation)	37	43	48	30
30 minutes of service population	100%	100%	100%	91.57%
The total time of the park's walk is in the park(h)	129.6	125.41	109.32	159.83

III. B. Planning area optimization results

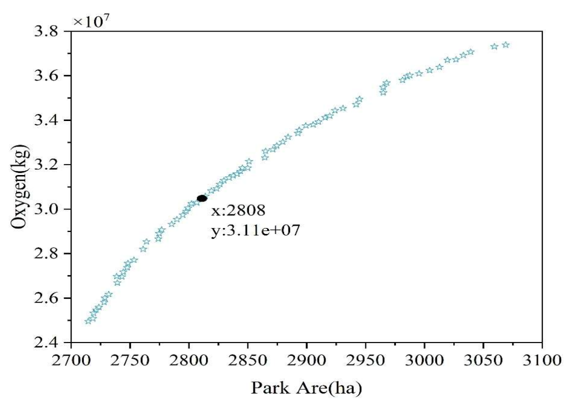
Generally speaking, each city garden department will determine the total area of park green space planned for that city according to its own development and according to the needs of city residents. Therefore, under the requirement of determining the total area of park green space, how to carry out the layout and construction of urban park green space, and how to reflect the fairness and efficiency have been the difficulties of the relevant departments in carrying out the layout planning of urban park green space. In view of the overall good situation of park green space construction in the study area, the per capita park green space occupies an area of 17.98m², which meets the target of 16m² per capita park green space in the central urban area of the city by 2020 of the urban green space system planning, and the study area, as a major area of Guangzhou's economic development, is very tense in terms of land use, and from the point of view of the urban development of the study area, it is determined that the study area is increased by about 100 hectares of park green space area. Through the optimization results of the target model, the solved park siting scheme one, scheme two, scheme three as an example, to determine the area of each planning candidate park. The model solution results are shown in Figure 5. It can be concluded that after optimization, the ecological service capacity of the park green space in the study area is enhanced compared with that before optimization, and the decision maker can make the final decision among these siting options according to his/her preference, and the results of the study are of great significance for improving the fairness and parity of the environmental art services in the smart city.



(a) Solution 1 corresponds to the candidate park area planning solution



(b) Solution 2 corresponds to the candidate park area planning solution



(c) Solution 3 corresponds to the candidate park area planning solution

Figure 5: Model 2 the corresponding candidate park area planning solution

III. C. Test results and analysis

III. C. 1) Spatial layout separation test

The best way to test the effectiveness of the spatial layout design method is to test the separation of spatial distribution. Changes in the distance between functional areas have a more obvious effect on the degree of separation, so the separation of public space distribution before and after the optimization design is tested under the condition of increasing the distance between the functional areas. According to the requirements of public space design, the range of allowable fluctuation of the separation degree is 0.577~0.596, and the comparison results of the separation degree before and after the optimization design are shown in Fig. 6.

From Fig. 6, it can be seen that the separation distance is proportional to the separation degree of spatial distribution. Before applying the method proposed in this paper, the separation degree of each functional area is low, and there is an area that is not effectively utilized. After applying the design method proposed in this paper, the separation degree of spatial distribution of functional areas is always within the permissible fluctuation range, which indicates that the application of the method proposed in this paper can carry out a reasonable optimization design for the layout of the main functional areas of the smart city space, and the design effect is better.

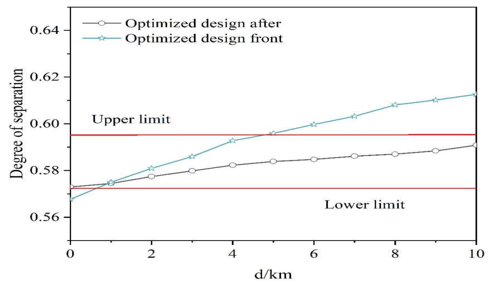


Figure 6: The comparison results of the optimal design before and after design

III. C. 2) Objective Function Testing

In the optimization design of the layout of the main functional area of urban environmental space, the objective function mainly selects the two factors of coordination and design cost related to the indicators of the number of buildings, green space area, traffic flow and other aspects. The size of the objective function affects the convergence speed and optimization effect of the algorithm, so the objective function is chosen as the test object, and the smaller the objective function is, the better the layout of the main functional area of public space is indicated. Setting the inertia weight ω to 0.3 and the learning factors both to 0.6, the results of the coordination and design cost objective function are shown in Figure 7.

As can be seen in Figure 7, when using the optimization algorithm to solve the objective function, with the increase in the number of iterations, the objective function results show a decreasing trend, and the minimum function value can be reached through continuous optimization. This is because in the quantum particle swarm algorithm, each particle adjusts and updates all particle information through quantum mechanics while maintaining the original position and velocity. As the number of iterations increases, the particles optimize the layout of the main functional area of the urban environmental space by constantly searching and updating the position information and selecting the appropriate speed direction based on the empirical and historical information, thus gradually approaching the optimal solution.

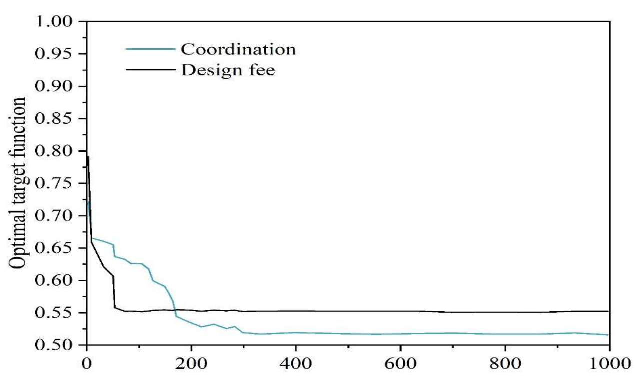


Figure 7: Target function

IV. Conclusion

In this paper, based on the advantages and disadvantages of simulated annealing algorithm and genetic algorithm, the algorithm is synthesized and proposed based on genetic-simulated annealing algorithm. The genetic-simulated annealing algorithm established by Rosenbrock's valley function was tested, and the results proved that the convergence speed of the algorithm was significantly improved, and the optimization ability was significantly stronger than the simple genetic algorithm. Secondly, model two can plan the goal of minimizing the green space area of the park, and reasonably plan the area of the study area. The design method proposed in this paper can reasonably optimize the spatial layout of the urban environment, so that its spatial distribution of separation is maintained within the range of 0.577 to 0.596, with better design effect, coordination and design cost objective function value is lower, the minimum function value is lower than 0.6, with better convergence. The results of the study are of guiding significance for the government and planning and construction related departments to implement the construction design of smart city construction.

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