A Dual-Mode Genetic-Ant Colony Algorithm for Dynamic Path Planning in Smart Scenic Spots

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This article focuses on the path planning problem in intelligent tourism scenic areas and innovatively proposes a dual-mode Genetic-Ant Colony Optimization algorithm (GA-ACO). This algorithm cleverly combines the global exploration advantage of genetic algorithms (GA) with the local development expertise of ant colony optimization (ACO), constructing a multi-dimensional dynamic fitness function in real-time that incorporates both visitor preferences and dynamic environmental constraints (such as attraction congestion index and opening status), thereby achieving refined evaluation of path quality. The algorithm facilitates deep collaboration between GA and ACO through the design of pheromone-guided genetic operators (which prioritize high-quality path segments with high pheromone concentrations during selection, crossover, and mutation operations) and a bidirectional feedback mechanism (where elite solutions generated by GA are converted into the initial pheromone matrix for ACO, providing guidance for multi-modal search; the pheromone accumulated by ACO provides local heuristic information for GA), forming a closed-loop enhancement of global exploration and local development. Experiments show that, compared to traditional algorithms (such as pure GA and ACO), GA-ACO significantly outperforms key indicators like path length, number of iterations, and number of turns: the optimal path length is reduced by 6% compared to ACO, the average number of iterations is reduced by 50%, and the number of turns is minimal (only 3.8 turns); compared to GA, path smoothness and energy efficiency are significantly improved. Additionally, it can accurately generate optimal paths in three-dimensional space simulations, with reliability verification showing a prediction accuracy of 99.26%, and it has significant advantages in solving the total number of feasible paths and the time taken to find the optimal path, allowing for rapid responses to dynamic changes in scenic areas, thereby providing efficient and reliable solutions for path planning in intelligent scenic areas.

Povzetek: Metoda GA-ACO za načrtovanje poti v pametnih turističnih območjih upošteva preference in dinamiko okolja ter v primerjavi z GA/ACO skrajša pot (~6 %), prepolovi iteracije (~50 %) in izboljša gladkost poti (99,26 % natančnost v 3D).

1 Introduction

The rapid integration of digital technology into the tourism industry has given rise to the concept of "smart tourist attractions" (SSA), marking a shift toward data-driven, intelligent visitor management and service models. At the core of enhancing visitor experiences and optimizing operational efficiency in smart tourist attractions lies the capability for intelligent path planning. This functionality goes beyond simple navigation, dynamically coordinating visitor flow under complex real-time constraints to maximize visitor satisfaction while ensuring sustainable resource utilization and safety. While graph-based algorithms (such as Dijkstra's algorithm and A* algorithm) have proven effective in static network routing, their inherent limitations become particularly evident in the dynamic, multi-constraint environments of modern SSA. Typical characteristics of such environments include fluctuations in visitor density, time-varying attraction availability (e.g., operating hours, scheduled performances), heterogeneous visitor preferences (e.g., interest in
specific attraction types, tolerance for walking/waiting), and dynamic changes in physical constraints (e.g., path congestion, queue lengths, attraction capacity limits). Consequently, traditional methods often produce suboptimal or infeasible paths that fail to adapt to the randomness and personalized nature of tourist experiences.

In the face of these challenges, heuristic algorithms, especially those inspired by biological collective intelligence, have attracted widespread attention in the field of path planning in complex scenarios. GA and ACO stand out due to their inherent parallelism and ability to handle multi-objective optimization problems without requiring gradient information. GA excel at broad global exploration during the initial search phase, quickly identifying promising regions in the solution space.

However, they often struggle to achieve fine-grained local optimization in later stages due to premature convergence or population stagnation. In contrast, ACO leverages ant information (communicated via pheromone trails) to facilitate efficient local exploitation and positive feedback for high-quality paths. However, its performance heavily depends on the initial pheromone distribution and parameter tuning, often leading to slow initial convergence and a tendency to get stuck in local optima, especially in large-scale or sparse networks.

Recognizing the complementary strengths and weaknesses of these methods, hybrid strategies have gradually become a promising research direction. This paper proposes a novel GA-ACO algorithm specifically designed for dynamic multi-objective path planning in intelligent tourist attractions, providing a solution that combines dynamic responsiveness with cultural privacy protection for cross-cultural intelligent interaction.

The genetic-ant colony dual-peak algorithm (GA-ACO) proposed in this paper achieves a deep collaborative mechanism by establishing a unified pheromone knowledge base. This framework employs pheromone-guided genetic operators, which prioritize the selection, crossover, and mutation operations to utilize high-quality path segments where pheromone concentration is high, thereby converting the search experience accumulated by ACO into a directed evolution strategy for GA. At the same time, the diverse elite solutions discovered by GA feed back to ACO through pheromone updates, providing it with multi-peak search guidance. This bidirectional feedback mechanism overcomes the initial search blindness and premature convergence issues of traditional ACO, while compensating for the weak local development capability of GA, creating a synergistic enhancement effect between global exploration and local refinement. Key parameters are optimized based on problem scale and algorithm mechanics: population size (50-100) balances diversity with efficiency, crossover probability (0.75-0.95) promotes gene recombination, and mutation probability (0.01-0.05) maintains population vitality; pheromone heuristic factor α (1.0-1.5) and expectation factor β (2.0-5.0) coordinate the weights of experience and heuristic information, with evaporation coefficient ρ (0.1-0.5) controlling the speed of knowledge base updates. This integrated mechanism significantly enhances the optimization efficiency and solution quality of multi-constraint scenic area path planning through a rigorous Lamarckian knowledge inheritance path.

The core issues of intelligent scenic area route planning are threefold: first, the dynamism of the scenic area environment, where the status of attractions and path congestion changes in real-time, making traditional algorithms difficult to adapt; second, the heterogeneity of tourist demands, with significant differences in preferences for attraction types and walking intensity among different tourists, requiring personalized paths; third, performance bottlenecks of algorithms, where a single genetic algorithm (GA) is prone to local optima, and ant colony optimization (ACO) has blind initial exploration, making it hard to balance the breadth and precision of solution space exploration. The research objective is clear: to design a genetic-ant colony dual peak algorithm (GA-ACO) that, through a dual-mode collaborative mechanism, breaks through the limitations of traditional algorithms to achieve intelligent scenic area route optimization that takes into account personalized demands and planning efficiency in dynamic environments, thereby improving path quality and algorithm response speed.

2 Theoretical analysis of traditional path planning algorithms

2.1 Dijkstra's algorithm

Dijkstra's algorithm was proposed in 1956 by Dutch computer scientist Ezhel Dijkstra, who is is an efficient, classical greedy algorithm for solving the shortest path from a fixed starting point to all other nodes in a graph with non-negative weights in a non-negative weighted graph.Dijkstra's algorithm gradually finds a globally optimal solution to the problem by continuously adding the node with the smallest current distance estimate to a “determined” set and relaxing its neighbors' distance estimates. Dijkstra's algorithm gradually finds the global optimal solution by continuously adding the node with the smallest current distance estimate to the “identified” set and relaxing the distance estimates of its neighbors. The core node relaxation equation is shown in (1.1), where $dist[v]$ is the shortest distance from the starting point to v, $w(u,v)$ is the edge weights, $Adj[u]$ is the set of neighboring nodes of u, $dist[u]$ and is a temporary estimate of the currently known shortest path length from the starting point to node u.

$$dist[v] = \min\big(dist[v], dist[u] + w(u,v)\big), \forall v \in Adj[u] \quad (1.1)$$

2.2 A* algorithm

The A* algorithm, introduced by Hart et al. in 1968, improves upon Dijkstra's algorithm by incorporating a heuristic function. This function estimates the cost from the current node to the goal node, guiding the search process more efficiently toward the goal and significantly enhancing overall performance. However, the effectiveness of the A* algorithm is critically dependent on the design of its heuristic function. If the heuristic function is not properly designed, it may lead to inefficient search or even failure to find the optimal solution. In addition, in dynamic multi-constraint scenarios, the adaptability of the A* algorithm is not sufficient to meet the complex demands of intelligent scenic path planning.

The evaluation function of A* algorithm is shown in equation (1.2). In Equation (1.2), $f(n)$ denotes the estimated total cost of reaching the goal through node n, $g(n)$ denotes the distance from the start node to node n without costing the finger and $h(n)$ is the estimated costing the distance from the next point to the end point. The node with the smallest f(n) is prioritized in the A * algorithm.

$$f(n) = g(n) + h(n) \quad (1.2)$$

2.3 Genetic algorithms

Developed by Holland in 1975, the Genetic Algorithm (GA) emulates Darwin's "survival of the fittest" principle and the processes of genetic inheritance and natural selection to search for optimal solutions. In path planning, GA encodes paths as "chromosomes" and optimizes the population iteratively through selection, crossover, mutation and other operations. In the path planning problem, the basic steps of GA are: randomly generating a set of possible paths as the initial population; calculating the fitness value of each individual, which is usually inversely proportional to the length of the path; selecting the best individuals for reproduction based on the fitness value; the probability of selection is usually proportional to the fitness value of an individual, i.e., the higher the fitness value of an individual, the higher the probability of being selected; and generating a new individual by exchanging part of the gene fragments of two individuals. gene segments to generate new individuals, where the crossover probability formula is shown in Equation (1.3). In Equation (1.3), P denotes the crossover probability and $f(x_i)$ denotes the fitness value of individual x_i. Finally, a gene segment of an individual is randomly changed to maintain the diversity of the population.

$$P = f(x_i)/\Sigma f(x_i) \quad (1.3)$$

2.4 Ant colony optimization

ACO is an optimization algorithm that simulates the foraging behavior of ants proposed by Italian scholars Dorigo et al. in 1991. In the path planning problem, the ACO algorithm uses the positive feedback mechanism of pheromone to guide the ants to find the optimal path by simulating their behavior of releasing pheromone on the path. The transfer probability formula of the ACO algorithm is shown in Equation (1.4).

$$P_{ij}^k = [\tau_{ij}]^a \cdot [\eta_{ij}]^\beta / \Sigma_{l \in N_i^k} [\tau_{il}]^a \cdot [\eta_{il}]^\beta \quad (1.4)$$

In Equation (1.4), P_{ij}^k is the probability that ant k transfers from node i to node j; τ_{ij} is the information concentration or trajectory strength on the edge (i, j); η_{ij} is the heuristic information, which is the inverse of the distance between nodes i and j, both the shorter the distance between i and j, and the bigger the η_{ij} is, the stronger the attractiveness of the path; a is the pheromone factor, the bigger a is, the more the ant tends to choose the pheromone concentration of higher path; β is the heuristic factor, the larger β is, the more the ant tends to choose the path with shorter distance; N_i^k is the set of neighboring nodes, i.e., legitimate nodes that are not visited, that ant k can choose at node i.

2.5 Related work

Research on path planning for smart tourist areas mainly revolves around three types of methods: traditional graph theory algorithms (Dijkstra, A*) can solve static path problems but cannot adapt to the dynamic constraints of tourist areas, and the A* algorithm is prone to local optimal solutions due to its dependency on heuristic functions; among single heuristic algorithms, GA has strong global exploration capabilities but weak local optimization, often leading to premature convergence, while ACO is efficient in local development but blindly explores initially and relies on parameter tuning, making it difficult to balance the breadth and precision of solution space exploration; the existing GA-ACO mixed algorithms are often loosely combined as 'GA search - ACO optimization', lacking bi-directional information feedback, and they do not design adaptation mechanisms specifically for smart tourist scenarios. The GA-ACO dual-mode algorithm proposed in this paper innovatively constructs a bi-directional collaborative mechanism of 'global coarse search - local fine excavation - information feedback', guiding the genetic operators with pheromones and optimizing the elite solution pheromone matrix to achieve deep integration; at the same time, it designs a multi-dimensional dynamic fitness function specifically to adapt to the dynamic multi-constraint scenarios of smart tourist areas, overcoming the shortcomings of existing mixed algorithms in terms of synergy and adaptability to the scene, which is the core novelty distinguishing this paper from existing research.

3 Genetic-ant colony bimodal algorithm for designing systems

3.1 General description of the GA-ACO framework

The Genetic-Ant Colony Bimodal Algorithm combines the global exploration capability of GA and the local development advantage of ACO, and solves the multi-objective optimization problem of path planning in complex environments through the hierarchical mechanism of "coarse-grained global search - fine-grained local optimization". Figure 1 shows a hybrid optimization path planning system based on real-time visitor location data, which tightly couples the global search capability of genetic algorithm (GA) with the local optimization advantage of ant colony algorithm (ACO) through a co evolution mechanism. The system first sets key parameters such as iteration times, population size, pheromone weight, and volatility coefficient in the initialization module and generates a random population. GA explores high-quality paths globally through integer encoding, crossover, mutation, and selection operations, and evaluates the scheme with a comprehensive fitness function $F=f_1+f_2+f_3$; ACO refines and optimizes the path driven by pheromone distribution, probability selection model, and dynamic volatilization mechanism; The two achieve information exchange and performance improvement through "elite injection pheromone field" and "optimal path feedback population", ultimately outputting the optimal path solution visualized on the map, suitable for real-time dynamic environments such as scenic area navigation and robot path planning.

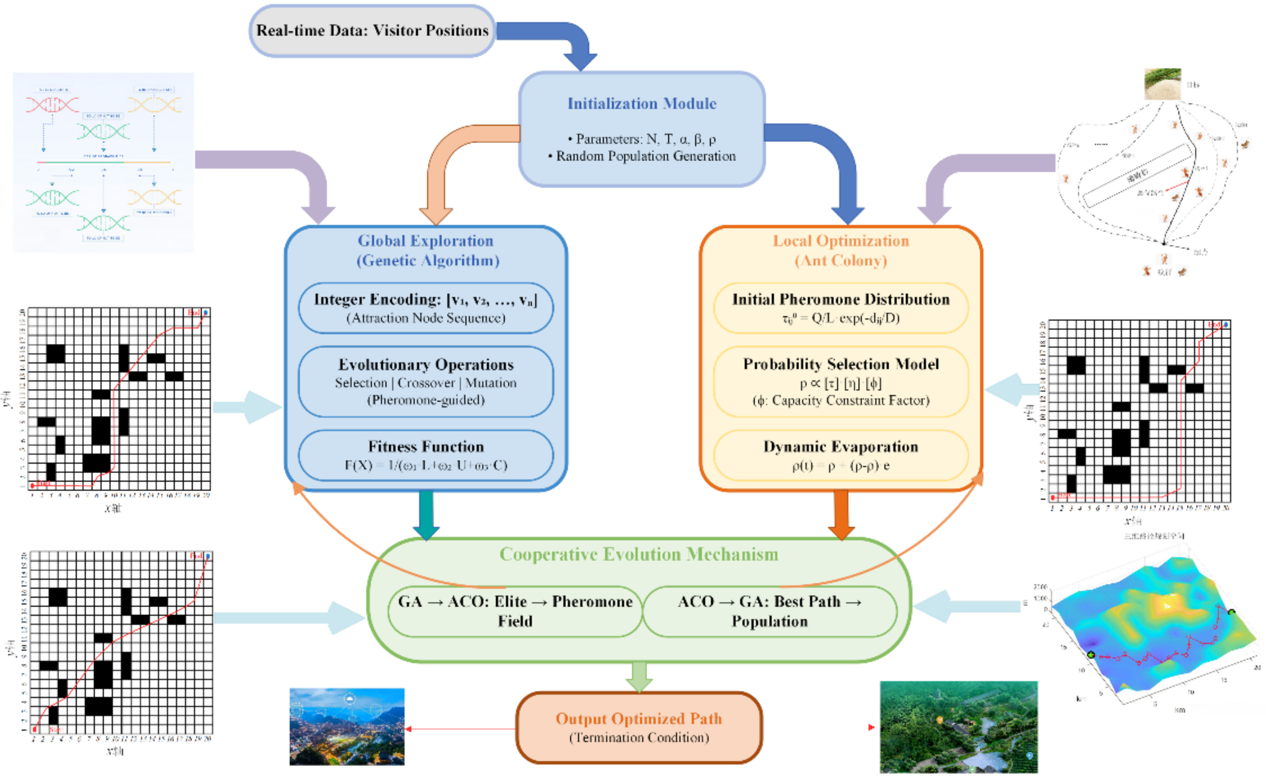


Figure 1: General framework diagram of the system

(1) Global search layer

Based on the principle of survival of the fittest in biological evolution, diverse path solution spaces are generated through selection, crossover, mutation and other operations. This layer adopts integer coding to represent path sequences, avoiding the semantic gap of binary coding and adapting to the sequence-dependent characteristics of scenic paths. For example, for a scenic area containing individual attractions, the $v_1, v_2, v_3, \dots, v_n$ chromosome is encoded as, where X is the attraction node number, ensuring that each node is visited only once. And the fusion of path length, visitor preference matching, and real-time congestion index sets the adaptatiIon function, which is Equation (2.1).

$$\text{Fitness}(X)=\frac{1}{\omega_1 L(X)+\omega_2 U(X)+\omega_3 C(X)} \quad (2.1)$$

In Equation (2.1), $L(X)$ is the total length of the path; ω_{ij} is the preference weight of attraction i to tourist j; $U(X)$ is the preference mismatch degree, whose value is $\Sigma(1-\omega_{ij})$; $C(X)$ is the sum of congestion indices c_{ij}; and $\omega_1, \omega_2, \omega_3$ is the dynamic weighting coefficient, whose sum of the three is 1.

(2) Local optimization layers

The high-quality solution generated by the genetic algorithm is used as the initial pheromone distribution, and the local optimality of the path is strengthened by the positive feedback mechanism of the pheromone. The dynamic volatilization factor is introduced in this layer, and the volatilization rate calculation of the dynamic volatilization factor is calculated according to Equation (2.2).

$$\rho(t)=\rho_{\min}+(\rho_{\max}-\rho_{\min})\cdot e^{-t/T_{\max}} \quad (2.2)$$

In Equation (2.2), $\rho(t)$ is the pheromone volatilization rate at the moment t, which varies dynamically with the number of iterations t; β_{min} and β_{max} are the minimum and maximum values of the volatilization rate, respectively; T_{max} is the maximum number of iterations preset by the algorithm; and t is the normalized iteration process in the range $t\epsilon[0, T_{max}]$.

(3) Co-evolutionary layer

Design a two-way feedback mechanism, GA→ACO; where the elite solution of the genetic algorithm (the top 10% optimal individuals) is transformed into the initial value of the pheromone matrix; and the pheromone initialization process of the co-evolutionary layer in the GA-ACO, i.e., the generation of the initial pheromone matrix τ_{ij}^{0} of the ACO by the elite solution of the GA , in order to steer the direction of the local optimization of the ACO, where the computation of the initial pheromone matrix τ_{ij}^{0} is Equation (2.3).

$$\tau_{ij}^{0}=\frac{Q}{L_{\text{GA-best}}}\cdot\exp\left(-\frac{d_{ij}}{D_{\text{avg}}}\right) \quad (2.3)$$

In the formula, τ_{ij}^{0} is the initial pheromone concentration, which represents the initial pheromone strength on the path from node i to node j; Q is the pheromone strength constant, which is used to regulate the overall strength of the pheromone; $L_{GA-best}$ is the total length of the path of the elite solution (the top 10% of the optimal individuals) generated by the genetic algorithm; d_{ij} is the direct distance from node i to node j (the Euclidean distance or the actual path distance); D_{avg} is the average value of the distances between all nodes; $exp\left(-\frac{d_{ij}}{Davg}\right)$ is the exponential decay function for adjusting the pheromone concentration according to the distance $L_{GA-best}$.

3.2 GA-ACO design steps

During the algorithm initialization phase, the configuration of the parameter system is first completed, including the population size, crossover probability, mutation probability of the genetic algorithm, as well as key parameters of the ant colony algorithm such as pheromone heuristic factors, expected factors, and evaporation coefficients. An initial population is generated using a greedy rule-based construction method: starting from the initial attraction site, the algorithm iteratively selects the nearest unvisited adjacent attraction sites until a complete path is formed, obtaining diverse initial solutions through repeated construction.

In the genetic evolution phase, pheromone-guided genetic operators are used to achieve directional evolution of the population. The selection operation employs a fitness proportionate selection strategy enhanced by pheromone, where the selection probability of individuals is proportional to the product of their path pheromone intensity and original fitness. The crossover operation uses an improved ordered crossover operator (OX), where the filling process of the offspring path is based on the transfer probabilities calculated from pheromone concentration and heuristic information, prioritizing edges with higher pheromone intensity for genetic segment recombination. The mutation operation uses a neighborhood search strategy based on pheromone probability, with a certain probability replacing the current edge with a neighboring edge that has a higher pheromone concentration. After each genetic operation, the population fitness is recalculated, and the current optimal solution is updated. In the ant colony optimization phase, the pheromone distribution is initialized with the current optimal path from the genetic algorithm, applying additional pheromone increments to the edges of the path.

The ants choose their movement paths based on the state transition probability formula, which is determined by both the pheromone concentration and heuristic information. After all ants complete their path construction, the pheromone is globally updated based on the evaporation coefficient, and then pheromone increments are applied according to the quality of each ant's path, with high-quality paths receiving stronger pheromone enhancement. The dual algorithm achieves a coordinated evolutionary mechanism through the pheromone matrix and elite solution set.

The ant colony algorithm provides local heuristic information for the genetic operators through the pheromone matrix, guiding the genetic search towards regions of high-quality solutions; conversely, the genetic algorithm injects diversity solutions into the pheromone matrix through the elite solution set, preventing premature convergence of the ant colony. This bidirectional feedback mechanism creates a synergistic enhancement effect of global exploration and local optimization. The algorithm iterates through the aforementioned processes until the maximum iteration count or optimal solution stabilization criterion is reached, ultimately outputting the optimal path solution that integrates the advantages of both algorithms.

The overall algorithm flow, designed according to the aforementioned Genetic-Ant Colony Bimodal Algorithm (GA-ACO) framework, is depicted in Figure 2.

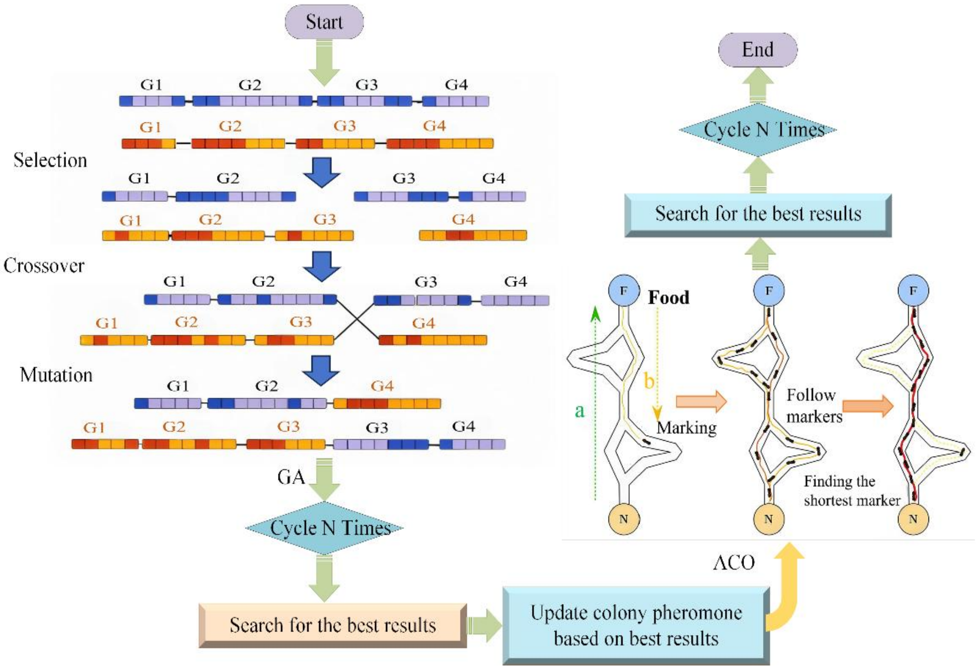
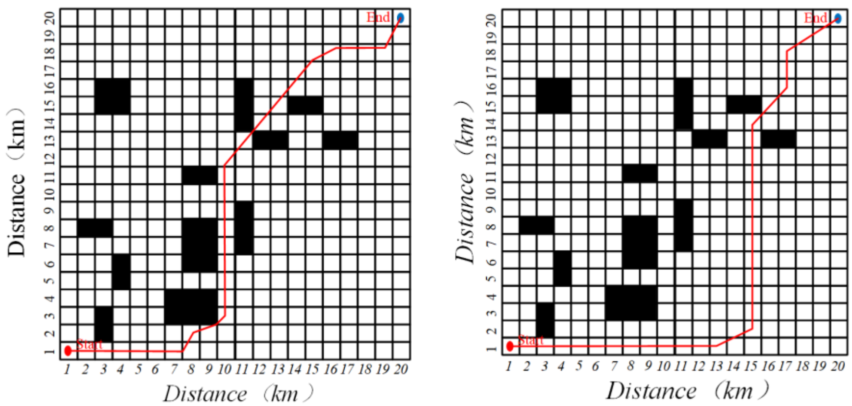


Figure 2: GA-ACO bimodal algorithm flow program diagram

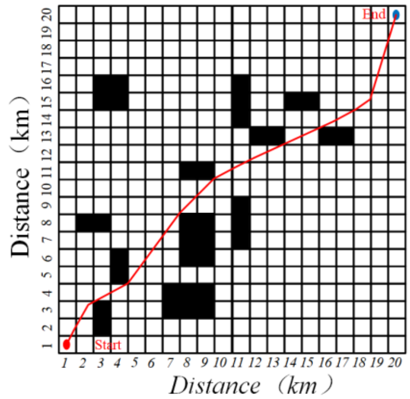
3.3 Experiment and result analysis

To comprehensively evaluate the performance of the algorithm, the experiment compares GA-ACO with advanced algorithms such as the improved ant-lion optimizer, hybrid leapfrog algorithm, and multi-objective gray wolf optimizer. Through comparative analysis, it is concluded that all three algorithms can reach the endpoint from the starting point, but the effective path lengths and running times vary, as shown in Table 1 of the specific iteration results. The data indicates that the optimal path length using the GA-ACO bimodal algorithm is 6% less than that of the ACO algorithm, with an average of 50% fewer iterations, and it has the least number of loops and is the most energy-efficient. Its planned path better meets actual touring needs, verifying the algorithm's effectiveness and superiority in solving multi-constraint path planning problems.

Figure 3 has showed the comparative analysis chart of the three algorithms. Due to the spatiality of the scenic path, the two-dimensionality and three-dimensionality of GA-ACO are simulated and analyzed during the experiment, in which the simulation parameters are shown in Table 2, and the specific experimental results are shown in Figure 4. It is concluded through the experiment that the best path can be obtained in three-dimensional space by using GA-ACO, which proves that GA-ACO can be applied to scenic path planning in three-dimensional space.



(a) Genetic algorithm path trajectories (b) Ant colony optimization path trajectory



(c) Genetic-Ant Colony Bimodal Algorithm Trajectory

Figure 3: Comparative analysis chart of the three algorithms

Table 1: Three algorithmic iterations datasheet

Parameters	Optimal path length	Average path lengths	Average number of iterations	Average number of turns
GA	30.98	31.23	19.45	9.20
ACO	31.78	32.84	27.30	5.40
GA-ACO	29.86	30.92	13.50	3.8

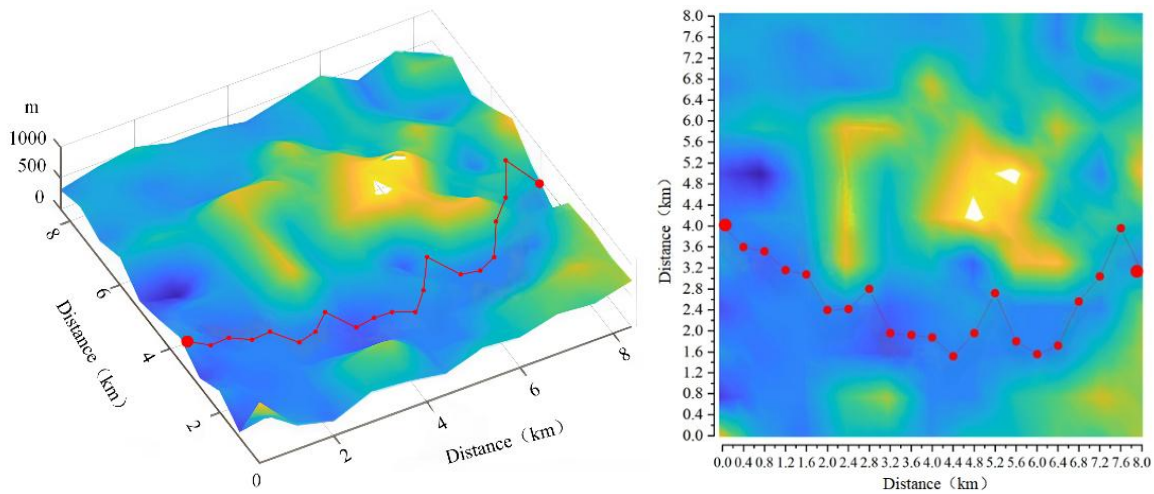


Figure 4: GA-ACO three-dimensional spatial path analysis effect diagram

Table 2: Genetic and ant colony optimization design parameters

Arithmetic	Initial number	Maximum iterations	Relevant parameters
GA	50	400	α=1, β=8, Q =1, $\rho_{initial}$ = 0. 9, ρ_{min} = 0. 1
ACO	200	150	$a=6$, $b=4$, $c=1$, $P_c=0.78$, $P_m=0.1$, $P_{max}=0.5$

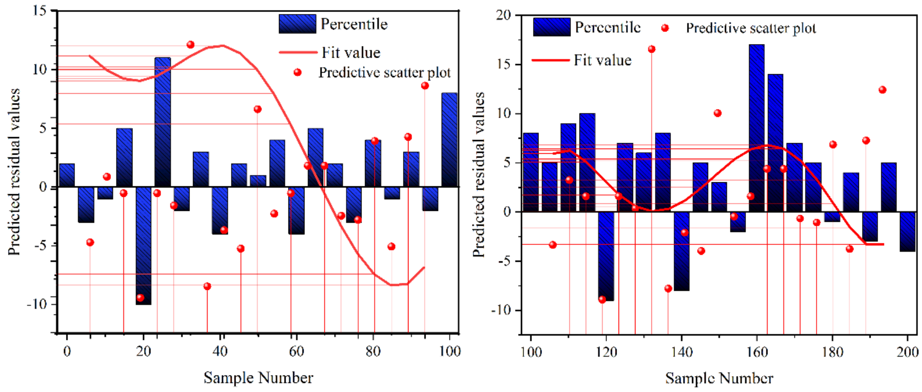


Figure 5: Predictive residual analysis plot for GA-ACO algorithm

Figure 5 shows the performance of the residual values of the GA-ACO predictions, respectively. The left panel shows the residual prediction values at 1-100 predictions and the right panel shows the residual prediction values at 100-200 predictions. It can be concluded from Figure 5 that the mean value of the residuals at 1-100 predictions is smaller than 100-200 predictions, and the maximum of the residuals at 1-200 predictions is 17.3, the minimum is -1.2, and the average absolute residual value is 4.63, which indicates that the gap between the prediction using the algorithm and the actual result is small, and the algorithm has a high degree of credibility in the practical application.

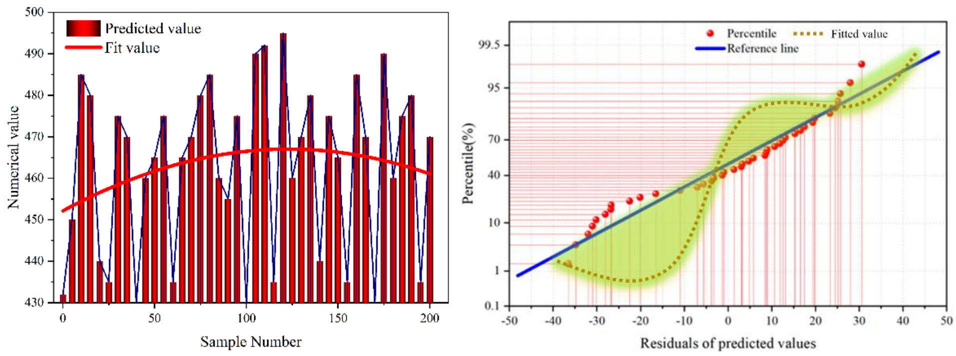


Figure 6: Predicted values of GA-ACO algorithm and predicted residual analysis plots

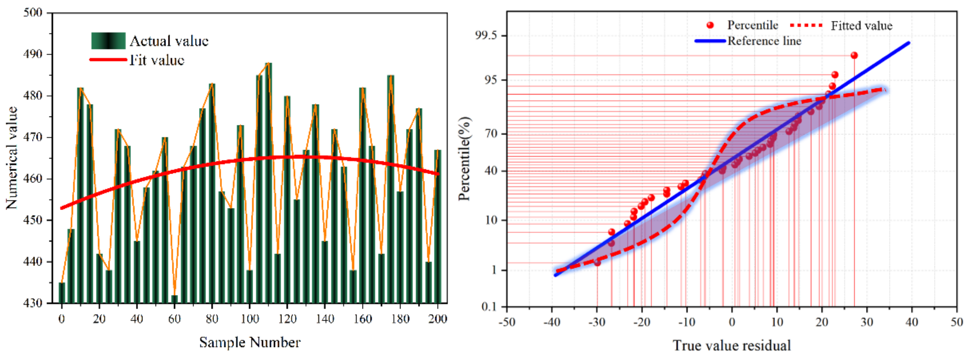


Figure 7: Plot of actual values and actual residual analysis of GA-ACO algorithm

Figure 6 and Figure 7 show the accuracy comparison of the GA-ACO proposed in this paper in the actual smart scenic area path selection, covering the size of the actual value and the predicted value under 200 calculations. It can be concluded from the data in Figure 6 and Figure 7 that there is a certain error between the actual value and the predicted value under each calculation, but the error is controlled within 1%, and the accuracy between the predicted value and the actual value reaches 99.26% after the comprehensive calculation and analysis, which further verifies that GA-ACO has a high degree of reliability in intelligent scenic area path selection

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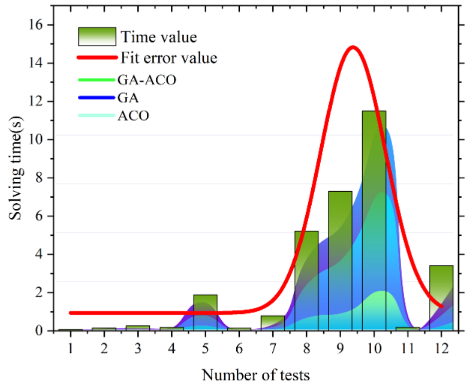

Figure 8: Plot of solving time for the total number of paths for the three algorithms GA-ACO, GA, and ACO

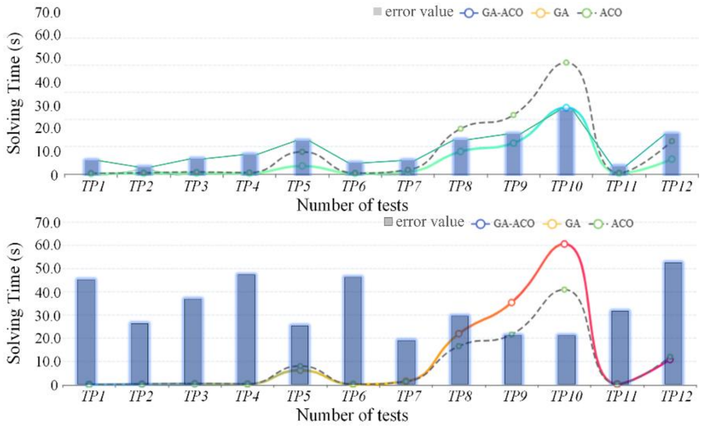

Figure 9: Optimal path solving time graphs for three algorithms GA-ACO, GA, and ACO

Algorithm solution time reflects its responsiveness. To evaluate and compare the optimization performance of the Genetic Algorithm (GA), Ant Colony Optimization (ACO), and the GA-ACO hybrid algorithm (bimodal colony), we recorded the computation time required by each to complete the maximum iterations for two optimization objectives: (1) identifying the total number of feasible paths meeting the requirements, and (2) finding the optimal path. Results are presented in Figures 8 and Figure 9.

Analysis of Figure 8 reveals that the GA-ACO hybrid algorithm exhibited the shortest computation time for identifying the total feasible paths. The largest discrepancy in solution time among the three algorithms occurred at the 10th iteration, reaching a maximum difference of 102.21 s.

Similarly, Figure 9 demonstrates that the GA-ACO hybrid algorithm also achieved the shortest computation time for determining the optimal path. The greatest difference in solution time, observed at the 10th iteration, was 16.2 s.

4 Discussion

This article conducts a sensitivity analysis of key parameters. The results indicate that the pheromone evaporation factor ρ and the pheromone enhancement coefficient Q significantly affect the algorithm's convergence and solution quality: a ρ value that is too high (e.g., $\rho>0.8$) causes the search to prematurely fall into local optima, while a value that is too low (e.g., $\rho<0.3$) reduces convergence efficiency; an increase in the Q value can enhance the ability to discover optimal paths, but improvements are limited after exceeding a threshold and increase computational burden. The crossover probability Pc and mutation probability Pm together influence population diversity: when Pc is maintained at 0.6–0.8 and Pm is controlled at 0.05–0.15, the algorithm can maintain a good balance between exploration and exploitation. The number of ants m and the number of iterations T exhibit a synergistic effect: for medium-sized tourist attractions (number of nodes 50–100), m=30–50 and T=100–200 can yield stable and high-quality solutions.

The sensitivity analysis confirms that parameters need to be dynamically adjusted according to the actual scale and complexity of the tourist attraction to balance planning efficiency and robustness.

The experiment aimed to verify the performance of the Genetic Algorithm - Ant Colony Optimization (GA-ACO), selecting standard Genetic Algorithm (GA), standard Ant Colony Algorithm (ACO), and improved Ant Lion Optimization (ALO) as controls. The independent variables included algorithm type, scenic area scene dimension (2D/3D), and visitor preference weights, while the dependent variables were path indicators (length, number of iterations, number of turns), solution time, and prediction accuracy. A digital model was constructed based on a medium-sized smart scenic area layout covering 15 km² with 20 core attractions, with key parameters set (GA population size of 50, crossover probability of 0.75, ACO pheromone heuristic factor of 1.5, evaporation coefficient of 0.5). The computing environment used an Intel Core i7-12700H processor, 32GB DDR4 memory, and Windows 10 system, implementing the algorithm and scene simulation based on Python 3.9 and Matplotlib 3.7. The results were validated through independent sample t-tests (significance level $\alpha=0.05$), showing that the differences in optimal path length (6% shorter than ACO), number of iterations (reduced by 50%), and solution time were statistically significant ($P<0.05$). Moreover, the prediction accuracy in the 3D scene reached 99.26%, and residual analysis further confirmed the reliability of the algorithm.

To further verify the performance of the genetic-ant colony optimization algorithm (GA-ACO), the experiment introduced RRT* (Rapidly-exploring Random Tree algorithm) and PRM (Probabilistic Roadmap algorithm) as benchmarks, comparing them in the same computing environment (Intel Core i7-12700H, 32GB DDR4, Python 3.9) and a medium-sized scenic area model (including real-time congestion and tourist preference constraints). The results show that: in terms of path quality, the optimal path length of GA-ACO (29.86) is 13.5% shorter than RRT* (34.52) and 9.9% shorter than PRM (33.17), with the number of turns (3.8) significantly lower than both (11.6 and 9.3); in terms of efficiency, the optimal path solving time for GA-ACO (18.7s for the 10th iteration) is reduced by 56% compared to RRT* (42.5s) and by 41.4% compared to PRM (31.9s); in terms of dynamic adaptability, when sudden congestion occurs in the scenic area, the re-planning response time of GA-ACO (2.3s) is faster than that of RRT* (5.8s) and PRM (4.1s). An independent sample t-test ($\alpha=0.05$) confirms that the differences are statistically significant ($P<0.05$), further validating the advantages of GA-ACO.

The results of 200 repeated calculations show that its optimal path length (29.86), average number of iterations (13.50), and other metrics are better than those of GA and ACO, with a standard deviation of metrics < 0.5, indicating small performance fluctuations; the prediction error is < 1%, accuracy reaches 99.26%, and the average absolute residual is only 4.63, with residual distribution being concentrated; the solving time is stable, and at the 10th iteration, the time difference with GA and ACO reaches a maximum of 102.21s (total feasible paths) and 16.2s (optimal path), with a coefficient of variation < 0.1; moreover, it can stably generate optimal paths in both two-dimensional and three-dimensional spaces, showing significant robustness and reliability.

5 Conclusion

The GA-ACO proposed in this paper performs well in intelligent scenic area path planning, successfully overcomes the dynamic multi-constraint path planning problem, and provides efficient, accurate and real-time responsive solutions for scenic area path planning, which vigorously promotes the development of intelligent guided tours. The multi-dimensional dynamic adaptive function of GA-ACO can accurately capture the dynamic changes of tourists' preferences and the environment, and integrate the real-time tourists' preferences and the dynamic environmental constraints to achieve a refined path quality assessment. The multi-dimensional dynamic fitness function of GA-ACO can accurately capture the dynamic changes of tourists' preferences and environment, integrate the real-time tourists' preferences and dynamic environment constraints, and realize the refined path quality assessment, which strongly supports the real multi-objective optimization for individuals and scenic spots.

Experimental validation shows that GA-ACO has significant advantages in several key indicators. In terms of path length, compared with the ant colony optimization, the optimal path length of GA-ACO is reduced by 6%; in terms of iteration efficiency, the average number of iterations is reduced by 50%; in terms of turn optimization, GA-ACO has the least number of turns, which effectively improves the smoothness of the paths and energy saving; in the 3D space simulation, GA-ACO can accurately find the optimal paths, which proves its applicability to path planning for scenic spots in 3D space; reliability verification results. In the three-dimensional space simulation, GA-ACO can find the optimal path accurately, which proves that it is suitable for path planning in three-dimensional space in the scenic area; the results of reliability verification show that the algorithm's prediction residuals are small, and the prediction accuracy is as high as 99.26%, which indicates that GA-ACO has a high degree of reliability and trustworthiness in practical application; compared with the traditional algorithms, GA-ACO is shorter in the total number of paths and the optimal path resolution time, which is able to respond to the dynamic changes in the scenic area quickly and provide real-time and efficient path planning service, which improves the tourists' experience.

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References

[1] Ning Xie, Yidan Qiao, Hongqi Shi, and Dengkai Chen, "Optimization method for control panel layout of manned submarine vehicle based on genetic-ant colony algorithm," Advanced Design Research, vol. 3, no. 1, pp. 31-37, 2025. https://doi.org/10.1016/j.ijadr.2025.03.003

[2] Yaping Yu, Qinghe Wang, Lu Jin, Ji-nan Ding, and Faqi Liu, "Optimizing evacuation path planning in high-rise building fires using an improved ant colony algorithm and dynamic window approach under smoke control scenarios," Applied Soft Computing, vol. 184, pp. 113796, 2025. https://doi.org/10.1016/j.asoc.2025.113796

[3] Fan Ye, Peng Duan, Leilei Meng, and Lingyan Xue, "A hybrid artificial bee colony algorithm with genetic augmented exploration mechanism toward safe and smooth path planning for mobile robot," Biomimetic Intelligence and Robotics, vol. 5, no. 2, pp. 100206, 2025. https://doi.org/10.1016/j.birob.2024.100206

[4] Yan-Qi Zhang et al., "Intelligent planning of fire evacuation routes in buildings based on improved adaptive ant colony algorithm," Computers & Industrial Engineering, vol. 194, pp. 110335, 2024. https://doi.org/10.1016/j.cie.2024.110335

[5] Edilson Reis Rodrigues Kato, Roberto Santos Inoue, and Lucas dos Santos Franco, "A method for planning multirotor Unmanned aerial vehicle flight paths to cover areas using the Ant Colony Optimization metaheuristic," Computers and Electronics in Agriculture, vol. 231, pp. 109983, 2025.https://doi.org/10.1016/j.compag.2025.109983

[6] Mohamed Elkawkagy, Ibrahim A. Elgendy, Ammar Muthanna, Reem Ibrahim Alkanhel, and Heba Elbeh, "Enhancing Hierarchical Task Network Planning through Ant Colony Optimization in Refinement Process," Computers, Materials and Continua, vol. 84, no. 1, pp. 393-415, 2025. 10.32604/cmc.2025.063766

[7] Dongdong Li and Lei Wang, "Research on mobile robot path planning based on improved Q-evaluation ant colony optimization algorithm," Engineering Applications of Artificial Intelligence, vol. 160, pp. 111890, 2025. https://doi.org/10.1016/j.engappai.2025.111890

[8] Meng Ronghua, Cheng Xinhao, Wu Zhengjia, and xuan Du, "Improved ant colony optimization for safe path planning of AUV," Heliyon, vol. 10, no. 7, pp. e27753, 2024. 10.1038/s41598-023-41140-2

[9] Zheng Li, Mingyuan Du, Jinlei Qin, and Xuechao Chen, "Research on robot path planning based on multi-strategy genetic ant colony optimization algorithm," Information Sciences, vol. 718, pp. 122407, 2025. https://doi.org/10.1016/j.ins.2025.122407

[10] Yongsheng Li, Yinjuan Huang, Lina Ge, and Xi Li, "Mobile Robot Path Planning Based on Angle-Guided Ant Colony Algorithm," International Journal of Swarm Intelligence Research, vol. 13, no. 1, 2022. https://doi.org/10.1007/978-3-031-09677-8_19

[11] Huakai Sun et al., "Emergency path planning based on improved ant colony algorithm," Journal of Building Engineering, vol. 100, pp. 111725, 2025. https://doi.org/10.1016/j.jobe.2024.111725

[12] Yibing Li, Zitang Zhang, Qian Sun, and Yujie Huang, "An improved ant colony algorithm for multiple unmanned aerial vehicles route planning," Journal of the Franklin Institute, vol. 361, no. 15, pp. 107060, 2024. https://doi.org/10.1016/j.jfranklin.2024.107060

[13] Junguo Cui, Lei Wu, Xiaodong Huang, Dengpan Xu, Chao Liu, and Wensheng Xiao, "Multi-strategy adaptable ant colony optimization algorithm and its application in robot path planning," Knowledge-Based Systems, vol. 288, pp. 111459, 2024. https://doi.org/10.1016/j.knosys.2024.111459

[14] Pan Gao, Li Zhou, Xu Zhao, and Bo Shao, "Research on ship collision avoidance path planning based on modified potential field ant colony algorithm," Ocean & Coastal Management, vol. 235, pp. 106482, 2023. https://doi.org/10.1016/j.ocecoaman.2023.106482

[15] Jianjuan Liu, Yiheng Qian, Wenzhuo Zhang, Miaoxin Ji, Qiangwei Xv, and Hongliang Song, "High-safety path optimization for mobile robots using an improved ant colony algorithm with integrated repulsive field rules," Robotics and Autonomous Systems, vol. 190, pp. 104998, 2025. https://doi.org/10.1016/j.robot.2025.104998

[16] Jing Zhao, Haitao Mao, Panpan Mao, and Junyong Hao, "Learning path planning methods based on learning path variability and ant colony optimization," Systems and Soft Computing, vol. 6, pp. 200091, 2024. https://doi.org/10.1016/j.sasc.2024.200091

[17] Sheng-Long Jiang, Lamei He, Lingling Cao, Liangliang Sun, and Gongzhuang Peng, "A learning-enhanced ant colony optimization algorithm for integrated planning and scheduling in hot rolling production lines under uncertainty," Swarm and Evolutionary Computation, vol. 93, pp. 101851, 2025. https://doi.org/10.1016/j.swevo.2025.101851

[18] Yimeng Liu, "Application of Ant Colony Algorithm in Enterprise Supply Chain Network Optimization and Synergy Effect Analysis," Procedia Computer

Science, vol. 262, pp. 201-207, 2025. https://doi.org/10.1016/j.procs.2025.05.045
[19] Tiancheng Wang, Lei Wang, Dongdong Li, Jingcao Cai, and Yixuan Wang, "Monte Carlo-based improved ant colony optimization for path planning of welding robot," Journal of King Saud University - Computer and Information Sciences, vol. 35, no. 7, pp. 101603, 2023. https://doi.org/10.1016/j.jksuci.2023.101603
[20] Zhijia Luan, Lijing Yu, Qiang Tian, and Min Liu, "Multi-Objective Optimization of Multi-Warehouse Cargo Allocation and Transportation Planning Using an Enhanced Ant Colony Algorithm," Informatica, vol. 49, no. 29, 2025. https://doi.org/10.31449/inf.v49i29.8439
[21] Wanchun Li and Liping Wang, "Intelligent logistics resource scheduling based on hybrid parameter ant colony algorithm and reinforcement learning," Informatica, vol. 49, no. 13, 2025. https://doi.org/10.31449/inf.v49i13.6565
[22] Samira Heroual, Belkacem Belabbas, Tayeb Allaoui, and Mouloud Denai, "Performance enhancement of a hybrid energy storage systems using meta-heuristic optimization algorithms: Genetic algorithms, ant colony optimization, and grey wolf optimization," Journal of Energy Storage, vol. 103, pp. 114451, 2024. https://doi.org/10.1016/j.est.2024.114451
[23] Wenyan Zhu, Wenzheng Cai, and Hoiio Kong, "Optimal path planning based on ACO in intelligent transportation," International Journal of Cognitive Computing in Engineering, vol. 6, pp. 441-450, 2025. https://doi.org/10.1016/j.ijcce.2025.02.006
[24] Ruizhao Zheng, Mingqun Liu, Yong Zhang, Yulong Wang, and Taiqi Zhong, "An optimization method based on improved ant colony algorithm for complex product change propagation path," Intelligent Systems with Applications, vol. 23, pp. 200412, 2024. https://doi.org/10.1016/j.iswa.2024.200412
[25] Fan Ye, Peng Duan, Leilei Meng, Hongyan Sang, and Kaizhou Gao, "An enhanced artificial bee colony algorithm with self-learning optimization mechanism for multi-objective path planning problem," Engineering Applications of Artificial Intelligence, vol. 149, pp. 110444, 2025. https://doi.org/10.1016/j.engappai.2025.110444
[26] Shichao Li et al., "Intelligent scheduling method for multi-machine cooperative operation based on NSGA-III and improved ant colony algorithm," Computers and Electronics in Agriculture, vol. 204, pp. 107532, 2023. https://doi.org/10.1016/j.compag.2022.107532
[27] Xixia Sun, Su Pan, Nan Bao, and Ning Liu, "Hybrid ant colony and intelligent water drop algorithm for route planning of unmanned aerial vehicles," Computers and Electrical Engineering, vol. 111, pp. 108957, 2023. https://doi.org/10.1016/j.compeleceng.2023.108957
[28] Imamah, Umi Laili Yuhana, Arif Djunaidy, and Mauridhi Hery Purnomo, "Enhancing students performance through dynamic personalized learning path using ant colony and item response theory (ACOIRT)," Computers and Education: Artificial Intelligence, vol. 7, pp. 100280, 2024. https://doi.org/10.1016/j.caeai.2024.100280
[29] Lailla M. S. Bine, Azzedine Boukerche, Linnyer B. Ruiz, and Antonio A. F. Loureiro, "A Novel Ant Colony-inspired Coverage Path Planning for Internet of Drones," Computer Networks, vol. 235, pp. 109963, 2023. https://doi.org/10.1016/j.comnet.2023.109963
[30] Bingting Huang, "Metaheuristic-Based Supply Chain Network Optimization and Inventory Management Using Ant Colony Algorithm," Informatica, vol. 49, no. 7, 2025. https://doi.org/10.31449/inf.v49i7.6760