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Application of Improved Ant Colony Optimization Algorithm in Urban Ecological Landscape Spatial Layout Optimization Method

Ruiqi Ma*

Xi'an FanYi University, Xi'an 710105, Shaanxi, China

Abstract

Traditional spatial planning methods have many limitations when facing complex urban environments. Therefore, this study introduces an urban ecological landscape spatial layout optimization method based on improved ACO (Ant Colony Optimization). By introducing new optimization strategies and parameter adjustments, the global search capability and convergence speed of the algorithm are improved. This study first defines different functional areas in the urban ecological landscape as nodes, and the connecting roads or ecological corridors between nodes as paths, and constructs a weighted graph model. Then, the algorithm is initialized by setting key parameters such as the number of ants, pheromone factor, heuristic function factor, etc. Next, various improvement strategies such as adaptive pheromone adjustment, pheromone range limitation, dynamic local pheromone update, continuous space adaptation and simulated annealing embedding are applied. In the path selection and search phase, ants select the next node based on pheromone concentration and heuristic information to form a complete path. Finally, pheromones are updated according to the path quality and a new round of iteration is started until the termination condition is met. The improved algorithm also shows better optimization effects in terms of ecological connectivity index, floor area ratio and green space coverage. In 20 layout optimization tasks, the improved algorithm improves the ecological connectivity index, the floor area ratio increases from an average of 1.54 to 2.8, and the maximum green coverage rate increases from 27.6% to 42.8%. These results not only verify the effectiveness of the improved algorithm but also demonstrate its wide applicability and strong optimization capabilities in different urban ecological landscape layouts.

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* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: 13720760069@163.com

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1. Introduction

Reasonable urban ecological landscape layout can not only improve the ecological environment quality of the city but also enhance the life satisfaction of residents and the economic vitality of the city. However, when faced with a complex and ever-changing urban environment, traditional urban planning methods are often restricted by multiple factors such as the functionality of urban construction and the nature of land use, resulting in local deviations in layout results, affecting the rationality and efficiency of the overall urban layout.

This paper explores the application of improved ACO in the optimization of urban ecological landscape spatial layout. By introducing new optimization strategies and parameter adjustment methods, this paper proposes a more efficient and practical optimization scheme to address the limitations of existing methods. The contributions of this paper include: (1) constructing a weighted graph model, defining different functional areas in the urban ecological landscape as nodes, and the connecting roads or ecological corridors between nodes as paths, which provides a mathematical basis for the application of the algorithm; (2) setting key parameters such as the number of ants, pheromone factor, and heuristic function factor, and analyzing the impact of each parameter on the algorithm performance; (3) applying a variety of improvement strategies - adaptive pheromone adjustment, pheromone range restriction, dynamic local pheromone update, continuous space adaptation and simulated annealing embedding to enhance the global search ability and convergence speed of the algorithm; (4) the optimization effect of the improved algorithm in terms of ecological connectivity index, floor area ratio and green space coverage is verified through experiments, demonstrating its wide applicability and powerful optimization ability in different urban ecological landscape layouts.

This paper is structured as follows: first, we review related work and summarize the achievements and shortcomings of existing research; then we introduce methods to improve the ant colony optimization algorithm, including problem modeling and abstraction, parameter initialization, application of improved strategies, path selection and search, and pheromone update and iteration; next, we present the experimental results and compare and analyze the algorithm performance before and after the improvement; finally, we summarize the research results of this paper and look forward to future research directions.

2. Related Work

From the optimal allocation of cultivated land resources to the rational planning of urban ecological landscapes, to the energy management of intelligent buildings, the application of various optimization algorithms provides new ideas and methods for solving complex spatial layout problems. Zhao et al. [1] took Fengkai County, Guangdong Province as an example, based on the micro-adjustment logic of "existing cultivated land transfer-in of restorable land", and comprehensively used spatial superposition, comprehensive evaluation and ant colony optimization algorithm to construct a cultivated land spatial layout adjustment model. With the balance of transfer-in and transfer-out quantities as the constraint condition, the cultivated land layout optimization at different administrative district scales was achieved. In order to explore methods suitable for optimizing the spatial layout of settlements in grassland pastoral areas, Feng et al. [2] constructed a spatial network system between Aobao and settlements; secondly, they conducted a network feature analysis and explored the interaction mechanism between the two; and finally determined the spatial type and layout optimization direction. Finally, they found that the spatial discreteness of grassland pastoral areas was obvious, and the intervention of Aobao nodes effectively improved the integrity of the settlement space network structure. Chen and Lin [3] determined the comprehensive weights of landscape factors based on the sensitivity of the ecological landscape, took the maximum closure, maximum connectivity and maximum connectivity rate of the landscape patches as the objective function, constructed an optimization model, and introduced an improved ant colony algorithm to solve it, thereby obtaining the best optimization solution. The results of the case demonstration and analysis show that the landscape ecological resistance threshold obtained after optimization by the proposed method is relatively high, and the spatial layout optimization effect is better. Luo et al. [4] took Wenru Characteristic Town, a characteristic town jointly built by reclamation and land, as the research object, and studied the optimization of the spatial layout of Wenru Characteristic Town from two aspects: road system and land use layout. In response to existing problems such as imperfect road system, low branch road density, unbalanced road network structure in reclamation areas, relatively scattered land use and unreasonable facility layout, they put forward optimization and adjustment suggestions for the road system and land use layout. Since the traditional urban ecological landscape land spatial layout method is restricted by many factors such as urban construction functionality and land use nature, there are local deviations in the spatial layout of ecological landscape land. There is a certain gap between the rationality of the obtained layout results and the expected design layout, which affects the urban layout progress and its overall layout effect to a certain extent. Therefore, Xu and Pu [5] combined the spatial attributes of urban ecological landscape land use and introduced two optimization schemes, namely, second-order clustering and bee colony algorithm, to jointly optimize its layout.

Sushma et al. [6] proposed a method based on the Ant Colony Optimization (ACO) algorithm for optimizing the vertical highway alignment design. The ACO algorithm guides the search process by simulating the pheromones released by ants in the process of searching for food and handles complex optimization problems. Almufti[7] proposed an optimization method for edge detection technology combined with the ant colony optimization (ACO) algorithm. Morin et al.[8] proposed a path planning method based on the ACO algorithm for search and rescue operations. Khan et al. [9] conducted experimental verification and found that the ACO algorithm performed well in energy optimization of smart city buildings and could effectively reduce energy consumption and improve the overall efficiency of the system. Kerber et al. [10] used ASO to assess maladaptive personality traits in DSM-5. This paper aims to explore the application of improved ASO algorithm in urban ecological landscape spatial layout optimization methods. By introducing new optimization strategies and parameter adjustment methods, this paper demonstrates how to improve the performance of ant colony optimization algorithm in urban ecological landscape spatial layout optimization, solve the limitations of existing methods, and propose a more efficient and practical optimization scheme.

3. Methods

3.1 Problem Modeling and Abstraction

In the optimization of urban ecological landscape spatial layout, problem modeling and abstraction transform complex real-world problems into mathematical models that can be processed by algorithms. Specifically, different functional areas in the urban ecological landscape are defined as nodes, which cover diverse functional areas such as parks, commercial areas, residential areas, industrial areas and ecological protection areas. At the same time, the connecting roads or ecological corridors between nodes are defined as paths. Paths not only represent the physical connection between nodes but also have attributes such as distance, connectivity, and functional relevance. These attributes jointly determine the connection strength and functional synergy between nodes.

Based on this, the nodes and paths are combined into a graph structure, where each node represents a functional area and each path represents the connection relationship between nodes. This graph structure can be formally represented as a weighted graph G:

$$G = (V, E) \tag{1}$$

Among them, V is a node set, covering the nodes of various functional areas in the city; and E is a path set, each path connects the nodes.

In order to evaluate the advantages and disadvantages of different layout schemes, the objective function is defined, taking into account multiple indicators such as ecological benefits, social benefits and economic benefits. Ecological benefits evaluate the integrity and connectivity of the ecosystem, such as ecological suitability, spatial compactness and nearest neighbor distance index; social benefits focus on evaluating the accessibility and convenience of residents, such as the distance from residential areas to parks; and economic benefits focus on the role of the layout of commercial and industrial areas in promoting economic development.

In addition, constraints are set to ensure the feasibility of the layout plan. These constraints include land use restrictions, such as certain areas cannot be used for commercial development due to ecological protection, as well as clear requirements of policies and regulations on the development of specific areas, and the greening rate of residential areas.

3.2 Parameter Initialization

In ACO, key parameters such as the number of ants, pheromone factor, and heuristic function factor are set, and the impact of each parameter on the algorithm is analyzed [11-12].

The number of ants is set to 50. A larger number of ants can enhance the global search capability of the algorithm and enable the algorithm to explore the solution space more comprehensively. Too many ants will increase computing time and resource consumption. The pheromone factor is set to 1.5. A larger value will make ants more inclined to choose paths with high pheromone concentrations, thus accelerating convergence. The heuristic function factor is set to 2.0. A value that is too large may cause the algorithm to fall into a local optimal solution, while a smaller value will make the algorithm more dependent on pheromones and increase the global search capability. The pheromone volatility factor is set to 0.1 and the pheromone constant is set to 10 to enhance the positive feedback mechanism of the algorithm and speed up the convergence. The maximum number of iterations is used to control the running time of the algorithm. Setting the maximum number of iterations to 100 allows the algorithm to explore the solution space more fully and improve the quality of the solution. By setting these parameters reasonably, the global search ability and local search ability of the algorithm can be effectively balanced, the convergence speed of the algorithm and the quality of the solution can be improved, so as to better solve the problem of urban ecological landscape spatial layout optimization.

3.3 Application of Improved Strategies

In ACO, in order to better solve the problem of optimizing the spatial layout of urban ecological landscape, a variety of improvement strategies are adopted. First, the pheromone volatilization and enhancement mechanism is dynamically adjusted according to the search process to achieve adaptive pheromone adjustment. In the early stage of the search, the pheromone evaporation speed is appropriately reduced so that ants can explore more different paths and find potential better solutions; in the later stage, the evaporation is accelerated to prompt the algorithm to converge to a better solution and avoid converging to the local optimum too early. For example, the pheromone volatilization factor ρ can be set to 0.1 at the beginning and gradually increased to 0.5 as the iteration progresses:

$$\rho = 0.1 + 0.4 \times \frac{t}{T} \tag{2}$$

t is the current iteration number, and T is the maximum iteration number.

Secondly, setting the upper and lower limits of pheromone concentration to prevent excessive accumulation of pheromones in some paths, ensure that other paths also have the opportunity to be explored, and maintain the diversity of the search.

Whenever an ant passes through a path, the pheromone of the path is locally adjusted immediately to achieve dynamic local pheromone updating. If the path is better, increasing the pheromone appropriately; if it is worse, reducing the pheromone to guide subsequent ants to explore a better path. The pheromone update amount $\Delta\tau$ is [13-14]:

$$\Delta\tau = \frac{Q}{L} \tag{3}$$

Among them, Q is a constant and L is the path length.

In view of the continuous characteristics of urban ecological landscape space, the ant pheromone retention method and walking rules are redefined so that the algorithm can better handle continuous space optimization problems. The method of evenly dividing the definition domain is adopted, the cross application of random operation and particle swarm operation is integrated, and the mutation operation of pheromone is added to jump out of the stagnant state.

Finally, the idea of simulated annealing is introduced in the local search process to accept poor solutions with a certain probability, helping the algorithm to escape the local optimal trap, especially when the algorithm is stagnant, to increase the possibility of finding the global optimal solution.

Through these improved strategies, the algorithm demonstrates stronger global search capabilities and faster convergence speed in the optimization of urban ecological landscape spatial layout, effectively avoiding local optimal traps and finding better layout solutions.

3.4 Path Selection and Search

In the ACO algorithm, the spatial layout of the urban ecological landscape is optimized. During path selection and search, ants select the next node based on pheromone concentration and heuristic information to form a complete path[15].

Ants start from the starting node and select the next node according to the probability transfer formula based on the pheromone concentration and heuristic information on the path. Ants start from the starting node and select the next node according to the probability transfer formula based on the pheromone concentration and heuristic information on the path.

3.5 Pheromone Update and Iteration

After each iteration, the algorithm updates the pheromone according to the quality of the path formed by the ants, thus providing a better basis for path selection for the next iteration.

The pheromones on the path will evaporate according to a certain volatility factor, simulating the natural volatilization process of pheromones. The volatility factor is between 0 and 1, which reduces the concentration of pheromones on the path and avoids excessive accumulation of pheromones, which leads to premature convergence of the algorithm.

Then, pheromones are deposited on the path based on the ants' performance on the path. The amount of pheromone left by each ant on the path is inversely proportional to the quality of its path, that is, the shorter the path or the higher the quality, the more pheromone is left. Specifically, the increment of pheromone is the sum of the amount of pheromone left by all ants on the path.

Finally, the volatilized pheromone concentration is added to the newly deposited pheromone amount to obtain the updated concentration, which will be used for the ants' path selection in the next iteration.

In each iteration, the ant starts from the starting node and selects the next node based on the pheromone concentration and heuristic information to form a complete path. The quality of each path is evaluated according to the comprehensive evaluation function, and the pheromone increment of each path is calculated. Then, the pheromone concentration on the path is updated according to the above steps. If the maximum number of iterations is reached, the iteration is stopped; otherwise, the next round of iteration is continued.

Through this pheromone update and iteration mechanism, the algorithm gradually optimizes the spatial layout of the urban ecological landscape and ultimately finds a layout plan with the best overall benefits.

4. Results and Discussion

4.1 Performance Comparative Analysis

In the field of urban ecological landscape spatial layout optimization, although traditional ACO has shown certain potential, it still has limitations when facing complex and changing urban environments. To this end, this study made targeted improvements to the algorithm, aiming to further improve its application effectiveness in urban ecological landscape planning. This paper constructs a simulated urban ecological landscape environment, runs the ant colony optimization algorithm before and after the improvement many times, and records the layout plan output by each run, the number of iterations required to achieve the preset accuracy, the standard deviation of the results of multiple runs, and the total time of the algorithm run. The results are shown in Table 1:

Table 1. Algorithm performance comparison

Metric	Pre-improved ACO	Post-improved ACO	Improvement/Reduction
Accuracy (%)	85.0	92.5	+7.5
Convergence Speed (Iterations)	150	100	-33.3
Stability (Standard Deviation)	2.5	1.2	-52.0
Computational Resource Consumption (Seconds)	1200	900	-25.0

Table 1 reveals the improvement of the improved algorithm compared with the previous algorithm. In terms of accuracy, the improved algorithm increases from 85.0% to 92.5%, which means that it can more accurately output the optimal urban ecological landscape layout plan. Secondly, the convergence speed is reduced from 150 iterations to 100, indicating that the algorithm is more efficient and faster in finding the optimal solution. In addition, the stability index is reduced from 2.5 to 1.2, showing that the consistency of the output results of the improved algorithm under different operating conditions has been enhanced, reducing the fluctuation of the results and improving the reliability of the algorithm. Finally, in terms of computing resource consumption, the total time required for the algorithm to run once is shortened from 1,200 seconds to 900 seconds, reflecting the optimization of the algorithm in computing efficiency, making it more competitive in practical applications.

4.2 Comparison of Application Results

This paper aims to understand the application effect of the improved algorithm in the optimization of urban ecological landscape spatial layout, and compares the ecological connectivity index, volume ratio and green space coverage in different layout optimization tasks before and after the algorithm optimization.

Figure 1 shows the results of the ecological connectivity index:

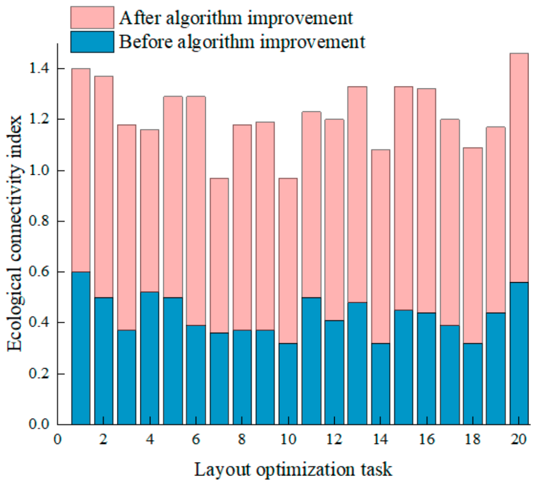

Figure 1. Ecological connectivity index

Among the 20 layout optimization tasks, the ecological connectivity index after algorithm improvement is always better than before algorithm improvement. Combined with specific data, in the first task, the ecological connectivity index before algorithm optimization is 0.8, which is higher than 0.6 before optimization. In the 20th task, it is 0.34 higher after optimization than before optimization. This result not only verifies the effectiveness of the improved algorithm in improving ecological connectivity but also demonstrates its wide applicability and powerful optimization capabilities when facing different urban ecological landscape layouts.

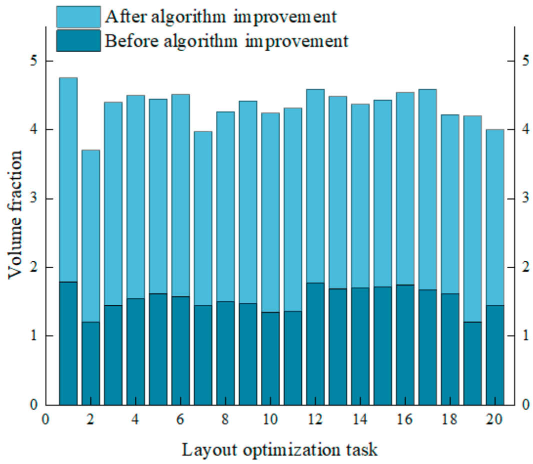

Figure 2. Floor area ratio

As shown in Figure 2, the comparison results of the floor area ratio in the optimization of urban ecological landscape space layout before and after the algorithm improvement show a clear upward trend. Before the improvement, the average floor area ratio is about 1.54; after the improvement, this average value increases to about 2.8. This means that, on average, the improved ACO algorithm can increase the plot ratio by about 1.26, which is a significant increase. The increase in the average plot ratio reflects the overall optimization effect of the improved algorithm. It shows that no matter what the specific characteristics of the urban ecological landscape layout are, the improved ACO algorithm can improve space utilization efficiency and increase building capacity to a certain extent. This improvement in universality means that the algorithm can work in a wider range of scenarios and help cities achieve more efficient and sustainable development.

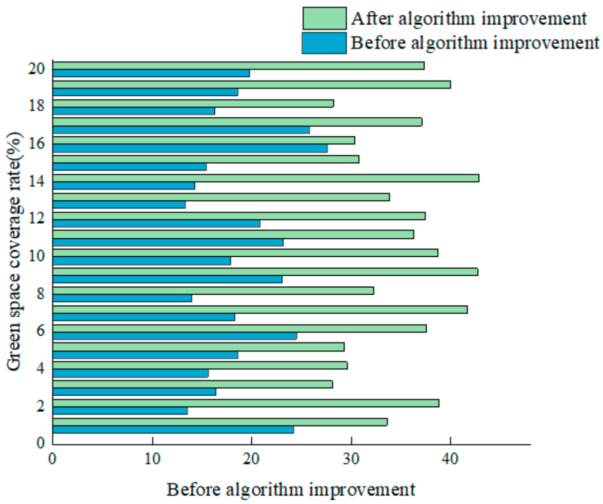

Figure 3. Green space coverage

Analyzing the data in Figure 3, from the comparison results of green space coverage in the optimization of ecological landscape space layout in different cities before and after the algorithm improvement, it can be seen that before the improvement, the maximum green space coverage rate is 27.6%, while the minimum is 13.3%, which shows the differences in green space coverage among different cities. However, after the algorithm is improved, the maximum value of green coverage jumps to 42.8%, while the minimum value is 28.1%. This data change shows that the improved ACO algorithm has achieved remarkable results in improving the green coverage of urban ecological landscape spatial layout. The significant improvement in the maximum value not only reflects the potential of the algorithm in optimizing green space coverage but also implies its flexibility and adaptability in dealing with different urban ecological landscape layouts. At the same time, the increase in the minimum value means that even in cities with originally low green coverage, the improved algorithm can effectively promote the increase of green coverage and narrow the differences between cities.

5. Conclusion

This paper successfully improved the global search capability and convergence speed of the algorithm and avoided the local optimal trap by constructing a weighted graph model, setting key parameters, and applying a variety of improvement strategies. In addition, the improved algorithm also showed better optimization effects in terms of ecological connectivity index, floor area ratio and green space coverage, verifying its applicability and strong optimization ability in the layout of ecological landscapes in different cities. Although the improved ACO algorithm proposed in this paper has achieved results in optimizing the spatial layout of urban ecological landscapes, the parameter setting of the algorithm is relatively complex and requires multiple adjustments and optimizations based on specific problems. Secondly, although the algorithm showed good convergence speed in the experiment, the calculation time may still be long when dealing with larger-scale or more complex urban layout problems. Looking forward to the future, we will continue to optimize the algorithm's parameter settings, explore smarter parameter adaptive adjustment strategies, reduce manual intervention, and improve the versatility of the algorithm. At the same time, we consider introducing more ecological and socio-economic indicators and constructing a more comprehensive comprehensive evaluation function to better reflect the multi-objective optimization needs of urban ecological landscape layout. Finally, through the application of actual urban cases, we verify the feasibility and effectiveness of the algorithm in actual planning and promote the theoretical and practical development of urban ecological landscape spatial layout optimization.

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