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Optimization of Landscape Path and Facility Layout in Public Environment Design Based on Ant Colony Algorithm

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ABSTRACT

As a key component of urban environmental resources, the design of landscape paths and facility layouts of urban public environments is not only related to the overall aesthetics of the city, but also to the quality of life of urban residents. In this paper, from the perspective of landscape layout, the ecological landscape spatial network is constructed by calculating the ecological landscape environmental adaptation degree and the ecological landscape pattern index. On this basis, the traditional ant colony algorithm is introduced and its heuristic function and path selection are improved, and the adaptive adjustment factor and angle guiding factor are added to improve the diversity and efficiency of path searching, so that the landscape layout optimization model based on the ant colony algorithm is obtained. Using this model to design a landscape layout optimization scheme for a scenic spot, the average fulfillment time of the optimized landscape path is 20.73 minutes, which is 19.52 minutes shorter than the average fulfillment time of the original planning scheme, indicating that the model in this paper is able to carry out the landscape layout optimization design effectively.

Keywords: ant colony algorithm, landscape layout optimization, heuristic function, adaptive adjustment factor

1. Introduction

In recent years with the process of urbanization, the city has undergone radical changes, although people's living and living environment is getting better and better, but the comfort of people's living environment is decreasing, in urban planning, the natural environment occupies a smaller and smaller area, replaced by homogenized skyscrapers, which makes the original ecosystem is destroyed [1-4]. The image of the city is affected, and the design of urban public areas in urban

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planning should be paid more attention to, and the landscape design and facility layout of its public environment should be diversified and rationalized [5-6].

The landscape of public environment is not only the embodiment of urban characteristics, but also an important environment for citizens to live. However, at present, China's urban public environment landscape design system is not sound, and with the enhancement of people's aesthetic consciousness, people's personalized demand for public environment landscape design is also increasing, which involves a wide range of landscape design, including residential landscape design, park plaza landscape design, pedestrian landscape design, rural landscape design, etc., as long as some outdoor greening scenes can be called public environment landscape design [7-9]. In recent years, landscape design is a progressive trend of development, and also made certain achievements, but in this process there are still many problems. In the landscape design there is a uniform design, so that the landscape design does not have its uniqueness and representativeness [10]. At the same time, most of the design only considered the layout of public space, and did not have an all-round understanding of the economic location, population density, health, urban culture, transportation and road conditions, surrounding housing, climatic conditions, native vegetation, etc., which resulted in the lack of public environmental functions, poor articulation with the peripheral environment, decreased happiness of residents, and decreased experience of tourists [11-14]. In addition, the layout of public service facilities is a crucial topic. It is not only related to the quality of life and happiness of residents, but also has a profound impact on the sustainable development and competitiveness of the city [15-16]. The facilities of urban public environment contain parks, roads, garbage disposal facilities, water pipes, street lights and public transportation facilities, which provide convenient transportation and living environment for urban residents [17]. A reasonable layout of public environmental facilities should give full consideration to the distribution of residents, travel modes, demand characteristics and the overall development plan of the city. However, there are many problems in urban public environmental facilities, such as lagging public facilities, administrative inefficiency, and inadequate maintenance and management, which are not conducive to the normal use of urban public facilities [18]. It can be seen that there is an urgent need to optimize the design of landscape and facility layout in urban public environment.

The landscape and facility layout of the city is related to the happiness of citizens and the image of the city, and scholars have contributed many optimization solutions and tools. In landscape design, Hosny et al [19] developed an automatic optimizer for sustainable urban landscape design, which considered plants in terms of cost and water demand, and the optimizer achieved the selection of target plants through the constructed landscape design database and optimization model.Liu et al [20] incorporated topography, vegetation, human flow, greenness, and low energy consumption into urban landscape planning and design. And the use of geographic information systems to create a multi-decision model for landscape garden site selection, hierarchical analysis method to create a model for landscape garden path planning, together to realize the green urban landscape design.Sun and Gu [21] used Artisan plug-in tools to assist designers to accurately and comprehensively understand the landscape's parameters such as topography, water source, and plane area, and at the same time, through the computer-assisted design of a model, combined with the influence of the environmental micro-factors, in which landscape planning activities are carried out to develop changes.Yu et al [22] constructed an optimization model for urban landscape and environmental design, in which design logic and foundation are used as theoretical support, Rhino software and Grasshopper collect and analyze landscape environmental parameters, mapping and superposition techniques clarify spatial distributions and simulate reproduction, and the innovative MR-PFP algorithm for strategy selection. In addition, a reasonable public area landscape needs to be designed in conjunction with urban development and urban culture, but the process of urban development and urban culture development are not synchronized, which leads to complex urban planning.Gao and Zheng [23] integrated multi-objective optimization algorithms and remote sensing techniques to balance the land use issues of landscape planning and urban development in a cultural neighborhood.

In the study of facility layout, under the consideration of citizen's demand, Chen and Fu [24] collected the distribution of different age groups' residence and public facilities related parameters, calculated the density of supply and demand of citizen's demand and public facilities and the level of public service accessibility for different citizens in the spatial area, evaluated the fairness of this accessibility with the Gini coefficient, and finally assessed the degree of match with the planning objectives, looking for the accessibility defects The Gini coefficient is used to evaluate the equity of the accessibility, and finally to assess the degree of matching with the planning objectives, so as to find the accessibility defects, and thus to optimize the layout of public service facilities. Under the consideration of climate change and cost-effectiveness, Zhang et al [25] used an improved non-dominated sorting genetic algorithm-II and a rainwater management model to optimize the layout of green infrastructures in terms of scale, location, and connectivity to cope with different climatic environments.

In this paper, we firstly explain the calculation and acquisition method of ecological landscape environmental adaptation degree and ecological landscape pattern index, so as to build the urban public environment landscape spatial layout network as the premise of constructing landscape layout optimization model. Then the traditional ant colony algorithm is used as the algorithm of landscape layout optimization model, and the traditional ant colony algorithm is optimized by improving the heuristic function and path selection, so as to comprehensively build the landscape layout optimization model based on the ant colony algorithm. After verifying the feasibility of this paper's model in the form of comparing similar algorithms, the application and analysis of this paper's model in real cases are carried out.

2. Construction of landscape spatial layout network

This chapter mainly analyzes and evaluates the habitat quality of urban public environment, calculates the environmental adaptability of public environmental landscape, finds the pattern index of public environmental landscape, and constructs the landscape spatial layout network, which serves as the basis for establishing the landscape layout optimization model.

2.1. Calculating the Ecological Landscape Pattern Index

Calculating the pattern index of urban ecological landscape space is the main method to quantitatively analyze the spatial layout of the landscape, which can intuitively reflect the specific distribution and information of each element of the ecological landscape in the study area.

Before calculating the ecological landscape pattern index, the quality of urban habitats is evaluated, so as to assess the security and resilience of the regional ecology. The specific calculation formula is shown in equation (1):

$$Q_{xj} = H_j\left(1 - \frac{\sum c_0}{D_k + p_0}\right) \tag{1}$$

where: Q_{xj} - Habitat quality factor for raster x in site type j.

H_j - Ecological landscape adaptation for site type j.

c_0 - Random vector.

D_k - Basic probability assignment for plot k.

p_0 - Semi-saturation coefficient.

From equation (1), it can be seen that there is a close relationship between the quality of regional habitat and the ecological landscape adaptation and half-saturation coefficient, while the ecological adaptation is determined by the biodiversity and environmental degradation degree together, as in equation (2):

$$H_j = \sum \sqrt{\frac{|w_r|}{\sum g_x h_p}} \tag{2}$$

where: w - Fixation constant.

g_x - Biodiversity.

h_p - degree of environmental degradation.

The land degradation index on position x' in the habitat quality type can be expressed as equation (3):

$$D_{x'} = H_j \sum\sum\left(\frac{e_e j_p}{d_f} + \frac{t_y}{\alpha_0}\right) \tag{3}$$

where: $D_{x'}$ - Land degradation index.

e_e - Biological abundance factor.

j_p - Threat source intensity.

d_j - Euclidean distance of threat sources.

t_y - Resistance of the habitat to disturbance.

α_0 - Danger index of the threat source.

From this, the sensitivity parameters of the threat source can be calculated, i.e., equation (4):

$$a_i = \frac{D_x \cdot l_p}{\sum \sqrt{f(t)/A_k}} \tag{4}$$

where: a_i - sensitivity parameter.

l_p - Number of patches in the categorized mosaic.

$f(t)$ - Arctangent function.

A_k - Positive diagonal weighting matrix.

In turn, the diversity coefficient of the patch landscape shape can be obtained, i.e., equation (5):

$$R_\alpha = \frac{\beta_x a_i}{\left\| h_i / (s_0 b_e) \right\|^2} \tag{5}$$

where: R_α - Diversity coefficient.

β - Number of patches per unit area $(100hm^2)$.

h_t - Fractal dimension of landscape perimeter area.

s_0 - Mixing coefficient, the larger the value, the more complex the landscape structure.

b_c - Landscape montaneity index.

Based on equation (5), the ecological landscape pattern index of the region is calculated, i.e., equation (6):

$$W_l = \frac{f(t')}{v_p} \sqrt{\sum \frac{R_a / G_x}{u_j j_c}} \tag{6}$$

where: W_l - urban ecological landscape pattern index.

$f(t')$ - Multivariate nonlinear function.

v_p - Patch density.

G_x - State matrix.

u_k - Proportion of area occupied by landscape type k.

j_e - Vegetation cover.

By analyzing and evaluating the quality of urban habitats, calculating the adaptability of the ecological landscape environment, and combining the diversity coefficient of the patch landscape shape, the index of the urban ecological landscape pattern is derived, which facilitates the construction of the following ecological landscape spatial network.

2.2. Building spatial networks of urban ecological landscapes

Based on the characteristics of the urban ecological landscape spatial pattern and the calculation of the ecological landscape index, the core ecological landscape source points are identified based on the principle of landscape connectivity, and the ecological source points are used as the starting point to construct the urban ecological landscape spatial network.

The sensitivity of ecological landscape is calculated with reference to the binding index of internal cohesive landscape patches, and the expression is shown in equation (7):

$$p_k = \frac{W_i X_i}{\exp\left(-h_i / d_a\right)} \tag{7}$$

where: p_k - Sensitivity coefficient.

X_t - Aroma uniformity index.

h_r - Empirical constant.

d_a - distance between two neighboring patches.

According to the sensitivity of the ecological landscape to determine the comprehensive weight of landscape factors, according to the comprehensive weight of each ecological factor to determine the core ecological landscape source points, the specific calculation method is formula (8):

$$r_k = p_k \phi_0 \omega_y \tag{8}$$

where: r_k - Accessibility of landscape factors.

ϕ_0 - Clustering index of the landscape factor.

ω_y - the combined weight of the γ th ecological factor.

The landscape area with accessibility less than the threshold is taken as the core ecological landscape source point, from which the starting point of the ecological landscape spatial network is determined.

The minimum cumulative resistance distance between the core ecological source points is further calculated, and the expression is equation (9):

$$D_e = \frac{r_k}{\theta_0 \varphi_k} \tag{9}$$

where: D_e - Minimum cumulative resistance distance between core ecological source points.

θ_0 - Resolving coefficient.

φ_k - Order lag variable.

Taking the screened core ecological source points as the starting point, the minimum cumulative resistance distance between the ecological source points and the minimum path between all patches constitute the potential ecological landscape corridor, i.e., ecological landscape spatial network, so as to complete the construction of the landscape spatial layout network, and lay the foundation for the final realization of the landscape layout optimization model.

3. Landscape layout optimization model based on ant colony algorithm

The traditional ant colony algorithm has a broader exploration ability and a stronger ability to seek the optimal solution. This chapter aims to apply the ant colony algorithm to the optimization design of landscape layout, so for the deficiencies of the ant colony algorithm in the design of layout structure, it is improved by improving the heuristic function and the path selection in the algorithm, so as to construct the landscape layout optimization model based on the ant colony algorithm.

3.1. Ant Colony Algorithm

Past scholars in the study of ants foraging process found that the ant colony as a whole showed some strange phenomenon, and this phenomenon in the ants as individuals did not appear. This strange phenomenon is manifested in the ants will release a special substance on the path, the name of this substance is called pheromone, each passing ant will leave pheromone on the road, so that the ants behind will learn this pheromone and understand the situation of the path behind them, which forms a kind of mechanism similar to positive feedback. In this way, after a period of time, the whole ant colony will follow the shortest path to reach the food source, the search principle is shown in Figure 1.

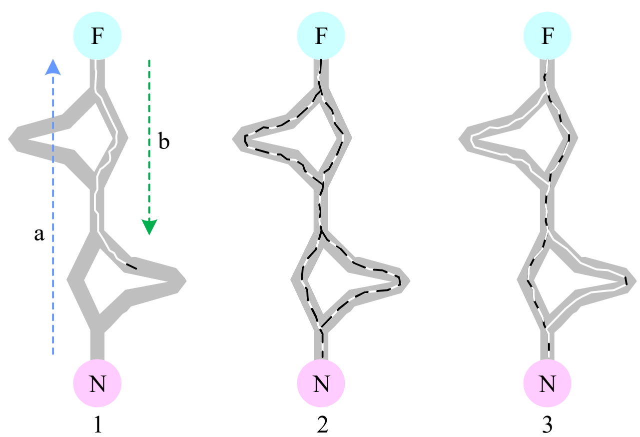

Fig. 1. Natural ant colony feeding map

3.2. Algorithm design of the model

The landscape facility layout can be spatially analogized to a spatially discrete raster pattern, and each raster patch can be thought of as a habitat for an ant colony. At the beginning of the model run, the number of ants is formulated according to the construction area of the landscape facility, and there is one ant and at most one ant in the raster. The grid with high suitability is analogous to the end point with food, and the ants move to the next grid as a node in the foraging path of the ants, and more than one ant is not allowed to exist in the same location at the same time (the model adopts the exclusion strategy), which is because the suitability of a certain place is super-high, and it is not in line with the actual situation to build all the landscape facilities in this place, and for each ant, it is only allowed to move one step in one time step, i.e., only one ant can be selected. For each ant, it is allowed to move only one step in one time step, i.e., it can only choose one grid as the location it wants to reach. In addition, the model stipulates that the final result of optimizing the layout of landscape facilities is to pursue the highest global suitability, which is mapped to the model that ants will leave their own information, i.e. pheromone, on the passing road during the process of searching for food. Other ants will judge the distance to the food and the suitability value of each journey according to the information left by their companions, and the global optimal solution will be found after many ants find the most suitable position for each of them in the process of searching for food.

In the process of foraging, ants in nature leave pheromones when searching for a path. The pheromone will disappear naturally within a certain period of time due to the influence of the environment. The ant colony chooses the path based on the concentration of pheromone on the path. Similarly, in the process of searching for the optimal solution of the ground class, artificial ants will judge the advantages and disadvantages of the solution based on the concentration of pheromone, past scholars have proposed the basic formula for the probability of ant colony selection, which is limited to space will not be repeated, the specific flow of the ant colony algorithm is shown in Fig. 2, and the model relies on the implementation of the GEOSOS platform.

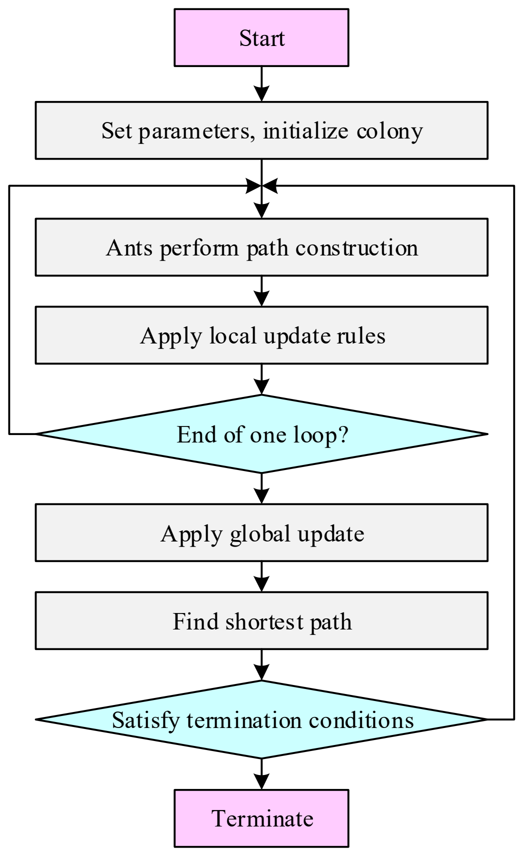

Fig. 2. Ant colony algorithm flow

3.2.1. Improvement of the ACO algorithm. Based on the shortcomings of the traditional ACO algorithm in the landscape layout design phase, this section will improve the traditional ACO algorithm and propose an improved ACO algorithm that is more suitable for landscape layout optimization.

In the process of landscape layout optimization, there are many computational data, complex computational process and other problems, for the traditional ant colony algorithm in the structural design phase of the solution efficiency is low, the output structure layout is unreasonable and other phenomena, this paper improves the heuristic function, path selection, the introduction of adaptive adjustment factor and angle guidance factor to increase the diversity of the path search and the efficiency of the search. Considering that the output path of ACO algorithm needs to meet the reasonable layout, this paper integrates the finite element analysis into the pheromone updating iteration process, updates the pheromone concentration of each node based on the finite element analysis results of the output path in the iterative process, and sets the exploration radius and the exploration direction to guide the ACO algorithm to output a reasonable layout.

3.2.2. Improvement of the heuristic function. In the traditional ACO algorithm, the heuristic function only considers the relationship between the current node i and the next node j, which will lead to the inefficiency of the global exploration of the colony in the early stage of the computation, and the algorithm will enter the deadlock state in a certain chance. In order to improve the search enlightenment, on the basis of the traditional algorithm, the heuristic effects of the current node i, the next node j and the target node G are considered at the same time, and at the late stage of the calculation, in order to enhance the role of the heuristic function, an adaptive factor ψ is introduced, which balances the algorithm's global exploration ability and convergence speed as in Eqs. (10)-(11):

$$\eta(i,j)=\left(\frac{1}{\omega_1 d_{ij}+\omega_2 d_{jG}}\right)\cdot\psi \tag{10}$$

$$\psi=e^{-2\left(\frac{N_{\max}-N_i}{N_{\max}}\right)^2} \tag{11}$$

where, d_{ij} denotes the distance from the current node to the next node. d_{jG} denotes the distance from the next node to the target node. ω_1 as well as ω_2 are the weight coefficients, and $\omega_1+\omega_2=1$. N_i denotes the current number of iterations. $N_{\max}$ denotes the maximum number of iterations. Where ψ plays a role in regulating the heuristic function in the pre-computation period ψ is much smaller than 1, which can weaken the role of the heuristic factor and increase the global exploration ability of the ant colony, and in the late stage of computation, the value of ψ is close to 1, which can strengthen the role of the heuristic factor and accelerate the convergence.

3.2.3. Improvement of path selection. In order to improve the layout rationality as well as the computational efficiency of the output paths of the iterative computation of the ACO algorithm, an angular guidance factor is introduced to intervene in the iterative computation of the ACO so as to improve the efficiency of path selection. The improved path selection probability is shown in Equation (12):

$$P_K(i,j)=\begin{cases}\dfrac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}[\mu(i,j)]^{\lambda}}{\sum_{u\in J_K(i)}[\tau(i,u)]^{\alpha}[\eta(i,u)]^{\beta}[\mu(i,u)]^{\lambda}} & if\ j\in J_K(i)\\ 0 & otherwise\end{cases} \tag{12}$$

where λ is the weight coefficient of the angle guidance factor: μ is the angle guidance factor, which is calculated as in equation (13):

$$\mu=\cos\phi=\frac{|y_j-y_G|}{d_{jG}} \tag{13}$$

The angle guidance factor mainly considers the influence of the angle between line segments d_{jG} and d_{SG} on the path exploration, the smaller the angle ϕ is, the more it deviates from the target node, and the larger the value of μ is, so as to strengthen the role of angle guidance. By this method, the selection strategy of the ant colony can be regulated to speed up the convergence rate, and the calculation principle is shown in Fig. 3.

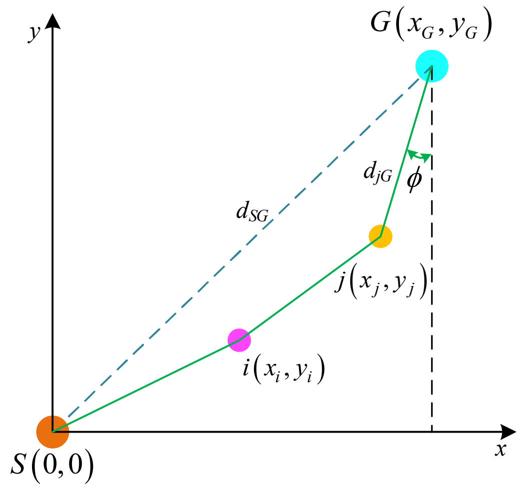

Fig. 3. Pheromone adjustment graph for key nodes

In order to improve the quality of the ACO search and avoid its falling into the local optimum phenomenon, a parameter-adaptive pseudo-randomized strategy is used for the computation, as in Eq. (14):

$$J = \begin{cases} \arg\max[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}[\mu(i,j)]^{\lambda}, q \le q_0 \\ p_{\kappa}(i,j), otherwise \end{cases} \tag{14}$$

where q_0 is the min value of the adaptive transfer probability, which is calculated as in equation (15):

$$q_0 = \delta_0 e^{-\frac{1}{2}\left(\frac{N_{\max}-N_i}{N_{\max}}\right)^2} \tag{15}$$

q is a random variable uniformly distributed in $(0,1)$. δ_0 is the scale factor, whose value range is $(0.1, 0.5)$. The smaller value of q_0 in the early stage facilitates the ant colony to improve the global exploration ability through the random search of transfer probability, and the larger value of q_0 in the later stage facilitates the ant colony to choose favorable paths according to the global information, thus improving the convergence speed.

This chapter combines the basic theory of traditional ant colony algorithm to elaborate the design idea of landscape layout optimization model based on ant colony algorithm. On this basis, by improving the heuristic function and path selection method in the algorithm, an improved ant colony algorithm that is more suitable for the design of urban public environment layout is proposed, and a landscape layout optimization model based on the ant colony algorithm is constructed.

4. Application analysis of landscape layout optimization model

In order to test the performance of the landscape layout optimization model in this paper, this chapter develops the feasibility analysis and practical application evaluation of the model respectively. In the feasibility analysis, this paper adopts the form of comparing similar algorithms, taking the uniformity index and configuration efficiency as the evaluation indexes to verify the feasibility of this paper's model. In the evaluation of practical application, the model of this paper is used to optimize the layout of a scenic spot and analyze the optimization results.

4.1. *Feasibility analysis of the model*

In order to verify the feasibility of this paper's model for the optimal configuration of landscaping in public environments, this subsection takes a garden as an example to simulate the structural optimization, comparing the performance of classical landscape optimization algorithms (particle swarm algorithm, genetic algorithm) and the method based on this paper's model. The plant composition of the garden includes trees, shrubs and grasses, etc. The results of the division according to height and function are shown in Table 1.

Table 1. Garden vegetation division statistics

Type		Height/m	function
arbor	megaphanerophyte	5-20	
	dungarunga	1.8-5	Divide garden space
shrub	Tall shrub	1.5-1.8	Provide enclosing degree
	Messhrub	0.9	Division of regional space
	Undershrub	0.4-0.5	Divide the flow direction
grass and trees	Cover	0.3	Enrich the bottom
	Herb	0.15	underside

Based on the plant composition data in Table 1, the actual experimental simulation was performed in MSVisualC++6.0. In the algorithm, the attenuation coefficient of the pheromone is within 0.5, the relative importance of the information is within 0.5, the initial value of pheromone intensity is set to 0.1, the corresponding colony size is set to 25, the number of particles is set to 35, the inertia parameter is set to 0.7, and the learning factor all take the value of 2.

4.1.1. Uniformity index analysis. Under the premise of ensuring the diversity of the landscape also need to ensure the uniformity of plant distribution in the garden. If the uniformity is low, then the plant distribution is messy and affects the overall perception of the landscape. The value of uniformity index ranges from (0,1), usually the closer the uniformity index is to 1, the more balanced the distribution of plant configuration in the landscape. Given different diversity indices, the uniformity performance of the three methods is compared in Figure 4, where A1 is the method of this paper, A2 is the particle swarm algorithm, and A3 is the genetic algorithm.

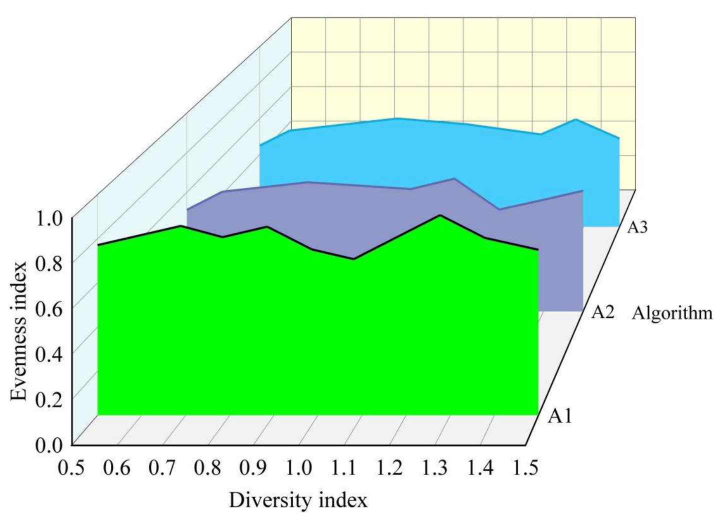

Fig. 4. Evenness index comparison

In Fig. 4, for different given diversity index, the uniformity index of this paper's model algorithm for landscape plant configuration optimization is higher compared to the other two optimization methods. On the whole, the uniformity index of the optimization of landscape plant configuration carried out by the model method of this paper can be maintained at about 0.8 on average. That is, under the premise of ensuring plant diversity, the method based on this paper's model plant configuration is more balanced and has good hierarchy.

4.1.2. Landscape configuration effectiveness analysis. By the different number of plants to be configured, the configuration time of the configuration scheme given by the three methods is shown in Fig. 5, which compares the superiority of this paper's algorithm for the effectiveness of plant configuration in landscaping.

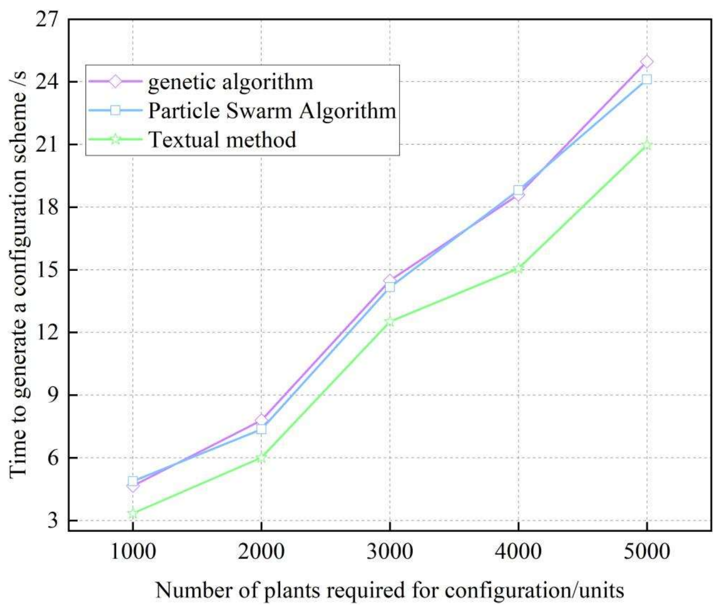

Fig. 5. Comparison of configuration scheme time was generated

The time variation of the configuration scheme generation by this paper's model in Fig. 5 is more consistent with the time variation trend of the remaining two methods. However, the generation time of the configuration scheme by the model in this paper is overall less than the remaining two methods, and for the given number of 1000-5000 required configurations, the generation time of the scheme by the model in this paper is within 3-21 seconds, i.e., the proposed algorithm of this paper can realize better plant diversity as well as uniformity of plant populations with the guarantee of the generation time of the configuration scheme.

4.2. Assessment of the practical application of the model

This subsection selects Park C in City G as the experimental object, which covers an area of about 24 hectares and has five entrances based on the orientation, namely, east, south, west, north and center, with seven major landscapes. At present, there are problems such as large distance gaps between landscapes, long distances, and some entrances are far away from the landscapes, i.e., irrational landscape layout, low accessibility of some landscapes, and poor visitor experience. Among them, the furthest passage time between some landscape facilities and entrances is 1.5 hours, the average passage time of landscape paths is 40.25 minutes, and the average passage time of landscape facilities is 35.62 minutes. Therefore, the model in this paper is used to develop the design of the optimization scheme for the original seven major landscape layouts and paths in this park.

4.2.1. Landscape Optimization Schematic Design. In the optimization scheme of Park C designed by the model in this paper, the shortest passing distances between seven landscapes (V_1, V_2, V_3, V_4, V_5, V_6, and V_7) are calculated as shown in Table 2.

Table 2. The shortest distance between attractions(km)

Scenic spot number	V_1	V_2	V_3	V_4	V_5	V_6	V_7
V_1	0	1.51	3.22	2.87	2.23	1.62	3.69
V_2	1.51	0	3.09	2.48	0.93	1.35	2.56
V_3	3.22	3.09	0	5.49	3.68	4.42	1.55
V_4	2.87	2.48	5.49	0	1.84	1.31	4.87
V_5	2.23	0.93	3.68	1.84	0	1.27	3.01
V_6	1.62	1.35	4.42	1.31	1.27	0	3.81
V_7	3.69	2.56	1.55	4.87	3.01	3.81	0

From Table 2, it can be seen that the shortest passage distance between landscapes is within the range of 0.93-5.49km. Assuming that the walking speed of tourists is 4km/h, the shortest passage time between landscapes can be obtained, and the calculation results are shown in Table 3.The shortest passage time between landscapes is within 9-55 minutes in the seven major landscape layout schemes designed by the model in this paper.

Table 3. Minimum travel time between attractions(minutes)

Scenic spot number	V_1	V_2	V_3	V_4	V_5	V_6	V_7
V_1	0	15	32	29	22	16	37
V_2	15	0	31	25	9	14	26
V_3	32	31	0	55	37	44	16
V_4	29	25	55	0	18	13	49
V_5	22	9	37	18	0	13	30
V_6	16	14	44	13	13	0	38
V_7	37	26	16	49	30	38	0

In order to further test the performance of landscape facility layout and path selection of Park C solved by the model in this paper, the famous Solomon's algorithm was used for the test examples in this part. Part of the Solomon algorithm was selected for testing and the relative error rate was calculated, and the comparative results of the known solutions in the database of the optimal solutions are shown in Table 4.

Table 4. Compare known solutions in the optimal solution database

Solomon Instance	Known Opt	Textual method	Error rate
An32k5	(5,2751)	(5,2870)	4.33%
An33k5	(5,1532)	(5,1620)	5.74%
An32k6	(6,2480)	(6,2560)	3.23%
Bn50k8	(8,1290)	(8,1350)	4.65%
Bn51k7	(7,1287)	(7,1310)	1.79%
Bn52k7	(7,4740)	(7,4870)	2.74%
En51k5	(5,3605)	(5,3810)	5.69%
En76k7	(7,905)	(7,930)	2.76%
En101k14	(14,5225)	(14,5490)	5.07%

Mn101k10	(10,2835)	(10,3010)	6.17%
Pn50k10	(10,2904)	(10,3090)	6.4%
Pn51k11	(10,5355)	(10,5490)	2.52%

The optimal solution of the park's landscape layout and path solved by the model of this paper has an error of no more than 7% with the known optimal solution, and within a certain error range, it can find the path sequence and path value which are very close to the known optimal solution provided by the database, and the solution accuracy of the model of this paper is very close to the known optimal solution, which reflects the reasonableness of the model of this paper for solving the line from the side, and it has the significance of reference.

4.2.2. Analysis of Landscape Optimization Results. Based on the landscape layout optimization scheme proposed in the model of this paper, the results of the landscape path accessibility of Park C are analyzed in Table 5. As can be seen from Table 5, the number of high value areas of the overall spatial accessibility of the optimized landscape paths increases significantly, and the differences in spatial accessibility are significantly reduced. The optimized landscape path is significantly improved both in terms of coverage and average fulfillment time. The average fulfillment time of the optimized landscape path is 20.73 minutes, which is 19.52 minutes shorter than the 40.25 minutes in the original planning scheme.

Table 5. The result of landscape path accessibility optimized by this method

Gate	East	South	West	North	Middle	Overall
<5 mins(%)	3.56	9.31	11.25	3.24	9.7	-
5-10 mins(%)	16.06	23.3	27.61	9.79	17.81	-
10-15 mins(%)	19.15	33.11	29.1	17.14	25.39	-
15-20 mins(%)	13	12.95	15.45	6.03	16.45	-
20-25 mins(%)	12.05	4.09	4.02	23.1	8.22	-
25-30 mins(%)	5.28	1.59	1.83	4.72	2.71	-
>30 mins(%)	30.9	15.65	10.74	35.98	19.72	-
Average time (min)	27.15	15.44	14.35	29.66	17.05	20.73

Based on the optimization scheme of landscape layout proposed in the model of this paper, the results of the accessibility of landscape facilities in Park C are analyzed in Table 6.As can be seen from Table 6, the number of high-value areas of the overall spatial accessibility of the optimized landscape facilities is significantly increased, and the difference in spatial accessibility is significantly reduced. The optimized landscape facilities are significantly improved both in terms of coverage and average fulfillment time. The average fulfillment time of the optimized landscape facilities is 12.84 minutes, which is 22.78 minutes shorter than the 35.62 minutes in the original planning scheme.

Table 6. This method optimizes the accessibility of landscape facilities layout

Gate	East	South	West	North	Middle	Overall
<5 mins(%)	30.76	32.08	31.85	23.95	26.38	-
5-10 mins(%)	28.55	33.75	32.24	15.48	21.28	-
10-15 mins(%)	15.83	16.42	16.15	24.59	19.87	-
15-20 mins(%)	6.16	7.07	6.85	11.07	13.14	-
20-25 mins(%)	4.12	2.38	3.5	8.92	3.60	-
25-30 mins(%)	1.15	1.25	1.49	2.63	2.44	-
>30 mins(%)	13.43	7.05	7.92	13.36	13.29	-
Average time (min)	13.49	10.13	10.70	15.59	14.28	12.84

5. Conclusion

In this paper, by constructing landscape spatial layout network as the optimization framework, using the ant colony algorithm with improved heuristic function and path selection as the core algorithm for layout optimization, the landscape layout optimization model based on the ant colony algorithm is constructed, which is an innovative attempt in the research of landscape layout optimization.

In the feasibility analysis of the model, compared with the other two similar algorithms, the model algorithm of this paper generates the scheme uniformity index around 0.8 and takes the least time to generate the scheme. In the practical application of the model, the average performance time of landscape paths and landscape facilities in the landscape layout optimization scheme designed by this model is 20.73 minutes and 12.84 minutes, which is 19.52 minutes and 22.78 minutes shorter than that of the original scheme, respectively.

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