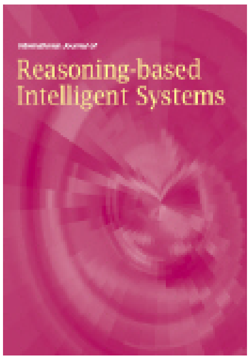

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Spatial layout design of garden landscapes based on a hybrid metaheuristic optimisation algorithm

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Abstract: As people's demand for high-quality landscaping improves, traditional design methods often face limitations such as difficulty in global optimisation. For this reason, this paper firstly deals with indicators of topographic location index, vegetation coverage and landscape risk index without dimension. A mathematical model of spatial layout is established, and the objective functions of coordination and minimisation of design cost are taken as the constraints. A hybrid genetic ant colony algorithm for landscape layout was designed, and several solutions were derived from the improved genetic algorithm, which were used to initialise the pheromone concentration of the ant colony algorithm. The mathematical model of spatial layout design was solved by continuous iteration to obtain the optimal design scheme. Experimental outcome indicates that the rationality index of the suggested approach is greater than 0.9, and the land space layout is reasonable, which improves the land utilisation rate.

Keywords: landscaping; spatial layout; genetic algorithm; ant colony algorithm; hybrid optimisation algorithm.

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1 Introduction

The design of garden landscape land use spatial layout needs to comprehensively consider multiple factors such as landscape change, functional needs, aesthetics, the balance between transparency and enclosure, environmental harmony, and ecological balance, and find the optimal balance among them in the design to achieve an excellent, harmonious, and sustainable development of the overall landscape (Sun et al., 2024). The acceleration of urbanisation not only changes the land use structure but also causes serious environmental pollution. Therefore, improving the urban ecological environment, providing high-quality activity spaces for residents, and strengthening garden landscape construction is a very necessary measure (Li et al., 2019). Garden landscapes not only increase urban vitality but also to some extent promote urban development and influence the city's image. Therefore, landscape construction is particularly important. In the design process, various complex elements are coordinated and skilfully combined to form a complete landscape space (Wu, 2021). At present, various places attach great importance to the spatial layout of garden landscapes, but there are still problems, such as the lack of characteristics in the landscape and low land use efficiency (Zhang and Deng, 2024). Especially in garden landscapes with complex land structures, it is difficult to rationally utilise land resources, which makes the spatial layout design of garden landscapes a research hotspot (Tian, 2022).

Traditional garden landscape spatial layout methods mainly achieve overall layout through the experience of designers. Han et al. (2023) proposed a parametric design method for the layout of urban park plant landscapes, using parametric design methods to realise the landscape layout. Liu and Nijhuis (2020) analysed the influencing factors and mechanisms of landscape layout, and obtained design parameters and rules from environmental, landscape, and cultural elements using Ecotect and Grasshopper software, respectively. They designed layout parameter models around different logical designs of points, lines, and planes, and generated layout design simulation diagrams. Bai (2022) took ecological civilisation construction as a principle of landscape design, combined with the needs of sustainable development, implemented the concept of low carbon, and permeated the concept of harmonious development between humans and nature into landscape design, but the land use efficiency of the above methods is not high. Yılmaz et al. (2018) constructed a regression equation for optimising garden landscape layout through kernel density estimation and district Gini index (Mucciardi and Benassi, 2023), but this method has subjectivity.

Traditional layout relies on manual experience and lacks the assistance of modern data-driven algorithms, leading to insufficient precision in spatial scale and difficulty in modelling and construction for complex terrains. Metaheuristic optimisation algorithms are not dependent on specific problems and search the solution space by simulating natural phenomena or abstract rules, aiming to find a global optimal solution or an approximate optimal solution, thereby improving the rationality of landscape layout. Examples of metaheuristic optimisation algorithms include genetic algorithms (GA) (Alhijawi and Awajan, 2024), particle swarm optimisation (PSO) algorithm (Gad, 2022), ant colony optimisation (ACO) algorithm (Deng et al., 2019), and simulated annealing (SA) algorithm (Fontes et al., 2023). Liu (2022) developed a two-step method based on GA to solve the optimal layout of garden landscapes, tested and analysed it for larger-scale problems, and the results showed that it has certain solving efficiency and effectiveness for large-scale problems. Li and Ma (2018) used SA to improve the initial positions on randomly generated expanded planes. Qin (2022) introduced the PSO algorithm to improve the efficiency and accuracy of optimal layout strategies, reduced the number of nodes in the algorithm, and improved the search speed. Zhang (2024) used the ACO algorithm to build a layout solution that changes over time, using discrete dynamic search and heuristic information to influence the garden landscape layout in different time periods, and verified the effectiveness of the final solution.

However, no algorithm can solve all problems. Although each algorithm has its advantages, it also has some disadvantages. In recent years, combining the advantages of different metaheuristic algorithms to form hybrid algorithms has become a new research trend. Hybrid algorithms use the advantages of various algorithms and combine them appropriately, which can minimise the impact of the defects of a single algorithm, thereby improving the overall performance of the algorithm. Xu and Diao (2023) designed a hybrid algorithm that combines iterative local search and centralised heuristics to solve the optimal strategy for garden landscape layout, improving land use efficiency. Aggarwal et al. (2023) combined variable neighbourhood algorithms with exact algorithms to solve the optimal landscape layout problem, improving the efficiency of layout optimisation. Ma (2025) proposed a novel two-layer ant colony algorithm as a solution algorithm for the optimisation problem of garden landscape layout, introducing local search to improve the candidate solutions.

From the research on existing methods for optimising garden layout design, it is known that the design of garden landscape space layout should take into account the different functional needs of the land, while also paying attention to aesthetics, and skilfully combining various landscape elements to achieve a comprehensive and coordinated effect. Landscape layout design based on single-element heuristic optimisation algorithms can address certain optimisation problems, but it exhibits significant limitations when handling complex, multi-constraint, and multi-objective landscape design tasks. Hybrid heuristic optimisation algorithms effectively compensate for these shortcomings by integrating the strengths of multiple algorithms, thereby enhancing the rationality and practicality of the design. Due to the different units of measurement and scales of the layout indicators of landscape land, the design of the spatial layout is quite difficult. To further optimise the land use efficiency of gardens and balance the allocation of land resources, this paper proposes a garden landscape spatial layout design method based on hybrid metaheuristic optimisation algorithms. The main work summary of this article is as follows.

1 Normalising indicators such as terrain position index, vegetation coverage, and landscape risk index. Taking regional characteristics, multilayer planting, and seasonality as design principles, combining the current land use situation, a spatial layout mathematical model is established, with the objective function being the coordination and minimum design cost, and the constraints are determined.

2 A garden landscape spatial layout optimisation solution method based on hybrid metaheuristic optimisation algorithms is proposed. By combining the search strategies of different algorithms, a balance is achieved between exploring new solution spaces and exploiting high-quality solutions.

3 According to the actual situation of garden landscapes, constraints are proposed for the chromosomes generated by GA, and parameters such as vegetation coverage and distance constraints are introduced to improve the fitness function and mutation rate of GA. Then, several solutions are obtained by the improved GA, and these solutions are used to initialise the pheromone concentration of the ACO algorithm.

4 Based on the pre-processed pheromone information, the ACO algorithm is used to optimise the garden landscape spatial layout and obtain the final solution. Experimental outcome implies that the designed approach outperforms the baseline method significantly, and can provide a more reasonable solution strategy for garden landscape layout design.

2 Relevant technologies

2.1 Genetic algorithm

GA corresponds a set of possible solutions to a population. First, the initial population is constructed, and then the next generation is generated through the genetic process. Then, the better individuals in the next generation are selected, and crossover operations are performed using different crossover strategies to produce more excellent new individuals (Deng et al., 2022). Finally, it is decided whether the individual will mutate based on the mutation probability. Through the above steps, the GA not only allows the offspring to inherit the excellent genes of the parents, but also allows the offspring to have the possibility of obtaining more excellent genes through mutation. The main steps of the GA approach are as bellow.

1 *Population initialisation:* First, the population size is determined according to the number of nodes. Each individual in the population will be initialised as an array of the same size as the number of nodes. If there are 100 nodes, each individual in the population will be initialised as an array containing 100 nodes. Then, the constraint conditions and encoding method are determined. Finally, the solution to the problem is corresponded to the chromosome according to the corresponding method.

2 *Node arrangement:* Common encoding methods for node arrangement include sequence encoding, integer encoding, real number encoding, and binary encoding. GA usually uses sequence encoding to arrange all nodes.

3 *Individual evaluation:* Define the individual fitness function and calculate the fitness value, and evaluate the individual based on the fitness value (Zhao et al., 2024).

4 *Selection operation:* The selection operation screens the individuals in the population according to the fitness value.

5 *Crossover operation:* Exchange part of the genes of all excellent individuals in the selection operation, and new population individuals will be generated during the exchange process.

6 *Mutation operation:* Change part of the genes in the individual, recalculate the new individual's fitness, and obtain an individual with higher fitness.

2.2 ACO algorithm

ACO, as a typical metaheuristic optimisation algorithm, attains an equilibrium between global exploration and local refinement in tackling intricate optimisation problems through mimicking the collaborative actions and pheromone-based communication of ant colonies (Liao et al., 2014). Each ant in the ant colony acts independently during the search process, and communication between individuals is only based on pheromones, which helps to greatly improve the global search capacity of the ACO algorithm. The basic algorithm steps of ACO are as follows.

1 *Initialise the population position:* First, it is necessary to determine the position of the ant colony individuals in the tabu list $tabu_k$. The position of the ant colony individuals is randomly placed.

2 *Update the tabu list:* Calculate the transition probability of the ant colony individuals according to the formula, and take the city with the highest probability as its transition target, while updating the tabu list $tabu_k$. At time t, the probability $P_{ij}^k(t)$ of ant k moving from city i to city j is calculated as follows.

$$P_{ij}^k(t) = f(x) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum_s [\tau_{is}(t)]^\alpha \cdot [\tau_{is}(t)]^\beta} & j, s \notin tabu_k \\ 0 & j, s \in tabu_k \end{cases} \tag{1}$$

3 *Calculate the pheromone increment:* During the movement process, the individual ants will volatilise the pheromone, thus reducing the attractiveness of the pheromone to the ant colony individuals. The calculation of pheromone volatilisation is as follows.

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \Delta\tau_{ij} \tag{2}$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k \tag{3}$$

4 *Judge the termination condition:* When the ant colony individuals have visited all the cities in the tabu list, the optimal strategy of this search is updated. Update the pheromone according to the set ACO model.

Although ACO and GA both belong to meta-heuristic optimisation algorithms, they originate from different biological inspiration models. ACO simulates ant foraging behaviour, while GA simulates biological evolution. They exhibit fundamental differences in core mechanisms, search logic, and applicable scenarios. It is precisely these distinctive characteristics that enable their combination to form significant complementary advantages, effectively enhancing optimisation performance.

3 Land use assessment and dynamic change analysis of garden landscape space layout

3.1 Evaluation of land use conditions of garden landscape space layout

To design the garden space and landscape space layout, making it have spatial aesthetic effects, the constituent elements of urban gardens are the basis. Urban gardens are mainly composed of elements such as natural, humanistic, and artificial environments. The landscape constituent elements are shown in Table 1.

Table 1 Components of the landscape

Landscape type	*Resource*	*Constituent elements*
Natural landscape	Topography and geomorphology	Islands, beaches, woodlands, grasslands, etc.
	Water body	Water quality, water temperature
	Biology	Animals and plants
Humanistic landscape	Architecture	Former residences of famous people and pavilions
Humanistic environment	Roads and decorations	Paving of different colours and materials
	Sketch	Street lamps, seats, etc.

The layout design should derive from and respond to the actual conditions of the garden landscape to ensure proper spatial organisation. After strict selection, the land use situation of the garden landscape will be evaluated from the following aspects.

1 *Topographic position index:* The ecological structure formed by different topography will also have differences. It is difficult to fully reflect the impact of topography on space utilisation only by elevation and slope. The topographic position index model is determined by the spatial pattern, position, and range of the watershed land index. Therefore, the topographic condition of the garden landscape is described by the topographic position index model, and its expression is as follows.

$$T = \lg\left[\left(\frac{E}{\bar{E}+1}\right)\times\left(\frac{S}{\bar{S}+1}\right)\right] \tag{4}$$

where E and $\bar{E}$ are the elevation value and the average elevation, S and $\bar{S}$ are the slope and the average slope. The higher the E and S values, the higher the T value will be.

2 *Vegetation coverage:* This influencing index is an important parameter to reflect the ecological environment status. The higher the vegetation coverage, the more conducive to plant growth and development, which indicates higher land use efficiency, thus indicating rational land use. There is a linear relationship between coverage and the Normalised Difference Vegetation Index (NDVI) (McDougall et al., 2022), so the coverage is calculated by the binary model.

$$NDVI_{\alpha}^{2} = Max\left(NDVI_{\alpha\beta}\right) \tag{5}$$

$$\overline{NDVI} = \frac{1}{q}\sum_{\alpha=1}^{q} NDVI_{\alpha} \tag{6}$$

where $NDVI_{\alpha}$ represents the normalised index value of the α^{th} month, $NDVI_{\alpha\beta}$ is the normalised index value of the α^{th} month and the β^{th} month, $\overline{NDVI}$ is the annual normalised index value, and q is the month.

3 *Landscape risk index:* The risk coefficient is composed of disturbance and vulnerability, which indicates the risk of land use situation. The higher the value, the higher the risk index, which indicates that the land use is more unreasonable.

The landscape disturbance is described by fragmentation U_{a1}, dominance U_{a2}, and separation U_{a3}. The weights of each index are 0.4, 0.2, and 0.4, respectively. The disturbance E_a is shown in equation (7), where the calculation of the three indicators U_{a1}, U_{a2}, and U_{a3} is shown in equation (8).

$$E_a = 0.4\times U_{a1} + 0.2\times U_{a2} + 0.3\times U_{a3} \tag{7}$$

$$\begin{cases} U_{a1} = \dfrac{N_a}{A} \\ U_{a2} = \ln M + \displaystyle\sum_{a=1}^{M} \frac{A_a}{A}\ln\left(\frac{A_a}{A}\right) \\ U_{a3} = \dfrac{1}{2}\sqrt{\dfrac{A_a}{A}}\times\dfrac{A}{A_a} \end{cases} \tag{8}$$

where N_a is the number of patches of land type a, A is the total area, A_a is the area of land type a, and M describes the total number of land types.

Vulnerability is the ability of the landscape to resist external disturbances. The higher the vulnerability, the higher the risk. The computation equation for the landscape vulnerability coefficient ERI_k is as bellow.

$$ERI_k = \sum_{a=1}^{M} \frac{A_{ak}}{A_k}\left(E_{ak}\times F_a\right) \tag{9}$$

where A_{ak} is the area of land a in k units, A_k is the area of k units, E_{ak} describes the disturbance of land a in k units, and F_a is the vulnerability of land type a.

4 *Ecological service value:* This index reflects the function of the ecosystem. The expression of the landscape value coefficient (ESV) is as follows, where VC_a represents the service value coefficient of land type a.

$$ESV = \sum_{a}^{M} A_a \times VC_a \tag{10}$$

3.2 Weight calculation of indicators affecting the spatial layout of garden landscape

These indicators undergo normalisation processing to eliminate dimensional differences, facilitating weight calculation, importance assessment of individual indicators, and offering foundational data for later layout planning. The following equation is applied to achieve dimensionless normalisation.

$$x_u' = \frac{x_u - \overline{x}}{\delta} \tag{11}$$

where x_u is a variable, $\overline{x}$ is mean measurement, and δ is the statistical dispersion.

Entropy serves as a metric for information quantification. An inverse relationship exists between the index value and its entropy: lower entropy corresponds to higher weight allocation. Conversely, the weight is smaller (Zhang and Wang, 2023). Using entropy to calculate weights, combined with the degree of index variation to obtain weights. The computational procedure consists of the following steps.

Step 1 Construct an evaluation matrix, followed by matrix B representing u evaluation indices across v instances.

$$B = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1u} \\ x_{21} & x_{22} & \dots & x_{2u} \\ \vdots & \vdots & \vdots & \vdots \\ x_{v1} & x_{v2} & \dots & x_{vu} \end{bmatrix} \tag{12}$$

Step 2 Use the following formula to normalise the variables, where y_{vu} represents the normalised variable, and $x_{v\min}$ and $x_{v\max}$ are the minimum and maximum values of the index.

$$y_{vu} = \frac{\left(x_{vu} - x_{v\min}\right)}{\left(x_{v\max} - x_{v\min}\right)} \tag{13}$$

Step 3 Combining the relevant theories of entropy, the entropy value H_u of u indices of v evaluated targets is calculated as follows, where $f_{uv} = y_{vu} \Big/ \sum_{v=1}^{v} y_{vu}$, when $f_{uv} = 0$ is true, Inf_{vu} will be meaningless. Then compute the weight W_u, as shown in Equation (15).

$$H_u = -\frac{1}{v}\left[\sum_{v=1}^{v} f_{vu} Inf_{vu}\right] \tag{14}$$

$$W_u = \frac{1 - H_u}{M - \sum_{u=1}^{M} H_u} \tag{15}$$

After the above assessment of the current situation of garden landscape, combined with the calculation results of the weights of each index, it is possible to find the problems in land use in the spatial layout, and also obtain the significance of every individual index, offering a valuable reference for later layout planning.

4 Construction of a mathematical model for the spatial layout design of garden landscape

In the spatial layout design of garden landscape, trees should be selected that are suitable for the local climate type and soil type. First, the biological growth habits should be fully considered, and the normal growth should be ensured on the basis of paying attention to biodiversity. Trees that are suitable for the local climate type and soil type should be selected, fully considering the biological growth habits, and ensuring normal growth on the basis of paying attention to biodiversity. Second, the functions of plants such as spatial division and aesthetics should be fully embodied. The design aesthetics should also be improved to ensure that the landscape units are coordinated. Finally, the functions of plants such as spatial division and aesthetics should be fully embodied. The design aesthetics should also be improved to ensure that the landscape units are coordinated.

For the problem of land use layout, converting the problem statement into model form constitutes a key phase. The mathematical formulation characterises the interrelationship between parameters and observed quantities. Owing to the substantial combinatorial complexity of the spatial arrangement task, a composite model needs to be constructed, expressing the elements such as objectives and relationships in the problem through symbols.

Before establishing the model, the landscape area is divided into m rows and n columns of units. Subsequently, the target area comprises $m \times n$ units with K distinct land types requiring allocation. k_1 and k_2 describe the land classes ($i = 1, 2, \dots, n, j = 1, 2, \dots, m$) of the units ($ij$) and ($i'j'$). $U_{ij,i'j'}$ is a dichotomous variable. If (ij) and ($i'j'$) are contiguous, the value is 1; otherwise, it is 0. V_{k_1,k_2} measures the extent of harmonisation among units (ij) of class k_1 and units ($i'j'$) of type k_2. Use X_{k_1} to represent the number of k_1 land types, X_{ijk_1} is also a binary variable. If the land type in (ij) unit is k_1, the value is 1; otherwise, it is 0. $S_{ij,i'j'}$ is the total number of adjacent times between unit (ij) and ($i'j'$). P_{ijk_1} is the cost of arranging k_1 types of land in (ij) unit.

For model simplification, the framework considers exclusively layout coordination (D) and design cost (P) as key parameters. The target function can be expressed as follows.

$$MaxD = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k_1=1}^{k_1}\sum_{i'=1}^{m}\sum_{j'=1}^{n}\sum_{k_2=1}^{k_2} U_{ij,i'j'} V_{k_1,k_2} \tag{16}$$

$$MinP = \sum_{i=1}^{m}\sum_{j=1}^{n}\sum_{k_1=1}^{k_1} P_{ijk_1} X_{ijk_1} \tag{17}$$

The above objective function should also satisfy the following constraints.

1 A unit needs to be adjacent to one or more units, that is, $\forall k_1, S_{ij,i'j'} \geqslant 1$.

2 Distance constraint: Use $d_{i_1 j_1 k_1 i_2 j_2 k_2}$ to detail the distance measurement between k_1 and k_2 expressed in units. The magnitude of this distance must exceed D; hence, the constraint is defined as $d_{i_1 j_1 k_1 i_2 j_2 k_2} > D$.

5 Design of garden landscape spatial layout based on hybrid metaheuristic optimisation algorithm

5.1 Improved GA

Intending to the issue that traditional metaheuristic optimisation algorithms cannot balance solution efficiency and convergence speed, this paper proposes an optimisation method for garden landscape spatial layout based on hybrid metaheuristic optimisation algorithm. The flow of the suggested approach is shown in Figure 1. By combining the search strategies of different algorithms, a balance is achieved between exploring new solution spaces and developing high-quality solutions. First, according to the actual situation of garden landscape, constraint conditions are proposed for GA to generate chromosomes, and parameters such as vegetation coverage and distance constraints are introduced to improve the fitness function and mutation rate of GA. Then, several solutions are obtained by the improved GA, and these solutions are used to initialise the pheromone concentration of the ACO algorithm. Finally, based on the pre-processed pheromone information, the ACO is adopted to improve the spatial layout of the garden landscape, obtaining the final solution.

The criterion for judging the quality of GA chromosomes is the fitness value. In traditional garden landscape spatial layout optimisation, the fitness function usually only considers distance. However, due to factors such as land use efficiency, traditional algorithms can no longer meet the requirements. Hence, it is essential to optimise the fitness function. The fitness function needs to consider the impact of land use efficiency, cost, and distance in the context of garden landscape spatial layout optimisation. The specific formula is shown in equation (18), where r is the land area, a is the cost, and d is the distance.

$$F(x) = rad \tag{18}$$

GA uses mutation operations to generate new individuals to avoid the algorithm falling into a local optimal solution. However, if the mutation probability is too high, the entire process will degenerate into a random process. If the mutation rate is too low, the algorithm may get stuck in a relatively optimal solution and cannot escape. Therefore, this section improves the mutation operation by using a dynamic mutation rate.

In the early stage of the algorithm, to avoid the algorithm getting stuck in a relatively optimal solution, a higher probability of mutation is set. As the individual generation value decreases and the results are optimised, the mutation rate is also reduced according to the decrease in the generation value. This can effectively preserve the excellent genes and improve the efficiency of optimisation. The mutation rate is shown in equation (19).

$$Pm = \frac{(1/CurrentGenerationValue)}{(1/MinGenerationValue)} \tag{19}$$

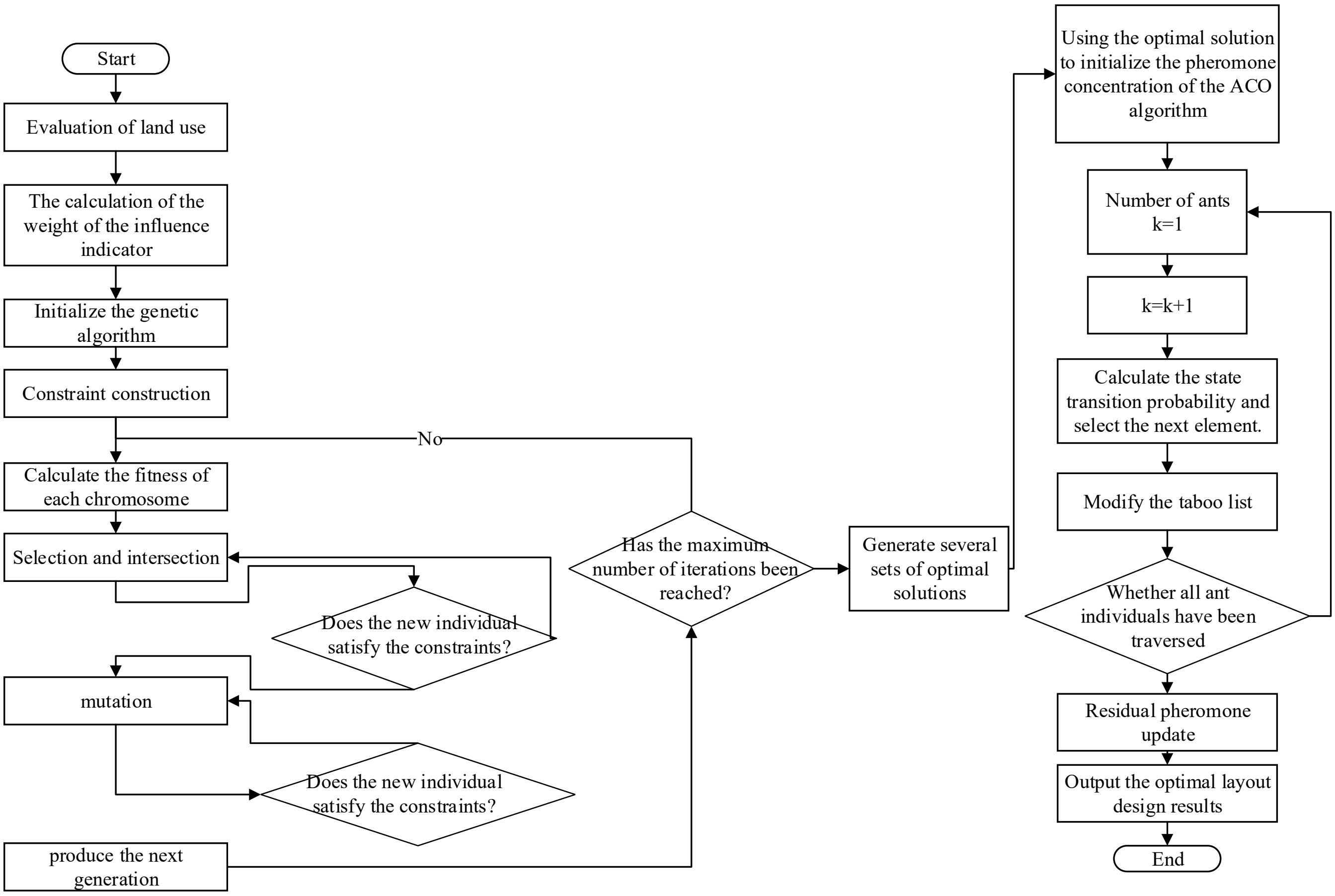
GA generates new chromosomes through crossover or mutation operations. In the scenario of garden landscape spatial layout optimisation, new chromosomes may not meet the constraints. Therefore, it is necessary to judge the newly generated chromosomes based on the constraints. If the constraints are not met, the crossover or mutation operations need to be performed again. This section improves the constraints, fitness function, and mutation probability of GA by combining the specific situation of garden landscape spatial layout, so that GA can be better applied to the scenario of garden landscape spatial layout optimisation.

5.2 Improved ACO algorithm

In the ACO algorithm for garden landscape spatial layout, the selection of the next node by the ant individual is obtained through the probability calculation of the optimal strategy. According to the special connectivity between nodes, the diversity of parameters, and the initial pheromone value, the probability of the optimal strategy selection is calculated as shown in equation (20). Among them, i is the ant number, j is the number of a certain optimal strategy for the layout, $allow_p$ is the set of optimal strategies that the ant can choose at the current position, $\alpha \geq 0$, $\beta \geq 0$ represent the relative importance of pheromone and computational cost, γ_{ij} is the layout optimisation factor.

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t) \cdot \gamma_{ij}^{\beta}(t)}{\sum_{z \subset allow_p} \tau_{ij}^{\alpha}(t) \cdot \gamma_{ij}^{\beta}(t)}, & j \in allow_p \\ 0, & \text{otherwise} \end{cases} \tag{20}$$

Figure 1 The flow of the suggested approach



To better guide the ant individuals to choose the excellent garden landscape layout, it is necessary to update the pheromone on each strategy according to equation (21) in a timely manner, where *rho* ∈ (0, 1) is the pheromone evaporation intensity coefficient, $\Delta\tau_{ij}$ is shown in equation (22), where *C* is a constant, and *P* is the fitness calculated by the ant according to the fitness function.

$$\tau_{ij}(t+1) = rho \cdot \tau_{ij}(t) + \Delta\tau_{ij} \quad (21)$$

$$\Delta\tau_{ij} = C \cdot P_k \quad (22)$$

According to the theoretical research of the ACO algorithm, the pheromone update strategies mainly have three types, namely ant-cycle update, ant-quantity update, and ant-density update. In solving the garden landscape layout problem, the ant-cycle strategy performs better and is more applicable in the application of garden landscape layout.

5.3 Mathematical model solving based on hybrid genetic ant colony algorithm

In the ACO algorithm for garden landscape spatial layout, the initial pheromone is empty, which causes the ACO to have a slow convergence speed in the early stage. To solve the above problems, a hybrid genetic ant colony algorithm (EGA-ACO) is proposed. It uses the advantages of GA's efficient parallelism and global search to set the initial pheromone values for the ACO approach, and improve the improvement efficiency. The EGA-ACO is used to optimise the garden landscape layout. The optimisation solving process of EGA-ACO is as follows.

Step 1 *GA parameter initialisation:* The main parameters to be initialised for the GA algorithm are population size, maximum generation, crossover rate, mutation rate, and termination condition.

Step 2 *Initialise chromosomes:* Construct constraint conditions based on the connectivity of nodes in the garden landscape layout, and initialise the GA chromosomes according to the constraint conditions.

Step 3 *Calculate fitness value:* Improve the fitness function according to the application scenario of garden landscape layout, and calculate the fitness value of the chromosome individual according to the improved fitness function. After obtaining the fitness value of the chromosome individual, perform selection, crossover, and mutation operations. The newly generated chromosomes after crossover and mutation operations need to be checked whether they meet the specified constraints. If they do not meet the constraints, the corresponding operations are performed again.

Step 4 *Determine the termination condition:* If the current number of iterations has reached the maximum number of iterations, the result is output and saved. Otherwise, repeat step 3 and 4.

Step 5 *Initialise pheromone concentration:* Initialise the pheromone concentration of the corresponding ant colony algorithm according to the optimal solution obtained from GA.

Step 6 *Initialise ACO algorithm parameters:* Initialise the parameters of the ACO algorithm, set the maximum number of iterations *g*; the pheromone evaporation intensity coefficient is *rho*; initialise the taboo table and set it to empty; randomly place the ants; create a pheromone matrix, and establish an $M * M$ pheromone matrix *phenomenon*[*m*][*m*] according to the number of nodes to be optimised.

Step 7 *Node selection:* Improve the ant transfer probability according to the actual situation of garden landscape layout optimisation. Place the ant colony at the starting point and select the next node according to the selection probability, and establish and modify the taboo table.

Step 8 *Update pheromone concentration:* Determine whether all ants have completed the search. If they have, update the global pheromone concentration; otherwise, repeat steps 6 and 7.

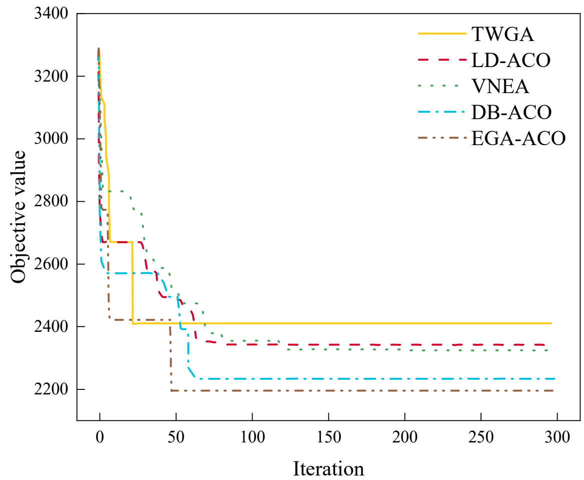
Step 9 *Termination condition judgment:* Determine whether the current generation has reached the maximum number of iterations. If not, repeat the operations of steps 6, 7 and 8.

6 Experimental results and analyses

The experiment employs the landscape architecture dataset from reference (Chen, 2023), which contains 13,596 diverse urban landscape design layouts, incorporating a wide range of spatial elements. For different types of landscape features, a data structure encompassing spatial location, morphological characteristics, and functional attributes is constructed to establish a comprehensive landscape architectural space data model. Data quality is ensured through data cleaning, outlier detection, and missing value handling, so as to meet the requirements of analysis. The suggested approach and the comparison approaches are implemented in Python 3.9 on a computer equipped with an Intel(R) Core (TM) i7-10700 CPU @ 2.90 GHz and 16.0 GB RAM. In the experiments, the crossover rate of GA is set to 0.9, with a population size of 100; for ACO, the heuristic factor α is set to 1, the expected heuristic factor β is set to 4, and the evaporation coefficient rho is set to 0.5.

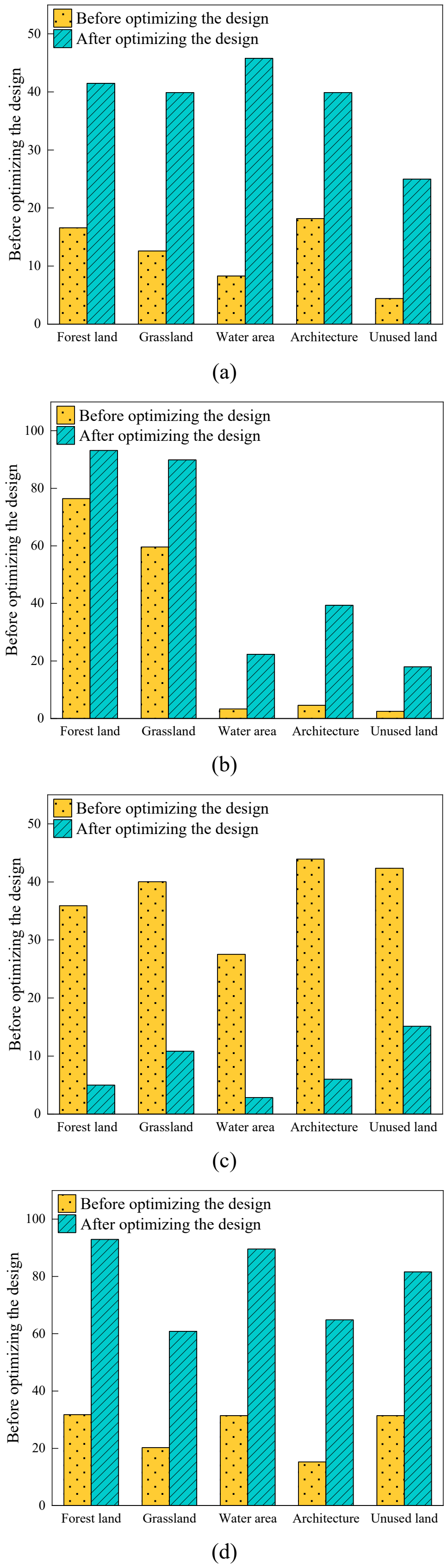
This paper first analyses the convergence of the EGA-ACO algorithm. The selected comparison algorithms are GA, ACO, PSO, and SA. The convergence comparison of the objective function of different algorithms is shown in Figure 2. Under the same number of iterations, the EGA-ACO algorithm has a faster decrease speed of the objective function value and a smaller value, indicating that the EGA-ACO algorithm has a faster convergence speed. It has the ability to find better landscape layout optimisation schemes. In summary, the EGA-ACO algorithm can effectively reach an approximate optimal solution or a global optimal solution. The GA algorithm tends to quickly converge to a local optimum, leading to search stagnation. The ACO algorithm gradually converges through the positive feedback mechanism of pheromones, but the initial lack of pheromones leads to blind search, requiring a large number of iterations to accumulate effective information. PSO relies on the group's historical best and individual's historical best to guide the search. If the initial particle distribution is unreasonable, it may converge too early. SA needs to balance exploration and exploitation. If the search strategy is improper, it may not find the global optimum.

Figure 2 The convergence comparison of the objective function of different algorithms (see online version for colours)



To more intuitively show the land use spatial layout before and after the design through EGA-ACO, the topographic position index, vegetation coverage, landscape risk index, and ecological service value are utilised as quantitative assessment norms. The assessment outcome is implied in Figure 3. Preliminary analysis revealed suboptimal land-use allocation, as evidenced by low pre-development topographic position index values. After the design, the topographic position index increased significantly. Pre-design vegetation coverage analysis revealed suboptimal conditions across most land types, with only grassland and forest ecosystems meeting minimum coverage thresholds. Prior to the design phase, an assessment of vegetation coverage demonstrated that most land types exhibited suboptimal conditions. Grassland and forest ecosystems were the sole exceptions, achieving the minimum coverage requirements, for example, adding aquatic plants in water areas and increasing greenery around buildings. Regarding the landscape risk index and ecological service value, it was observed that the landscape risk exhibited a substantial decline following the design implementation, and the service value increased. This layout result can exert greater ecological value.

Figure 3 Quantitative indicators of landscape layout effectiveness, (a) topographic position index (b) vegetation coverage rate (c) landscape risk index (d) ecological service value (see online version for colours)



For the goal of highlighting the advantages of EGA-ACO in garden landscape layout optimisation, four methods, TWGA (Liu, 2022), LD-ACO (Zhang, 2024), VNEA (Aggarwal et al., 2023), and DB-ACO (Ma, 2025), are introduced as comparisons. Under different landscape layout areas, the rationality index of layout optimisation was tested, as shown in Table 2. The rationality index of EGA-ACO is 0.91–0.98, the rationality index of DB-ACO is 0.84–0.9, the rationality index of VNEA is 0.76–0.85, the rationality index of LD-ACO is 0.69–0.78, and the rationality index of TWGA is 0.59–0.71. The rationality index of EGA-ACO has a significant improvement compared to the other four methods.

TWGA method solves the mathematical model of landscape layout optimisation through GA. Although GA is good at global exploration, it lacks a fine local development mechanism, and the quality of the solution may be limited due to insufficient subsequent optimisation. LD-ACO constructs a time-varying landscape layout solution through ACO, but it still has the problems of high computational complexity and getting stuck in local optima. VNEA designed a two-layer ACO to solve the garden landscape layout optimisation, but when there are multiple similar solutions to the problem, the excessive accumulation of pheromones may cause the ants to gather on suboptimal strategies too early. DB-ACO solves the optimal landscape layout problem by combining variable neighbourhood algorithm and exact algorithm, but the search time for the optimal solution is long, so the rationality index is not as good as EGA-ACO. When using the EGA-ACO method, not only GA and ACO were optimised, but the mutation operation was also simplified. Since EGA-ACO solved, the globally optimal solution for the landscape configuration model, the rationality index was improved to above 0.9. A reasonable garden landscape layout improves the design level and maintains the biodiversity of the ecosystem.

Table 2 Rationality indices for layout optimisation

Layout area/ km^2	10	20	30	40	50	60	70	80	90	100
TWGA	0.64	0.68	0.71	0.62	0.65	0.68	0.71	0.69	0.7	0.59
LD-ACO	0.78	0.72	0.69	0.75	0.74	0.77	0.69	0.73	0.72	0.76
VNEA	0.81	0.79	0.83	0.76	0.85	0.81	0.8	0.85	0.81	0.78
DB-ACO	0.90	0.85	0.87	0.89	0.85	0.87	0.84	0.88	0.85	0.86
EGA-ACO	0.95	0.91	0.97	0.92	0.95	0.93	0.98	0.96	0.95	0.97

7 Conclusions

The design of garden landscape space layout should take into account the different functional needs of the land, while also paying attention to aesthetics, skilfully combining various landscape elements to achieve a comprehensive and coordinated effect. This paper proposes a garden landscape space layout design method based on hybrid metaheuristic optimisation algorithms, aiming to solve the problem of the high difficulty of space layout design in existing methods.

First, this paper non-dimensionalises indicators such as terrain position index, vegetation coverage, and landscape risk index. Taking regional characteristics, layered planting, and seasonality as design principles, combined with the current land use status, a spatial layout mathematical model is established, with the objective function of coordination and minimum design cost, and constraints are established. Then, a solution method for optimising the garden landscape space layout based on hybrid metaheuristic optimisation algorithms is proposed. Several solutions are obtained by improving the GA algorithm, and these solutions are used to initialise the pheromone concentration of the ACO algorithm, effectively solving the problem that the ACO algorithm converges slowly at the beginning and is prone to fall into local optimal solutions. Finally, according to the actual situation of garden landscape layout, some improvements are made to the ACO algorithm to obtain the optimal garden landscape layout strategy. Experimental outcome indicates that the suggested approach not only can search for better layout schemes, but also significantly improve the rationality of garden landscape layout.

Although the integration of GA and ACO has yielded promising results, any hybrid algorithm inevitably introduces new complexities and challenges. The current approach still requires improvement in several aspects.

1 The hybrid algorithm not only inherits control parameters from GA and ACO but also introduces new collaborative parameters. Current parameter tuning relies heavily on trial-and-error experimentation, lacking systematic adaptive adjustment mechanisms. This imposes high debugging costs in practical applications. Future research will explore search-process-feedback-based adaptive parameter techniques, enabling automatic adjustment of critical parameters according to search states to reduce manual intervention.

2 The performance advantages of hybrid algorithms are partially dependent on the characteristics of the problem being solved. For instance, when dealing with problems featuring exceptionally complex or dynamically changing solution spaces, the robustness and adaptability of current algorithms may prove insufficient. A major challenge lies in enabling algorithms to automatically perceive problem characteristics and adjust their internal behaviour accordingly. Future work will focus on testing the algorithms' performance in dynamic environments to evaluate their rapid response and re-optimisation capabilities.

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Declarations

All authors declare that they have no conflicts of interest.

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