International Journal of Engineering Inventions
e-ISSN: 2278-7461, p-ISSN: 2319-6491
Volume 14, Issue 3 [March. 2025] PP: 44-54

Multi-factor ant colony algorithm based path planning

Xinlin Yang, Yihang Wang, Yanting Ni*
School of Mechanical Engineering, Chengdu University,Chengdu,CHINA
Corresponding Author: Yanting Ni

ABSTRACT: *This paper presents an improved multi-factor ant colony algorithm for solving the path planning problem of Automated Guided Vehicles (AGVs) in industrial manufacturing systems. Firstly, the importance of AGV path planning and the limitations of traditional ant colony algorithms are introduced. Subsequently, the improved ant colony algorithm is elaborated in detail, including the improved grid map storage model, multi-factor comprehensive state transition probability, and pheromone updating model. Comparative experiments on a 20x20 regular obstacle map show that the improved algorithm outperforms the traditional ant colony algorithm in terms of path length, height variance, number of turns, and comprehensive indicators. Further experiments with added obstacles validate the superiority of the improved algorithm. In conclusion, the improved multi-factor ant colony algorithm demonstrates high practical value and potential for application.*

NOMENCLATURE

Symbol	Description	Unit
ACO	ant colony optimization	
AGV	*Automated Guided Vehicles*	*vehicle*
FGDACO	Dynamic ant colony optimization for fuzzy gain	
GDGACO	Gain-based dynamic green ant colony optimization	
EPIACO	Emergency path planning improves ant colony optimization algorithm	
d	Route length	*m*
i	Raster symbols	
v	The height difference between the grids	
r	Number of turns	
u	two-dimensional smoothness inspiration	
MAX	maximum distances	
MIN	minimum distances	
C	constant	

Greek letter

τ	Pheromone concentration	
φ	The correction distance to the grid	
ω	correction parameter	
μ	correction parameter	

Subscripts

ij	Raster coordinates
rc_x8	Matrix of 8 grids

Date of Submission: 04-03-2025 Date of acceptance: 16-03-2025

I. INTRODUCTION

As industrialization speeds up, automation technologies are increasingly used in manufacturing. AGVs, key to modern logistics and production systems, have their path - planning as a core research focus for enhancing system efficiency and safety. This planning not only affects AGVs' operational efficiency but also the overall system's logistics, costs, and product quality. In complex industrial settings, AGVs need to navigate efficiently and safely, avoiding collisions and path blockages while optimizing length, time, and energy consumption [1-3].

Traditional path-planning algorithms mainly focus on the shortest path, yet in practice, AGV path - planning must consider various factors like smoothness, safety, energy consumption, and collision avoidance during multi - AGV collaboration. These factors often conflict, making balancing them a key challenge in path - planning. In recent years, ant colony optimization (ACO), a heuristic algorithm, has gained wide attention due to its effectiveness and robustness in solving complex path - planning problems. But the traditional ACO still has limitations like slow convergence and a tendency to fall into local optima when handling multi-factor path-planning [2-5].

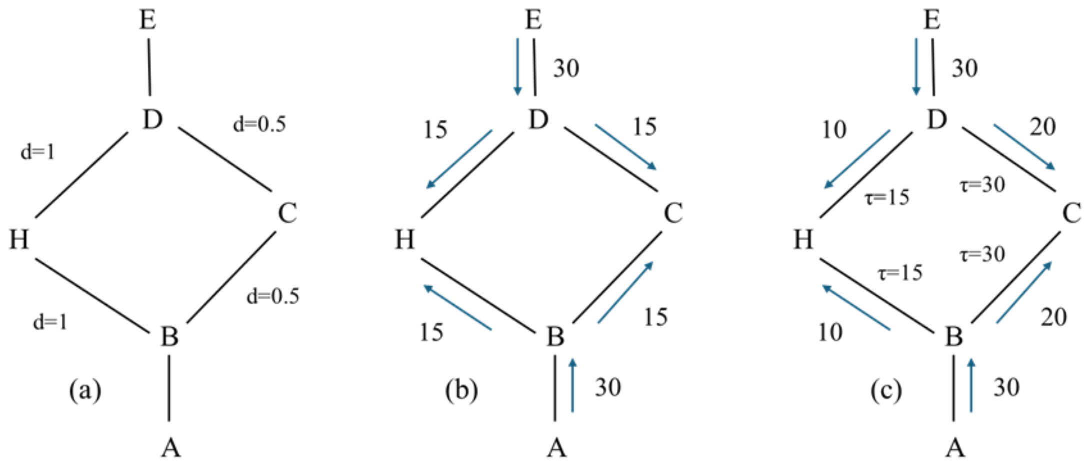
To overcome these limitations, researchers have proposed various improved ACO algorithms. These enhanced algorithms introduce new pheromone update mechanisms, heuristic functions, and path-smoothing strategies to boost search efficiency and path quality. This paper presents an improved multi-factor ACO, aiming to consider various factors such as path length, smoothness, and safety to enhance the efficiency and quality of AGV path-planning. With an improved grid map storage model, multi - factor composite state transition probability, and optimized pheromone update model, the algorithm shows greater practical value and potential for promotion in real - world applications.

Mohamed A. Damos et al. proposed an efficient method for optimizing tourist paths in hilly areas based on an improved ACO (Ant Colony Optimization) algorithm. By improving the pheromone update technique and implementing new initialization parameters, the limitations of the traditional ACO and Genetic Algorithm (GA) were addressed. This method provided a comprehensive and efficient way for planning hiking trails in hilly areas, considering dynamic tourist objectives such as temperature, atmospheric pressure, and health conditions, thereby promoting the development of tourism [6].Sangeetha Viswanathan et al. proposed a Fuzzy Gain-based Dynamic Ant Colony Optimization (FGDACO) for dynamic path planning, which effectively planned collision-free, smooth paths with feasible path lengths and minimal time. During path planning, the pheromone update mechanism of the ant colony system was enhanced using a Sigmoid gain function, enabling effective utilization of pheromones, and the results were verified [7].V. Sangeetha et al. proposed an efficient Gain-based Dynamic Green Ant Colony Optimization (GDGACO) metaheuristic, which enhanced the pheromone mechanism of the ACO and reduced the total energy consumed during path planning [8].Shitong Bao et al., aiming at the problem of slow convergence speed of the ant colony algorithm in 3D path planning for UAVs, proposed a heuristic function and local search strategy of an improved ant colony algorithm with an angle factor. Compared with traditional algorithms, the overall path planning was shortened by 22 km, and the convergence speed was 51.3% of the original algorithm, enhancing the ability of the ant colony algorithm to find optimal solutions in 3D environments. This also effectively improved the convergence speed and search efficiency of the algorithm, demonstrating its feasibility and effectiveness in 3D trajectory planning for UAVs [9]. Huakai Sun et al. proposed a new Emergency Path Planning Improved Ant Colony Optimization Algorithm (EPIACO). EPIACO includes six improvement mechanisms: initial pheromone distribution, a heuristic function with direction judgment, an adaptive pheromone fluctuation factor, a differentiated pheromone update rule, an improved state transition probability strategy, and path smoothing. It was demonstrated using a fire evacuation case, proving the algorithm's practicality and flexibility [10]. Dai Yuan Zhang et al. proposed a Generalized Ant Colony Algorithm, which extended the definition of the ACO and conducted a more general study on it. The functional update strategy replaced the parametric algorithm update strategy, accelerating the convergence speed of the ACO. Applying the Generalized Ant Colony Algorithm to robot path planning can improve the robot's search speed and reduce the convergence time cost [11]. Li Jian et al., in the current prevalence of electric vehicles, proposed an improved ant colony optimization algorithm for dynamic energy-saving path planning of electric vehicles. This algorithm integrated a traffic flow prediction model and an electric vehicle-specific energy consumption model, enhancing the efficiency and accuracy of path planning through redesigned heuristic factors and state transition rules [12]. Li Chen yang et al. proposed an ant colony algorithm based on a Gaussian distribution pheromone evaporation mechanism. This algorithm reduced the collision probability with obstacles during the search navigation process, improving the search efficiency and obstacle - avoidance ability of mobile robots in complex environments. By establishing a grid environment model and introducing a Gaussian distribution pheromone fluctuation mechanism for optimal path planning, it solved the problem that the algorithm could not effectively converge to the optimal solution when encountering special obstacle distributions, achieving more efficient obstacle avoidance [13].

Based on previous research, this paper improves the ant colony algorithm and applies it to path planning. By optimizing pheromone distribution, reducing turns during operation, and enhancing iteration stability, the ant colony algorithm is made more practical.

II. IMPROVE THE PROCESS

During the process of finding the optimal path, ants rely on the collective behavior of the ant colony to discover the best route. As ants search for the optimal path, they leave pheromones on the paths they traverse, and subsequent ants choose paths based on the strength of these pheromones. When reaching an intersection that has not been explored before, ants will randomly select and release pheromones, with the amounts of pheromones being inversely proportional to the length of the path. Over time, pheromones on shorter paths will continuously increase, while those on longer paths will gradually decrease or disappear. Eventually, the ant colony will find a suitable optimal path [14]. Fig. 1 illustrates search principle of an ant colony.



（a）Pheromone Setting（b）The number of ants at T = 0（c）The ant population at T = 1
Fig.1 Ant Colony Search Principle

shown in Fig This is shown in Figure 1, Set the ant nest as point A, the food source as point E, and the obstacle as BCDH. As shown in Figure a, when there are obstacles between the ant nest and the food source, the ants can only reach E from A via C or H, or reach A from E via C or H. The length of B-C-D is d=1, and the length of B-H-D is d=2. As shown in Figure b, the initial state has 30 ants each at the ant nest A and the food source E. For convenience, the time of pheromone residue is set as T=0. Initially, there are no pheromones on the paths BC, CD, BH, and HD. The ants at A and E can randomly choose paths at intersections. Statistically, the probabilities of ants choosing BC, CD, BH, and HD are the same, so there are 30 ants on each of the two paths. [15]. As shown in Figure c, after a unit time T = 1, the pheromone left by ants in this time is denoted as τ. Since path B-C-D is shorter, it has more residual pheromones (τ = 30), while path B-H-D, being longer, has fewer pheromones (τ = 15). Twenty ants reach E from B, C, and D. Over time, ants increasingly choose the shorter path B-C-D, ultimately finding the shortest route between the nest (A) and the food source (E). This illustrates the core principle of the ant colony algorithm. [16].

Traditional path - planning algorithms usually only consider the shortest path, but they can't be applied to most real situations. This is because mobile robots need to adapt their paths to the environment in terms of distance, smoothness, and safety. If only the shortest path is pursued, the robot may have to turn multiple times, go uphill and downhill often, or pass through dangerous areas. This not only increases the target cost but may also harm the robot's performance and shorten its life. Moreover, these path evaluation factors are often mutually exclusive, and it is impossible to achieve both. Finding a balance among these factors is a multi - objective planning problem. The multi - heuristic - factor ant colony algorithm uses three heuristic factors: path length, number of turns, and elevation difference. It enables ants to find the optimal path based on various local information, considering multiple factors. It also proposes a multi - factor pheromone update model, allocating pheromones according to the path's comprehensive evaluation index. This, combined with an improved grid map storage model and non - uniform initial pheromones, speeds up the algorithm's computation and convergence [17].

First, the creation of an improved grid-based map storage model is proposed. There are two types of grid map transition models: four-direction and eight - direction. The eight - direction model, which allows for more flexible and smooth route planning, is adopted in this paper. For easier storage, a one-dimensional grid labeling method is used. The transition matrix is defined as $D_{rc\times8} = (d_{ij})_{rc\times8}$, where the value of element d_{ij} represents the distance from the i-th grid to its adjacent grid in the j-th direction, with i = 1, 2, 3, ..., rc , j = 1, 2, 3, ..., 8. The definition of the direction code j is shown in Figure 2.

1	2	3
8		4
7	6	5

Fig.2 The adjacency grid steering designator

Among them, even - numbered codes represent straight moves, and odd - numbered codes diagonal moves. When making diagonal transfers in most eight-direction transfer models, there is often a risk of collision with adjacent obstacle grids, as shown in Figure 3. The common solution is to further expand the original obstacles to leave enough space to avoid collisions. However, this method requires proper control of the degree of expansion. Excessive expansion may block the originally passable path. This paper proposes an improved turning mechanism to avoid the risk of collision from the perspective of logical rules. As shown in Figure 4, when the ant moves diagonally, it can only transfer to the diagonal grid when both two straight grids on the two sides of the line connecting the current grid and the grid to be turned to are free grids. Based on this turning mechanism, the transfer matrix dij can be constructed, as shown in the following formula (1).

$$d_{ij}\begin{cases} l & G(i)=0\,\&\,\mathrm{mod}(j,2)=0\,\&\,G(\mathrm{i}_1)=0 \\ \sqrt{2}\times l & G(i)=0\,\&\,\mathrm{mod}(j,2)=1\,\&\,G(i_2)=0\,\&\,G(i')+G(i'')=0 \\ \infty & else \end{cases} \tag{1}$$

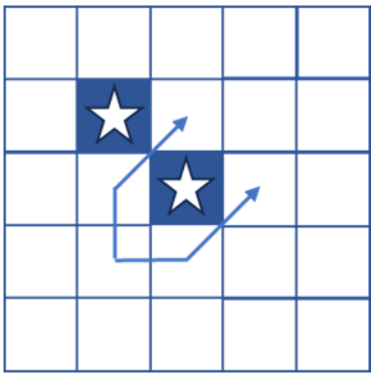


Fig.3 Impermissible ways of walking

Among them, i1 represents the number of the straight-direction grid, and i2 represents the number of the diagonal-direction grid. i' and i'' respectively represent the two straight-direction grid numbers that are vertical to the diagonal line. represents intransferable (including the case of going out of bounds), and mod (j, 2) is used to judge the parity of j, to determine whether the next step is straight or diagonal.

Second, this paper proposes a comprehensive state transition probability algorithm based on multiple factors. In the early stage of the algorithm, due to the small difference in initial pheromone and the high randomness of transition, the movement of the ant colony is very chaotic, which affects the convergence of the algorithm. At this point, the heuristic function plays a key role. To better guide the ants, the following changes are made:

$$\eta_{i,j}^{m}(t)=\varphi_{i,j}(q)+r_{i,j}^{m}(q)+v_{i,j} \quad (2)$$

Among them, $\varphi_{i,j}(q)$ represents the corrected distance from the center of a certain adjacent grid of grid i to the center of the target grid. $r_{ij}(q)$ represents the turning condition when the m-th ant in the t-th iteration transfers from grid i to grid j. v_{ij} represents the height difference when transferring from grid i to grid j.

The distance factor refers to the Euclidean distance from the grid after the transfer to the target grid. The shorter the distance, the higher the transfer probability. Since the distances from the centers of adjacent grids to the target grid center are initially large and offer little differentiation, a corrected distance function $\varphi_{i,j}(q)$ is introduced. It normalizes these distances to highlight differences, and is defined as follows:

$$\varphi_{i,\ j}(q)=\begin{cases}\dfrac{MAX_{\mathrm{d}}-\mathrm{d(j,q)}}{MAX_{\mathrm{d}}-MIN_{d}}\times\omega+\mu & \mathrm{MAX_d}\neq MIN_{\mathrm{d}}\\ \dfrac{1}{2}\omega+\mu & \mathrm{MAX_d}\neq MIN_{\mathrm{d}}\end{cases} \quad (3)$$

$$MAX_{\mathrm{d}}=\max\left\{\mathrm{d}\left[\mathrm{allowed_i}(a),q\right]\right\} \qquad (a=1,2...card(allowed_i))$$

$$\min\left\{\mathrm{d}\left[\mathrm{allowed_i}(a),q\right]\right\} \qquad (a=1,2...card(allowed_i))$$

Among them, ω and μ are correction parameters. They can take different values depending on the problem environment. MAX_d and MIN_d are the maximum and minimum distances from adjacent grids to the target grid. The aim is to normalize these distances. a is the ordinal number of elements in a set, and card is the number of elements in the set.

Considering the smoothness of the path in a two-dimensional plane, it is expected that the number of turns in the path is as small as possible, and the following two-dimensional smoothness heuristic function is introduced.

$$r_{i,j}^{m}(t)=\begin{cases}u/card(allowed_i) & \mathrm{card(visited_{t、\ p\to i})=1}\\ \eta u & \mathrm{card(visited_{t、\ p\to i})>1\&i\text{-}j=g\text{-}i}\\ (1-\eta)u/card(allowed_i) & \mathrm{card(visited_{t、\ p\to i})>1\&i\text{-}j\neq g\text{-}i}\end{cases} \quad (3)$$

$$(\mathrm{j}\in\mathrm{allowed_i},\ \ \mathrm{g=visited_{t,\ p\to i}^{m}(end-1)})$$

In the formula, u is a constant for two-dimensional smoothness inspiration, and η is a coefficient (percentage constant) for the importance of straight travel. Values are assigned to them as needed. "Visited" is the ordered set of grid numbers visited by the m th ant up to the i th grid in the t th iteration. "g" is the number of the previous grid of the grid with label i that the ant has passed through. "i-j = g-i" means that the turning direction from grid g to grid i is the same as that from grid i to grid j. If the current direction is the same as the previous one, there's no turn in this move, and the heuristic function for moving in that direction is larger; otherwise, it's smaller. This guides the ant to move straight where possible and avoid zigzag paths around obstacles.

Later, the initial pheromone was improved. Traditionally, the initial pheromone is a fixed value, i.e., uniformly distributed. This can cause ants to move in a disordered way and easily get stuck, which is not good for guiding later ants in pathfinding. To make the initial pheromone more instructive for ants, the following improved formula5,6 is proposed.

$$\tau_{i,j}(0)=C+f(j) \quad (5)$$

$$f(j)=1/card(C_u(allowed_j)) \quad (6)$$

In the formula, C is a constant. f(j) is the obstacle - avoidance safety function. It calculates the reciprocal of the number of adjacent obstacle grids of the grid to be transferred. Cu is the complement symbol. U is the set of all adjacent grids of grid j. $allowed_j$ is the set of feasible adjacent grids of grid j. The closer the grid to be transferred is to an obstacle, the lower the initial pheromone on that route, and vice versa. This helps ants avoid obstacles quickly, prevents them from getting stuck, and speeds up the algorithm's convergence.

III. RESULTS AND DISCUSSION

The improved and traditional ant colony algorithms were compared on a 20x20 regular obstacle map. Fig. 5 shows the traditional algorithm's results, and Fig. 6 displays the improved version's outcomes.

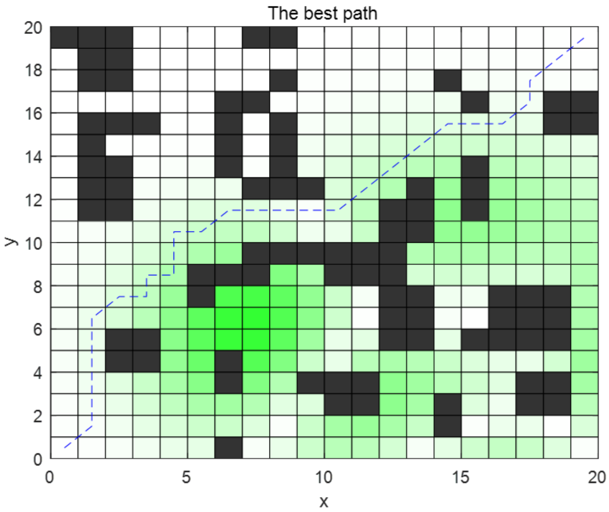


Fig.5 Simulation results of traditional ant colony algorithm

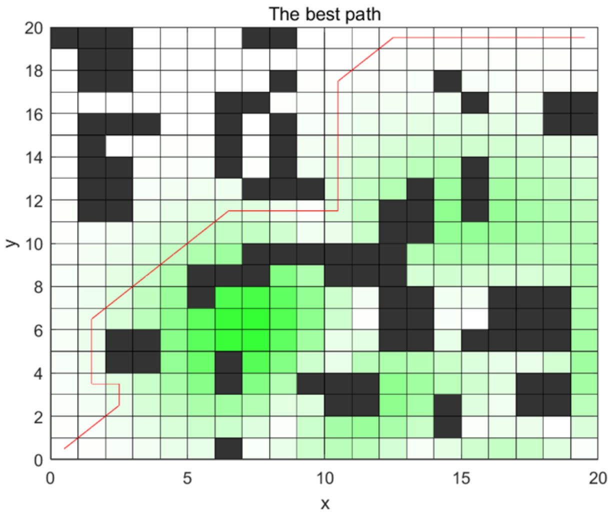


Fig.6 Diagram of the simulation results of the improved ant colony algorithm

Table(1). Comparison of algorithm data1

Metrics for optimal paths	**Traditional ant colony algorithms**	**Improved algorithm**
length	32	34
Height Mean Square Deviation (x100)	7.312	7.124
Number of turns	13	10
Composite indicators	62.24	56.12
The number of iterations stabilized	18	7
Program running time	2.287s	2.671s
Iterative stabilization estimation time	0.996s	1.212s

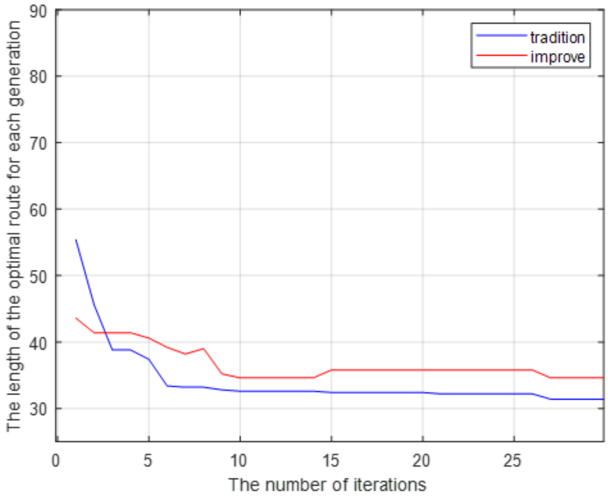


Fig.7 The length of optimal route for each generation

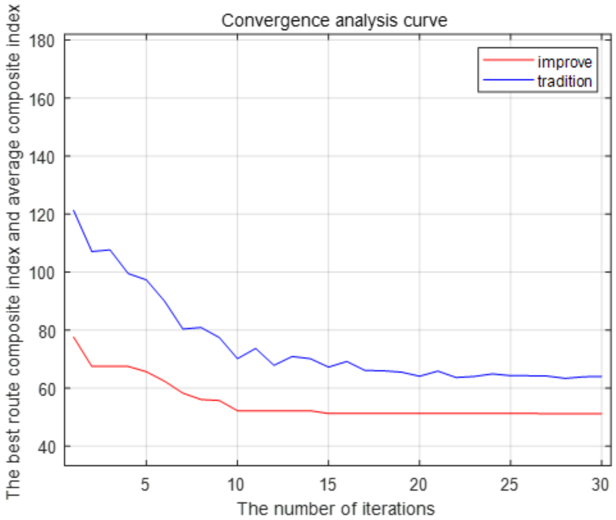


Fig.8 The best route composite index and average composite index

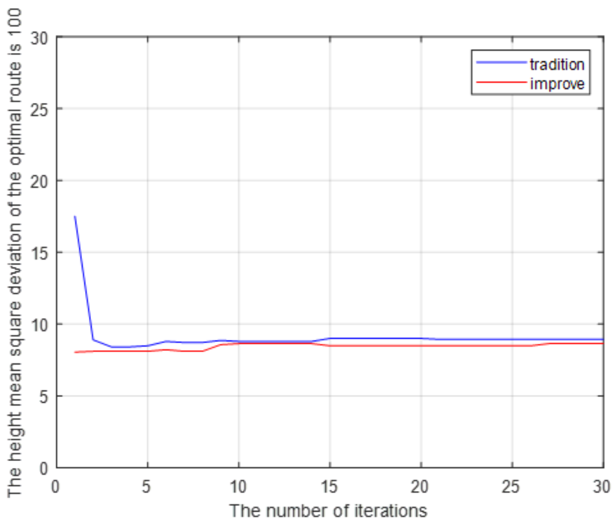


Fig.9 The height mean square deviation of the optimal route is 100

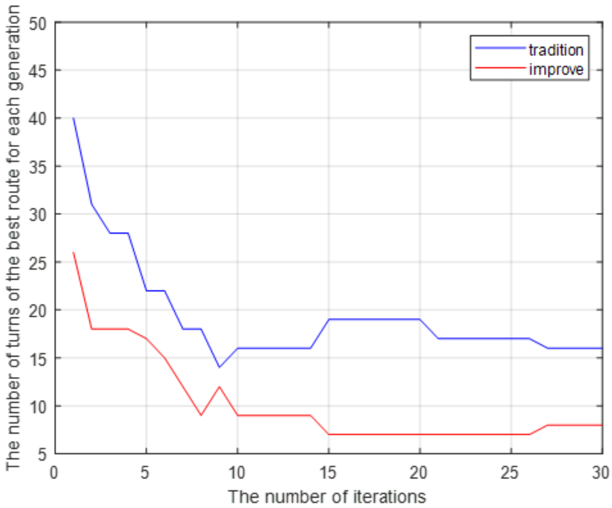


Fig.10 The number of turns of the best route each generation

As shown in Fig. 7, 8, 9, and 10, the blue line represents the traditional ant colony algorithm, while the red line indicates the improved version. The experimental results reveal that the three algorithms have similar optimal path lengths, with the traditional one being slightly shorter. However, in terms of 3D path smoothness, the traditional algorithm is quite unstable in the early iterations. In contrast, the improved algorithm, incorporating elevation difference heuristic factors and height variance evaluation indices, shows a downward trend in its iteration curve and achieves a significantly lower height variance of the optimal path. When it comes to 2D turning situations, the improved algorithm has far fewer turns and a more stable convergence curve than the traditional one. Overall, the improved algorithm outperforms the traditional one in comprehensive indices and iteration stability, with only a slightly longer iteration time. Therefore, when pursuing comprehensive path performance, this chapter's algorithm demonstrates a clear advantage.

To further verify the experimental reliability, an additional 20% of obstacles were added, and the experiments were repeated, yielding the following results:

Fig.11 Simulation results of traditional ant colony algorithm

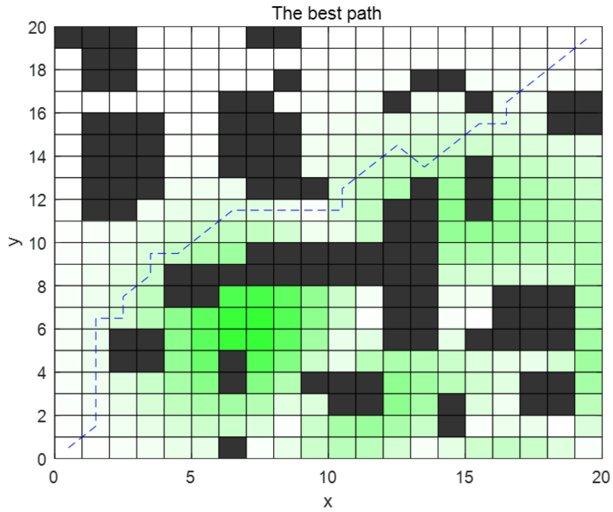


Fig.12 Diagram of the simulation results of the improved ant colony algorithm

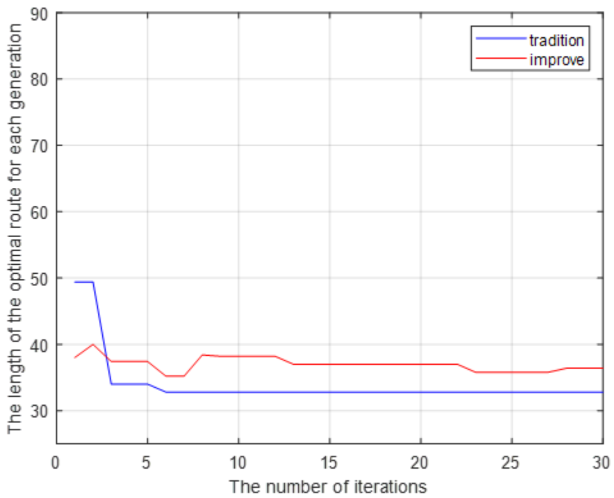


Fig.12 The length of the optimal route for each generation

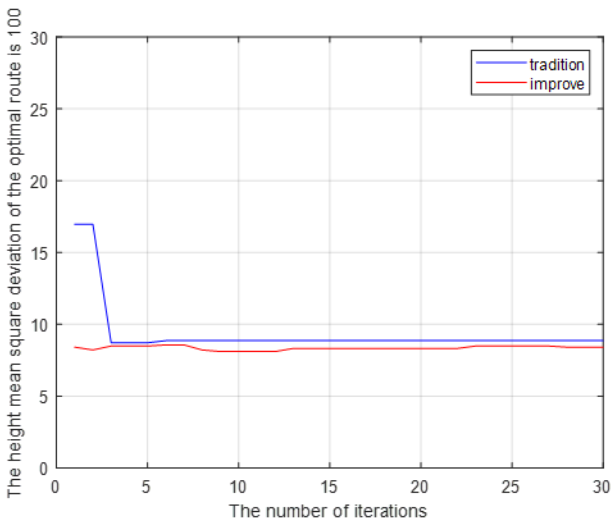


Fig.13 The height mean square deviation of the optimal route is 100

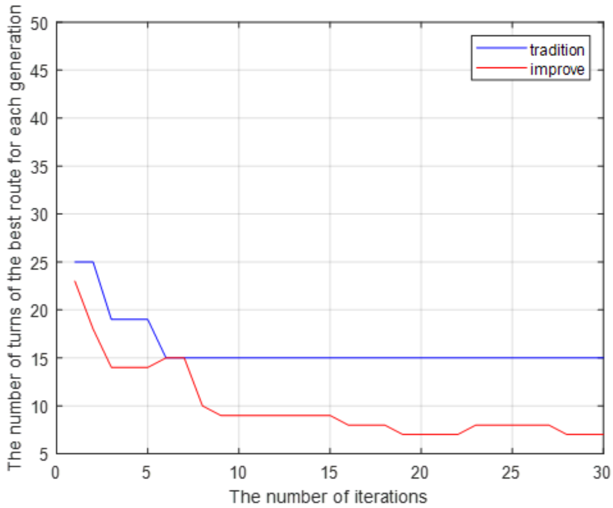


Fig.14 The number of turns of the best route for each generation

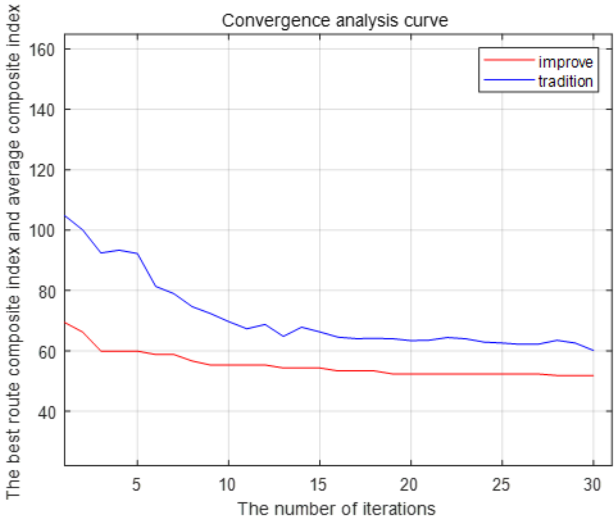


Fig.15 The best composite index and average composite index

Table(2). Comparison of algorithm data2

Metrics for optimal paths	Traditional ant colony algorithms	Improved algorithm
length	33	36
Height Mean Square Deviation (x100)	8.12	8.01
Number of turns	15	7
Composite indicators	62.24	56.02
The number of iterations stabilized	7	12
Program running time	3.271s	3.618s
Iterative stabilization estimation time	1.512s	1.733s

Simulation results show that while this chapter's algorithm is slightly worse than the traditional ant colony algorithm in path length and runtime, it is significantly better in 3D smoothness. From route maps, this algorithm bypasses many high-peak areas. It has a slightly higher number of stable iterations than the traditional one, but its more concise program and faster execution speed result in a shorter actual time to stability. Though this algorithm takes longer in computation time than the traditional ant colony algorithm, its superior performance makes the trade-off acceptable and it is more practical in real-world applications.

IV. CONCLUSION

This paper proposes an improved multi-factor ant colony algorithm to solve the path-planning problem of AGVs in industrial manufacturing systems. Comparative experiments on a 20x20 regular obstacle map yield the following results.

1. The improved algorithm has fewer turns than the traditional one.

2. The improved algorithm's composite indicators are better than the traditional algorithm.
3. The iterative stability of the improved algorithm outperforms the traditional one.

Overall, the improved multi-factor ant colony algorithm has high practical value and potential for solving the AGV path-planning problem.

REFRENCES

[1]. Hu Hongtao; Yang Xurui; Xiao Shichang; Wang Feiyang, J. [2023] "Anti-conflict AGV path planning in automated container terminals based on multi-agent reinforcement learning" International Journal of Production Research,Vol.61 , Issue I :pp.65-80

[2]. Sun Yinghui; Fang Ming; Su Yixin, J. [2021] "AGV Path Planning based on Improved Dijkstra Algorithm" Journal of Physics: Conference Series. Vol. 1746, Issue I: pp.012052-

[3]. Meisu Zhong; Yongsheng Yang; Yasser Dessouky; Octavian Postolache, J. [2020] "multi-AGV scheduling for conflict-free path planning in automated container terminals" Computers & Industrial Engineering. Vol 142, Issue C: pp.106371-106371

[4]. Jun-E Liu; Shujun Zhang; Hongling Liu, J. [2019] "Research on AGV Path Planning under "Parts-to-Picker" Mode" Open Journal of Social Sciences. Vol 7, Issue 6: pp.1-14

[5]. Suman Gothwal; Tilak Raj, J. [2018] "Optimisation of AGVs path layout in flexible manufacturing system using 0-1 linear integer programming" Int. J. of Process Management and Benchmarking. Vol 8, Issue II: pp.182-205

[6]. Mohamed A. Damos; Wenbo Xu; Jun Zhu; Ali Ahmed; Abdolraheem Khader Journal, J. [2025] "An Efficient Tourism Path Approach Based on Improved Ant Colony Optimization in Hilly Areas" International Journal of Geo-Information, Vol 14, Issue I: pp.33-34.

[7]. Sangeetha Viswanathan; Krishankumar Raghunathan; Ravichandran Kattur Soundarapandian; Cavallaro Fausto; Kar Samarjit; Pamucar Dragan; Mardani Abbas, J. [2021] "A Fuzzy Gain-Based Dynamic Ant Colony Optimization for Path Planning in Dynamic Environments"Journal Symmetry. Vol 13, Issue 2: pp.280-280

[8]. V.Sangeetha; R. Krishankumar; K.S.Ravichandran;SamarjitKarJournal,J.[2021]"Energy-efficient green ant colony optimization for path planning in dynamic 3D environments"Soft Computing. Vol 25, Issue 6: pp.1-21

[9]. Shitong Bao; Bao Shitong; Lu Yonggen; Li Keyu; Xu Peizhen. J. [2020] "Research on Path Planning of UAV Based on Ant Colony Algorithm with Angle Factor"Journal of Physics: Conference Series. Vol 1627, Issue I: pp. 012008-

[10]. Huakai Sun; Kai Zhu; Weiguang Zhang; Zhefeng Ke; Haihang Hu; Ke Wu; Tianhang Zhang, J. [2025] "Emergency path planning based on improved ant colony algorithm" Journal of Building Engineering. Vol 100, Issue 2025: pp.111725-111725

[11]. Haoran Liu, J [2024] "AGV Path Planning based on Improved Ant Colony Algorithm" Journal of Innovation and Development. Vol 6, Issue 2: pp.42-46

[12]. Q L Vuong; C Rigaut; Y Gossuin, J [2018] "Refraction law and Fermat principle: a project using the ant colony optimization algorithm for undergraduate students in physics" European Journal of Physics. Vol 39, Issue 4: pp.045806-045806

[13]. Hui Tian, J [2021] "Research on robot optimal path planning method based on improved ant colony algorithm"International Journal of Computing Science and Mathematics. Vol 13, Issue1

[14]. Alpa Reshamwala; Deepika P Vinchurkar, J. [2013] "Robot Path Planning using An Ant Colony Optimization Approach:A SurveyInternational"Journal of Advanced Research in Artificial Intelligence. Vol 2, Issue 3

[15]. Dai Yuan Zhang; Peng Fu, J. [2014] "Robot Path Planning by Generalized Ant Colony Algorithm" Applied Mechanics and Materials. Vol 2963, Issue 494-495: pp.1229-1232

[16]. Li Jian; Li Jie; Fang Hongji; Jiang Junfeng,J.[2024] "Dynamic Energy-Efficient Path Planning for Electric Vehicles Using an Enhanced Ant Colony Algorithm" Tehnički vjesnik. Vol 31, Issue 2: pp.434-441

[17]. Li Chenyang; Liu Qianjie; Song Shuang; Huang Tengchao; Zhu Qingyuan,J.[2022] "Path Planning for Mobile Robots Based on an Improved Ant Colony Algorithm with Gaussian Distribution" Journal of Physics: Conference Series. Vol. 2188, Issue I.