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An A Algorithm-Based Optimization Model for Multi-Vehicle Scheduling in E-Commerce Warehousing

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Abstract: With the rapid advancement of automation and intelligence in the logistics industry, the requirements for warehouse scheduling in e-commerce logistics are becoming increasingly strict. To meet current social demand for e-commerce logistics warehouse scheduling, a new optimization decision model is proposed based on the A-star (A*) algorithm and a collision-avoidance heuristic. The experimental results show that, compared with the traditional warehouse scheduling model, the research model demonstrates significant advantages in path planning accuracy, vehicle collision avoidance efficiency, and scheduling time. In the multi-vehicle cargo distribution scenario, the proposed model can effectively bypass obstacles and avoid the risk of collisions when multiple vehicles are traveling simultaneously. When the number of vehicles was 1, 2, 3, and 4, the actual travel time of the proposed model was 17.7s, 18.2s, 21.1s, and 22.1s, respectively, with almost no error compared with the simulation test results. When compared with traditional path planning algorithms, the research model reduces path planning time by 12.5% to 18.3% and reduces the vehicle collision rate by more than 30%. This indicates that the proposed model not only effectively avoids vehicle conflicts in complex warehousing environments but also achieves more efficient path optimization and scheduling execution. In summary, the optimization decision for e-commerce logistics warehouse scheduling proposed in the study conforms to the concept of 21st-century e-commerce logistics warehouse scheduling management, improves the efficiency of warehouse scheduling, reduces transportation cost, and provides certain insights and directions for warehouse scheduling.

Keywords: A*, automated logistics, collision, multi-vehicle routing, path planning, scheduling optimization.

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1. Introduction

With the rapid development of e-commerce and logistics, warehousing management is an important link supporting e-commerce operations, which directly affects the market competitiveness of e-commerce enterprises in terms of efficiency and intelligence level (Li, 2023). Among the various links of e-commerce logistics, warehouse management is particularly crucial, as it directly affects the efficiency of a series of processes such as storage, picking, packaging, and distribution of goods. Therefore, how to optimize warehouse scheduling to improve logistics efficiency and reduce cost has become an important issue in e-commerce logistics management (Bera et al., 2021; Zhou et al., 2026). Sodiya et al. (2024) investigated many novel approaches using artificial intelligence techniques, such as reinforcement learning, which provides a recent view of the studied problem with newer approaches adapted to real-time warehouse scheduling. In fact, recent trends in AI-driven warehouse automation are revolutionizing the way warehouses operate, enabling real-time decision-making, adaptive behavior, and optimization of warehouse processes. Edge computing, reinforcement learning, and digital twins are the key technologies driving these trends, offering new opportunities for improving efficiency, flexibility, and responsiveness in warehouse operations. Sadowski et al. (2022) used the FlexSim simulation tool to explore the warehouse flexibility in logistics supply chain networks. The dynamic behavior of the warehouse system was conceptualized. The experimental results indicated that external changes could affect the restructuring of daily and warehouse processes. Therefore, the warehouse flexibility was developed proactively through changes in the process environment. To improve the positioning performance of Automated Guided Vehicles (AGVs) for logistics and warehousing, Yan (2021) constructed a logistics and warehousing AGV positioning system based on an improved Long Short-term Memory (LSTM) algorithm. The logistics and warehousing AGV system had good positioning and navigation functions. Xue et al. (2024) proposed a Distributed Differential Game (DDG) framework to address the dynamic interaction process between AGVs and the limitations of sensing and communication range. Compared with traditional methods, the DDG successfully reduced task completion time by 16%. Zhang et al. (2022) proposed a non-destructive sorting method based on bio-mimetic soft fingers to address the limitations of traditional manual sorting and rigid robotic sorting systems on warehouse development. The experimental results showed that the method achieved non-destructive grasping and precise sorting, with a sorting range of 70-120mm and a sorting accuracy of up to 95%.

The A-star (A*) algorithm, as an efficient path search algorithm, has been successfully applied in multiple fields due to its excellent performance and wide applicability (Wang et al., 2023; Dai et al., 2025). Applying the A* algorithm to e-commerce logistics warehouse scheduling provides enhanced optimization of the flow of goods in warehouse scheduling (Cahyo et al., 2024). Wu et al. (2022) developed a low-carbon fresh food cold chain logistics delivery route optimization model that considered customer satisfaction, time, space, weight, and delivery rules. Different calculation examples verified the effectiveness and correctness. Hu et al. (2022) developed a comprehensive Underground Logistics System (IULS) solution based on the A* algorithm to address the inefficiency of truck-dominated forward and reverse physical distribution activities. For a satellite city with a great demand for reconstruction and distribution, the method could save millions of dollars in expenses annually. To improve the path planning efficiency of robots, Liu et al. (2021) developed a dynamic fusion routing algorithm. This algorithm constructs a map using the Delaunay Triangulated Irregular Network (Delaunay) and then performs the path planning search using the A* algorithm. The experimental results showed that in an experimental environment with the same number of starting points, target points, and obstacles, the method reduced the planning path length, path nodes, and overall turning cost of mobile robots, and improved the success rate.

However, the A* algorithm still has significant limitations in practical e-commerce logistics environments, such as finding only one optimal path instead of all possible paths. Therefore, this study innovatively combines the A* algorithm with a collision-avoidance heuristic to plan logistics paths. A path-planning model based on the A* algorithm is designed. In addition, based on the path-planning model, the scheduling of transportation vehicles in the logistics park is analyzed and adjusted. Finally, a decision model for optimizing e-commerce logistics warehouse scheduling based on the A* algorithm is developed. This study aims to rationally allocate e-commerce logistics warehousing resources and efficiently execute scheduling tasks. This paper consists of three sections. The first section introduces how to improve the path-planning model based on the A* algorithm and how to establish an optimization decision model for e-commerce logistics warehouse scheduling. The second section presents performance testing of the new system, and the last section summarizes the article.

2. Methods and Materials

To efficiently and intelligently manage e-commerce logistics warehousing, the study first introduces the A* algorithm. Second, the improved A* algorithm is combined with a collision-avoidance heuristic to propose a path-planning model. In addition, the study analyzes the scheduling mode of e-commerce logistics warehousing. The warehouse path in the logistics park is designed based on the A* algorithm path-planning model. Finally, a decision model for optimizing e-commerce logistics warehouse scheduling based on the A* algorithm is proposed.

2.1. Construction of Path Planning Model based on A* Algorithm

Traditional warehouse scheduling methods often rely on manual experience, making it difficult to adapt to the dynamic and complex nature of e-commerce logistics (Huidan et al., 2021; Li, 2025). With the development of artificial intelligence and algorithm optimization technology, intelligent scheduling methods based on path planning algorithms have gradually become a research hotspot. Common graph search path planning algorithms include A* and Dijkstra. The A* algorithm finds the shortest path a path between two points on a graph by combining the advantages of the best-first search algorithm and Dijkstra. It uses heuristic methods to guide the search direction (like the best-first search) while still guaranteeing the shortest path (like Dijkstra) (Wang et al., 2023; Angthong et al., 2024). The traditional A* algorithm path optimization process is displayed in Fig. 1.

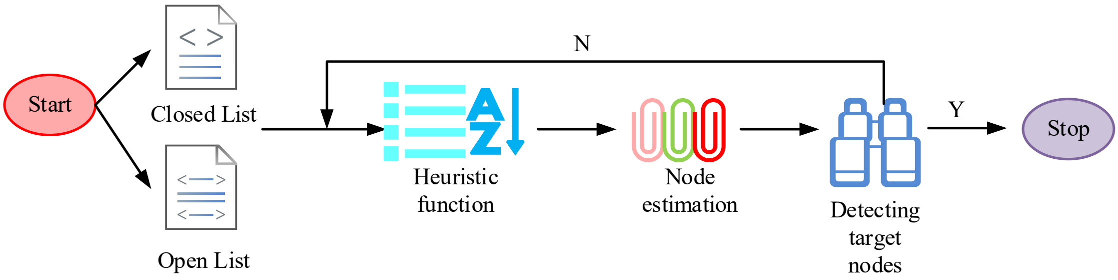


Fig. 1. Traditional A* algorithm path optimization process

Fig. 1 shows the optimization process of the traditional A* algorithm in path planning, including four key steps: node selection, heuristic function calculation, object detection, and path backtracking. First, a starting node is selected as the current node, and the two main data structures, Open and Closed List, are initialized. Second, a heuristic function is selected to estimate the cost from the current node to the target node. The starting node is added to the Open List. The target node is detected. If the current node is the target node, the path is found. If not, the above steps are repeated until the path is found. Finally, by tracing back from the target node to the starting node, the parent node link is used to reconstruct and output the path. The heuristic functions of the general A* algorithm include Manhattan Distance (MD) and Euclidean

Distance (ED) (Liu et al., 2024). The MD and ED are shown in Eq. (1).

$$\begin{cases} MD: h(n) = |x_n - x_{goal}| + |y_n - y_{goal}| \\ ED: h(n) = \sqrt{(x_n - x_{goal})^2 + (y_n - y_{goal})^2} \end{cases} \tag{1}$$

In Eq. (1), (x_n, y_n) represents the coordinates of node n. (x_{goal}, y_{goal}) represents the target node's coordinates. MD represents a grid-like layout, while ED represents an open space. The actual cost of going from an initial node to an n node in the state space is shown in Eq. (2).

$$g(n) = g(parent) + cost(parent, n) \tag{2}$$

In Eq. (2), $g(n)$ represents the actual cost. $g(parent)$ represents the parent node of node n. $cost(parent, n)$ represents the cost from $g(parent)$ to n. After adding $g(n)$ and $h(n)$, the final total cost of the node is obtained. From this, if $h(n)$ meets the condition of not exceeding the actual shortest path, the A* algorithm can ensure finding a shortest path. To expand the search direction, the study improves the A* algorithm using an extended search direction matrix. The number of search directions corresponding to different step size parameters obtained by the improved A* algorithm is shown in Eq. (3).

$$S = 8 \times \left[1 + \frac{R \times (R-1)}{2} \right] \tag{3}$$

In Eq. (3), R represents the step size parameter, which is the Chebyshev distance from the current node to the farthest candidate node awaiting expansion. S represents the number of directions in which the current node can expand. The value of the step size parameter R will directly affect the search effect. When R =1, only expansion in four directions, up, down, left and right, is allowed. The search speed is relatively fast, but the path smoothness is insufficient. When R =2 or R =3, the number of expansion directions increases significantly, which can effectively reduce large-angle turns and make the path closer to the actual driving trajectory of the vehicle. Combining the grid map characteristics of the warehousing environment and the distribution of obstacles, the study sets the R to 2. In the specific implementation process, a candidate direction set is first generated based on the coordinates of the current node. Then, the nodes that meet the conditions are screened out in combination with the cost function. Finally, they are added to the open list to ensure the coherence and optimality of the search process. Meanwhile, to calculate the danger value of each node, a safety distance matrix based on a two-dimensional Gaussian distribution is established with the current node as the center. The schematic diagram of safety value calculation is shown in Fig. 2.

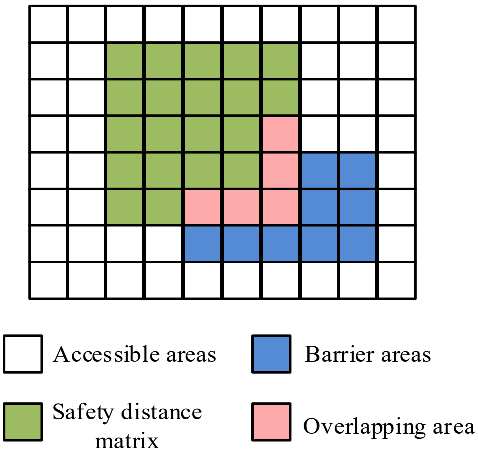


Fig. 2. A schematic diagram of the safety value calculation

In Fig. 2, the green area is the range of the safety distance matrix, and the pink area is the obstacle area that is in the safety distance matrix. In the raster map, the passable area is 0, and the obstacle area is 1. The hazard value of node N can be obtained through the elements in the safety distance matrix multiplied by the value of the corresponding position in the raster map and then summing up the values. The safety distance matrix $M_{s(m,n)}$ is shown in Eq. (4).

$$M_{s(m,n)} = e^{-\frac{1}{2}\left(\frac{\sqrt{m^2+n^2}}{a}\right)^{2\times b}}, -d_o \le m \quad n \le d_o \tag{4}$$

In Eq. (4), a and b represent proportional parameters. m and n represent the positions of matrix elements relative to the center of the matrix. d_o represents the safety distance threshold. The danger value $Risk(N)$ of the node is shown in Eq. (5).

$$Risk(N) = \sum M_s(m,n) \times MAP(m,n) \tag{5}$$

In Eq. (5), MAP represents the grid map matrix. The center of the matrix corresponds to the current position of the vehicle, and the surrounding areas calculate the safety weights of different positions according to Eq. (4). Considering that the dispatched vehicles are 1.2m long and 0.8m wide, with an average traveling speed of 6m per second, and in combination with the braking performance, the study sets the safety distance threshold at 5.0m. During the implementation process, the safety matrix is multiplied point by point with the raster map to obtain the danger value of the current node, and the risk is quantified through Eq. (5). When the danger value exceeds the threshold, the node is eliminated as a candidate path. Through this mechanism, the algorithm can dynamically avoid potentially dangerous areas during the search stage, thereby enhancing the safety of the path. Using grid maps for path planning often results in many turns and large turning angles, which are not conducive to practical engineering applications. Accordingly, the study optimizes the path calculated by the A* algorithm based on cubic uniform B-spline curves. The B-spline curve $B_{spline}(u)$ is shown in Eq. (6).

$$B_{spline}(u) = \sum_{i=0}^{n} P_i N_{i,k}(u) \tag{6}$$

In Eq. (6), u represents the normalized non-decreasing node vector. P_i and $N_{i,k}$ represent the coordinates of the control vertex and the B-spline basis function of the k-degree curve, respectively. However, faced with sudden collisions, without effective emergency evacuation rules, it is easy to cause serious traffic congestion in the park. Therefore, a conflict detection mechanism is developed and implemented to ensure that vehicles can timely identify potential collision risks and take appropriate avoidance measures to maintain smooth and safe traffic in the park. According to the execution actions of vehicles in different states, collision forms are divided into two types, namely node collision and head-on collision (Mclaughlin et al., 2021). Node conflict usually refers to the situation where multiple vehicles attempt to pass through the same path node at the same time, resulting in a collision hazard. A head-on collision refers to the situation where multiple vehicles collide along the same path due to opposite directions. To effectively solve the collision problem of vehicle paths, a Collision Avoidance Heuristic Algorithm (CAHA) is constructed based on the improved A* to calculate the shortest path. The structural framework of the CAHA is shown in Fig. 3.

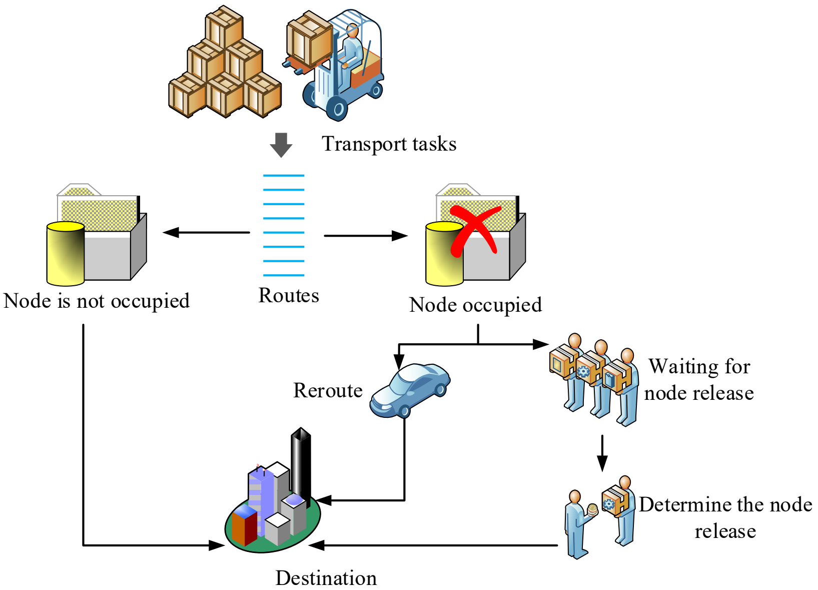


Fig. 3. An architectural framework for collision avoidance heuristic algorithm

As shown in Fig. 3, the Collision Avoidance Heuristic Algorithm (CAHA) optimizes transportation tasks through the following steps. First, the transportation task is input into the control center, and the initial driving route is determined. When a collision risk is detected at a certain node of the transport vehicle, the algorithm will instruct the vehicle to pause and wait at the previous safety node. Once the traffic situation at the node is alleviated, vehicles can continue to transport tasks. In the course of traveling along the predefined path, if conflicts are encountered at intersections or node times of the paths planned by the improved A* algorithm, the automated vehicle needs to make the necessary operational adjustments. These adjustments can be divided into two categories: re-planning transportation routes and optimizing transportation time. The priority of the automatic vehicle is determined by the priority order of the nodes it occupies. The system prioritizes the vehicle that receives the task earliest, ensuring that the scheduling route is the shortest path, prioritizing vehicles that have already occupied nodes. To prevent node collision, the system pre-selects an alternate shortest path to avoid potential conflicts. During traveling, if the node ahead is occupied by another autonomous vehicle, the vehicle will wait at that node. Once the control center confirms that the node is no longer occupied by a higher priority vehicle, it will be taken over by the currently waiting vehicle, and the control center will update the node status and notify all relevant vehicles to ensure real-time synchronization of node occupation information. In this way, the waiting autonomous vehicle will be able to continue traveling, and other vehicles will be informed that the node has been occupied, thus effectively avoiding collision accidents. After intelligent scheduling, autonomous vehicles are able to operate safely and efficiently in complex transport networks. The path hazard assessment value F_R is shown in Eq. (7).

$$F_R = \sum_{i=1}^{T} R(\rho(N_i, N_{obs})) \tag{7}$$

In Eq. (7), $\rho(N_i, N_{obs})$ represents the distance from the i-th sampling point to the nearest obstacle. However, in path planning, it is impossible to cover all possible scenarios when constructing the model. Therefore, to ensure the model is close to reality while effectively conducting path planning, some reasonable assumptions are proposed for vehicle path planning, aiming to simplify the model and improve its applicability and flexibility in the real world. This process is displayed in Fig. 4.

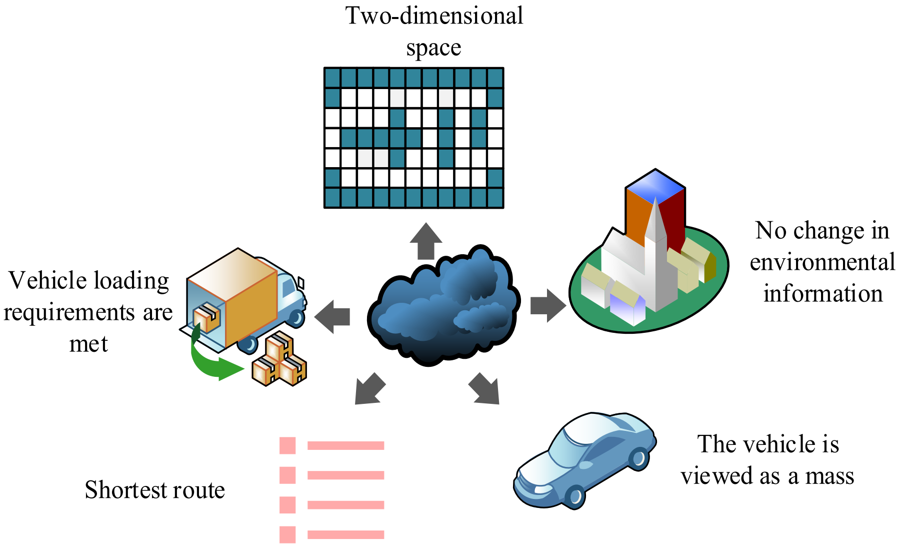


Fig. 4. Assumptions for vehicle path planning

As shown in Fig. 4, five key assumptions are proposed in the research on vehicle path planning to simplify the problem and enhance the practicality of the model. First, the study simplifies the driving environment to a two-dimensional space for analysis and calculation. Second, the surrounding environmental information remains relatively stable while the vehicle is in motion, ignoring short-term dynamic changes. In addition, the vehicle is treated as a particle, and its motion is strictly limited to the predetermined driving route to ensure the accuracy of path planning. The study also assumes that the vehicle loading capacity meets the demand for transferring goods in the warehouse, eliminating transportation interruptions caused by insufficient loading. Finally, to effectively avoid potential path conflicts, vehicles prioritize the shortest path while retaining flexibility in choosing their travel route. During each trip, different shortest paths are selected based on real-time conditions to optimize overall transportation efficiency and reduce conflict risks. These assumptions together form the foundation of the path planning model, aimed at achieving efficient and reasonable vehicle scheduling. Based on these improvements, a path planning model based on A* is established, namely the CAHA-IA* model, which uses an improved A* and a CAHA. It not only obtains the shortest transportation path, but also effectively avoids vehicle conflicts.

2.2. Construction of Optimization Decision Model for E-Commerce Logistics Warehouse Scheduling

E-commerce logistics is an important component of modern supply chain management, which plays a crucial role in optimizing warehouse scheduling decisions to optimize overall logistics efficiency and reduce costs (Pasternak et al., 2022). The study first simplifies the logistics park into a two-dimensional plan based on its actual layout. The two-dimensional plan is shown in Fig. 5.

Fig. 5 shows the two-dimensional layout of the logistics park. The logistics park includes four dedicated warehouses, each serving the storage needs of goods in different regions. In addition, the park is equipped with seven fixed loading and unloading points for daily cargo loading and unloading of long-distance transportation vehicles. Multiple external vehicles deliver goods to these warehouses every day, while vehicles within the park carry out corresponding delivery tasks to various warehouses based on the daily flow and type of goods. At this point, there are challenges in transferring goods in the warehouse. The factors that affect scheduling time mainly include the number of running vehicles, vehicle location, and dispatchers (Hasanvand et al., 2023; Huang, 2025). There is a significant correlation between the factors that affect scheduling time and the proportion of vehicles in the logistics park. More vehicles indicate greater complexity in scheduling. In addition, human factors and unpredictable variables such as emergencies and information asymmetry can also interfere with the scheduling process. These factors are intertwined, often leading to efficiency bottlenecks in the manual scheduling mode of logistics parks. There are currently two main types of automated vehicle scheduling modes, namely decentralized control mode and central control mode (Wang et al., 2024; Sreelakshmy et al., 2022). A central control mode is adopted to replace the traditional manual scheduling mode, achieving fully automated scheduling and transportation. The reward function plays a crucial role in balancing resource consumption and task execution quality globally during task scheduling. The reward function r is shown in Eq. (8).

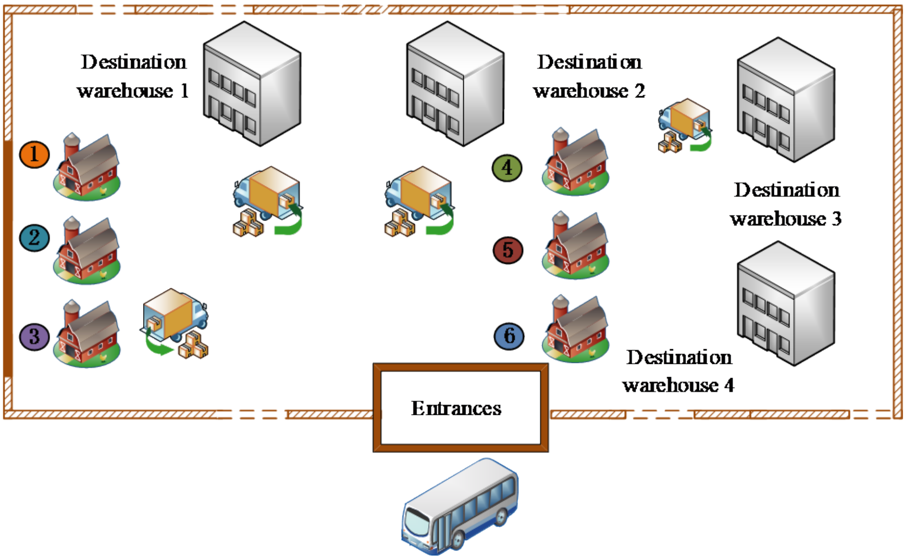


Fig. 5. Two-dimensional plan of the logistics park

$$r = \beta \cdot \frac{E_i}{E_{\max}} + (1-\beta) \cdot \frac{p_t}{p} \tag{8}$$

In Eq. (8), E_i and $E_{\max}$ represent the remaining available resources after node i and the maximum value of node resources, respectively. β represents the equilibrium factor, which is used to adjust the weight of resource utilization and task completion in the reward function. p_t and p respectively represent the number of tracked target positions within the perception area of the node and the number of all target positions that can be detected within the perception area of the node. The reward function is designed to encourage nodes to utilize their resources efficiently while ensuring the quality of task completion. By adjusting the value of β, the relative importance of resource utilization efficiency and task completion in the reward function can be changed. The weight $\varpi_{j,t}$ of each task is shown in Eq. (9).

$$\varpi_{j,t} = \varpi_{j,t-1} \cdot e^{k \bullet r_{t+1}} \tag{9}$$

In Eq. (9), r_{t+1} represents the reward obtained by a node after executing a specific task. $\varpi_{j,t-1}$ represents the weight value of the j-th task at time $t-1$. The weights of the tasks are adjusted according to the rewards that the nodes receive for performing them. Tasks that receive higher rewards are given higher weights in the future, thereby increasing the probability of nodes choosing to execute these tasks. After completing a task, the node will adjust the probability distribution of the task based on the feedback reward information. The adjusted $p_{j,t+1}$ is shown in Eq. (10).

$$p_{j,t+1} = (1-k) \cdot \varpi_{j,t} + \frac{k}{A} \tag{10}$$

In Eq. (10), k represents the equilibrium factor, which is used to control the adjustment amplitude of the probability of selecting new tasks to maintain the diversity of task selection and avoid premature convergence to suboptimal solutions. A represents the total number of all tasks, normalizing the probability distribution. In this way, the system can dynamically adjust the execution probability of tasks according to their current weights and equalization factors, thus optimizing resource allocation and improving the efficiency of task completion. In addition, the warehouse path of the logistics park is designed based on the CAHA-IA* model, as shown in Fig. 6.

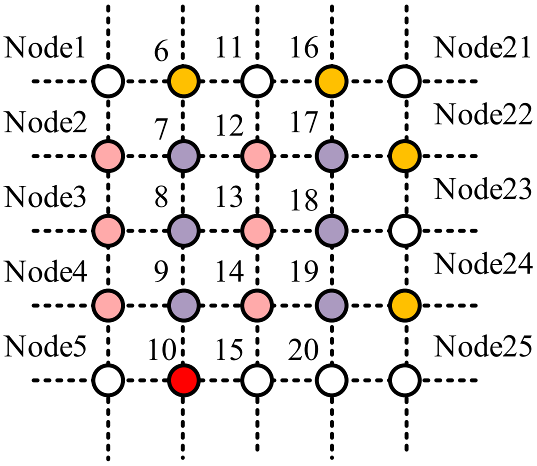


Fig. 6. Warehouse paths in logistics parks

Fig. 6 shows the specific locations of different warehouses and distribution nodes, intersections, and park gates. Nodes 2, 3, 4, 12, 13, and 14 in Fig. 6 represent six different warehouse configurations. Nodes 6, 16, 22, and 24 represent four different destination warehouses. Nodes 7, 8, 9, 17, 18, and 19 represent six different intersections. Node 10 represents the entrance of the logistics park. No vehicles are passing through nodes 1, 5, 11, 15, 20, 21, 23, or 25. The squared error ε^2 of the motion trajectory regression is shown in Eq. (11).

$$\varepsilon^2 = \sum_{1}^{n} (y_i - ax_i - b)^2 \tag{11}$$

In Eq. (11), a and b represent the calculated slope of the regression equation and the intersection point between the trajectory and the y-axis, respectively. x_i and y_i represent location information. Based on the various improvements mentioned above, a new optimization decision model for e-commerce logistics warehouse scheduling is proposed. The process framework of this model is shown in Fig. 7.

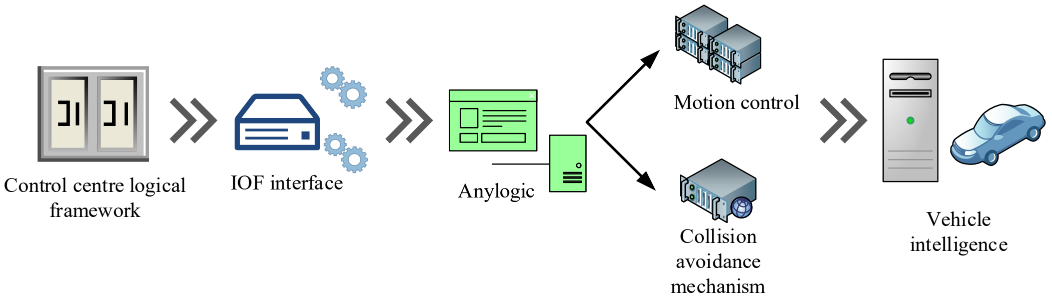


Fig. 7. Warehouse scheduling optimization decision-making model

As shown in Fig. 7, the study first develops an intelligent control center framework based on the principle of active control, laying the foundation for trajectory optimization of autonomous vehicles. This framework designs input-output interfaces based on trajectory optimization standards and is compatible with the CAHA-IA* trajectory optimization model. Next, Anylogic simulation software combines the motion control and collision avoidance functions of vehicle intelligent agents to create an autonomous driving vehicle model that can follow micro trajectories and simulate its behavior in passive mode. Finally, the study introduces a blackboard information sharing mechanism to simulate the communication between the control center and autonomous vehicles, achieving effective information exchange between vehicles and the control center providing an innovative communication solution for intelligent transportation systems. When designing the experiments for vehicle paths, the study adopts data preprocessing and random sampling operations to ensure data accuracy and experimental validity. The data preprocessing steps include removing noise from the data, filling in missing values, standardizing measurement units, and converting the customer's geographic location from geographic coordinates to a grid coordinate format suitable for the algorithm. Random sampling is then achieved by randomly varying variables such as the number of customers, demand distribution, and topography. During the experiments, the equalization factor is used to prevent the algorithm from falling into sub-optimal solutions quickly. The task weights are dynamically adjusted based on the rewards obtained by the nodes after completing the tasks. This design enables algorithms to more intelligently determine the order of task execution and resource allocation. In terms of path planning, the optimized A* algorithm selects the most cost-effective route by carefully evaluating the cost function of each node, thereby reducing the total travel distance and cost.

3. Results

To verify the performance of the CAHA-IA* model and the e-commerce logistics warehouse scheduling optimization decision model, a suitable experimental environment is first established, and the test data are preprocessed, with a portion of the data used for model training. Second, the performance and simulation experiments are conducted on both the CAHA-IA* path planning model and the e-commerce logistics warehouse scheduling optimization decision model to verify the practical application effect in logistics warehouse scheduling.

3.1. Performance Testing of CAHA-IA* Path Planning Model

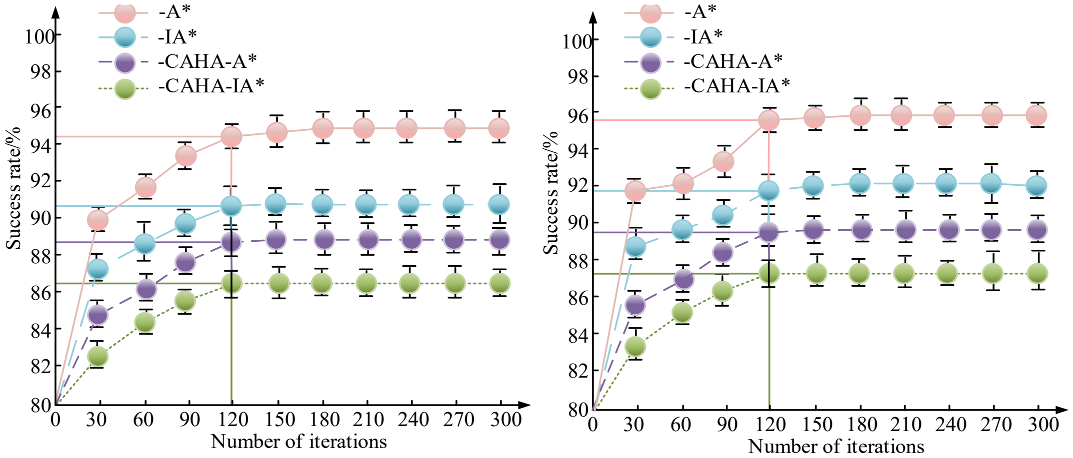
The study selects Lenovo Qitian series desktop computers and Huawei desktop cloud devices as operating conditions. The CPU is an Intel i5 2.7 GHz, the operating system is Windows 10, and the algorithm language is Java. AnyLogic is used to visualize real dynamic models. The step size parameter R=3 is set for the CAHA-IA* path planning model. The scale parameters a=2, b=1 are set for the safe distance matrix. The safe distance threshold is d_o=2. The VRP Instances dataset, CVRPLIB dataset, ABEFMP dataset, and Solomon dataset are used as the test data sources. The ABEFMP dataset is derived from the open access public dataset library of logistics scheduling and routing optimization. It is a widely used benchmark dataset for vehicle routing problems, especially those with capacity constraints, and includes instances from multiple categories. The Solomon dataset is a well-known standard test set in vehicle routing problems, particularly used for research on vehicle routing problems with time windows. The VRP Instances dataset provides examples of vehicle path problems with time windows, which are suitable for evaluating and comparing different vehicle path problem-solving algorithms. The CVRPLIB dataset is a vehicle routing problem library that provides examples of many types of vehicle routing problems, including capacity-limited vehicle routing. These four datasets are separated into training and testing sets in an 8:2 ratio. The information on the type and amount of data in the Solomon dataset and ABEFMP dataset is shown in Table 1.

Table 1. Information on the type and amount of data in the two datasets

Data set	Types	Training set	Testing set
Solomon	R1	126	32
	RC1	234	59
	R2	186	47
	RC2	177	45
	C1	231	58
	C2	165	42
ABEFMP	A	42	11
	B	68	17
	E	56	14
	F	88	6
	M	75	19
	P	126	32

Based on the dataset information in Table 1, the study sets the vehicle to 15 and the maximum iteration to 300. After data normalization and cleaning, random sampling is performed. Each group of experiments is independently repeated 10 times under the same conditions to ensure the stability and repeatability of the experimental results. The study first conducts ablation testing on the CAHA-IA* model, taking the success rate of path planning as the indicator. The test results are shown in Fig. 8.

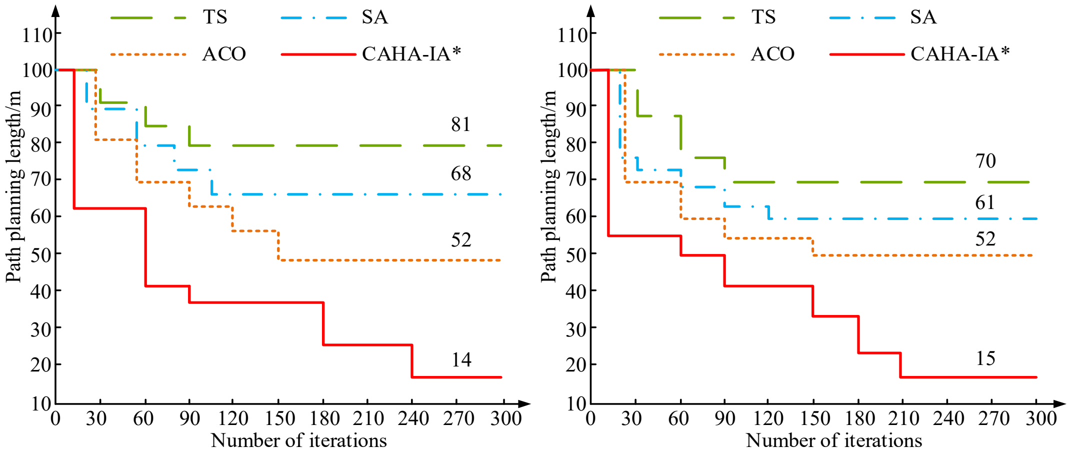
Fig. 8(a) displays the success rate curves of path planning for each module in the Solomon dataset. Fig. 8(a) displays the success rate curves of path planning for each module in the ABEFMP dataset. As shown in Fig. 8, with the increase of iterations, the success rate in each module of the CAHA-IA* model gradually increased and then tended to balance. Whether in the Solomon dataset or the ABEFMP dataset, the -A* module had the worst performance, with the highest path planning success rate of 87.68%. After improving the search direction matrix and cubic uniform B-spline curve, the success rate in the -A* module increased by about 3%, and the highest success rate in the -IA* module was 87.29%. After improvement by the CAHA, the performance was significantly improved. The CAHA-IA* model had the best comprehensive performance, with a best performance of 94.26% in the Solomon dataset. The best performance in the ABEFMP dataset was 95.53%. To verify the statistical significance of the improvements in each module, the study conducted Analysis of Variance (ANOVA) and pairwise comparisons (Tukey HSD test) on the repeated experimental data. The results showed that the differences in the success rates of path planning among the modules all reached a significant level ($p<0.05$). In summary, each module component has a positive impact on the final model, which can effectively improve the success rate of path planning. In addition, the study also introduces popular path planning models, such as Tabu Search (TS), Simulated Annealing (SA), and Ant Colony Optimization (ACO) to compare the path planning length, as displayed in Fig. 9.



(a) Solomon

(b) ABEFMP

Fig. 8. Path planning success curves for each module in the CAHA-IA* model



(a) Solomon

(b) ABEFMP

Fig. 9. Comparison curves of path planning lengths for different models

Fig. 9(a) displays the path planning lengths for different models on the Solomon dataset. Fig. 9(b) displays the path planning lengths for different models on the ABEFMP dataset. According to Fig. 9, in the Tabu Search (TS) model test, as the iteration increased, the path length gradually shortened, with the shortest being 70 m ± 2 m. In the Simulated Annealing (SA) model, the shortest path length of the model was 61m ± 1.5m. The shortest path of the Ant Colony Optimization (ACO) model was 52m ± 1.0m. The changes in the CAHA-IA* model were most significant, with the shortest planned path being 14m ± 0.5m. From the above data, the CAHA-IA* model performs better in actual logistics and warehouse scheduling path planning tasks, with obvious effectiveness and superiority. In addition, the study compares the operational complexity of different models. The test results are shown in Table 2.

Table 2 shows the running times of different models on the training and test sets. In Table 2, the CAHA-IA* model exhibited relatively low computational complexity in the experimental design of the vehicle path problem. The running time of all four models increased slowly with the increase in the number of runs. The running time of USV, GWO-AOA, ESO, and the proposed model increased by 2.1s, 1.8s, 1.7s and 0.8s in the training set. The running time in the testing set increased by 1.4s, 0.9s, 0.4s and 1.2s, respectively. However, the increase is small enough that it does not affect the model's overall performance. The proposed CAHA-IA* model had the shortest running time of 25.4s. This further proves its advantage in computational efficiency. The proposed model not only simplifies the computational process but also can efficiently carry out path planning for logistics parks, which significantly improves the efficiency and effectiveness of automated warehouse scheduling, and demonstrates higher operational efficiency and accuracy. The CAHA-IA* model has low computational complexity due to its optimized algorithm design, which achieves high operational efficiency and accuracy through the data pre-processing, random sampling, equilibrium factor adjustment, dynamic updating of task weights, improved application of the A* algorithm, and experimental result analysis, achieving efficient computation.

Table 2. Comparison of running time of different models

Data set	Models	1st (s)	2nd (s)	3rd (s)	4th (s)	5th (s)	6th (s)	7th (s)	References
Training set	USV	45.2	45.6	46.1	46.3	46.9	47.1	47.3	Li J et al.
	GWO-AOA	42.0	43.5	43.0	43.1	43.3	43.6	43.8	Sreelakshmy K et al.
	ESO	41.2	41.5	41.7	42.5	42.6	42.8	42.9	Wang T et al.
	Research model	26.8	26.5	26.6	27.0	27.1	27.2	27.6	This work
Testing set	USV	42.6	42.7	42.9	43.2	43.3	43.6	44.0	Li J et al.
	GWO-AOA	38.8	38.6	38.9	39.0	39.1	39.3	39.7	Sreelakshmy K et al.
	ESO	36.5	36.5	36.6	46.7	36.8	36.8	36.9	Wang T et al.
	Research model	25.4	25.6	25.8	26.2	26.4	26.5	26.6	This work

In vehicle routing planning research, it is usually assumed that the environment is a two-dimensional space and the information is stable, which helps to reduce the computational complexity in theoretical analysis and algorithm verification. However, these simplified assumptions have obvious limitations in actual logistics scenarios. First, in the actual warehousing environment, there are dynamic obstacles, such as other operation vehicles, personnel, or mobile devices. The two-dimensional static assumption cannot effectively handle these changes, which may render the planned path infeasible or increase the likelihood of collisions. Second, in logistics scenarios, multi-layered shelves, elevators, and other three-dimensional structures are widespread. Vehicle movement is not only restricted by two-dimensional planes but also needs to consider vertical space constraints. The two-dimensional planning assumption cannot reflect this actual limitation. Finally, environmental information may be updated at any time during actual operations, such as during the handling of goods or the temporary closure of passages. Information stability can lead to a mismatch between the planned path and the actual environment, reducing scheduling efficiency and security. Therefore, to enhance the applicability and robustness of vehicle routing planning algorithms in actual logistics, it is necessary to expand and optimize dynamic obstacle handling and three-dimensional space constraints. To further verify the applicability, the study also extends the CAHA-IA * model to three-dimensional spatial scenes. The three-dimensional warehousing environment simulates complex structures such as high shelves, multi-level aisles, and vertical lifting platforms. In this test, CAHA-IA* can search for paths through an extended three-dimensional heuristic function and achieve obstacle avoidance in both horizontal and vertical directions in combination with anti-collision strategies. Meanwhile, to examine the robustness and generalization ability of the model in complex situations, dynamic obstacle test cases are designed. In the experiment, 5% to 20% of dynamic obstacles (such as randomly moving forklifts and temporarily occupying the road AGVs) are set up, and the obstacle avoidance success rates and average recovery time of different models are recorded. The results are shown in Table 3.

In Table 3, with the increase in the proportion of dynamic obstacles, the overall performance of the three models has declined. However, the CAHA-IA* model always maintains significant advantages in obstacle avoidance success rate, average recovery time, and collision rate. When the proportion of dynamic obstacles was 20%, its obstacle avoidance success rate, average recovery time, and collision rate were 89.6%, 4.2s, and 3.5%, respectively, indicating that this model not only performs well in static environments but also can effectively deal with dynamic obstacles and uncertain factors, and has good robustness and generalization ability.

3.2. Simulation Testing of E-Commerce Logistics Warehouse Scheduling Optimization Decision Model

To verify the simulation performance of the e-commerce logistics warehouse scheduling optimization decision model, an experimental environment is established using MATLAB for simulation testing. The actual vehicle scheduling data from a company's e-commerce logistics park are used as the test data, and the driving speed of all vehicles is set to 6m/s. This speed setting is based on the following two aspects: First, 6m/s (approximately 21.6km/h) is a common operating speed range for AGVs in medium- and large-scale warehousing environments within the industry and conforms to industry reference standards for automated warehousing and transportation systems at home and abroad. Second, to avoid simulation results lacking practical significance due to too low a speed or the complexity of the collision detection and avoidance mechanism due to too high a speed, the study, after referring to existing standards and considering the constraints of the experimental scenarios, set the actual vehicle speed at 6m/s to balance the feasibility and safety of the model. The study first selected a stable corner of the experimental site as the starting point for mapping and constructed a regular obstacle grid map of 100×200. The distance parameter information is shown in Table 4.

Table 3. Comparison of obstacle avoidance performance of different models in dynamic obstacle scenarios

Proportion of obstacles	Models	Obstacle avoidance success rate/%	Average recovery time/s	Collision rate/%
5%	A*	78.5	4.3	6.2
5%	IA*	87.1	3.6	3.9
5%	CAHA--IA*	95.8	2.4	1.1
10%	A*	72.4	5.2	8.4
10%	IA*	83.6	4.5	5.3
10%	CAHA--IA*	93.2	3.1	1.8
20%	A*	65.7	6.8	12.9
20%	IA*	79.2	5.9	7.4
20%	CAHA--IA*	89.6	4.2	3.5

Table 4. Distance parameter information

Serial number	Nodal	Distance from each warehouse to the park entrance/m
1	Destination warehouse 1	210
2	Destination warehouse 2	240
3	Destination warehouse 3	210
4	Destination warehouse 4	210
5	Warehouse distribution 1	190
6	Warehouse distribution 2	160
7	Warehouse distribution 3	130
8	Warehouse distribution 4	190
9	Warehouse distribution 5	160
10	Warehouse distribution 6	130

Based on the data information in Table 4, the simulated route map of the vehicle and the effect diagram of the route trajectory during the vehicle scheduling process are obtained by randomly generating data, as shown in Fig. 10.

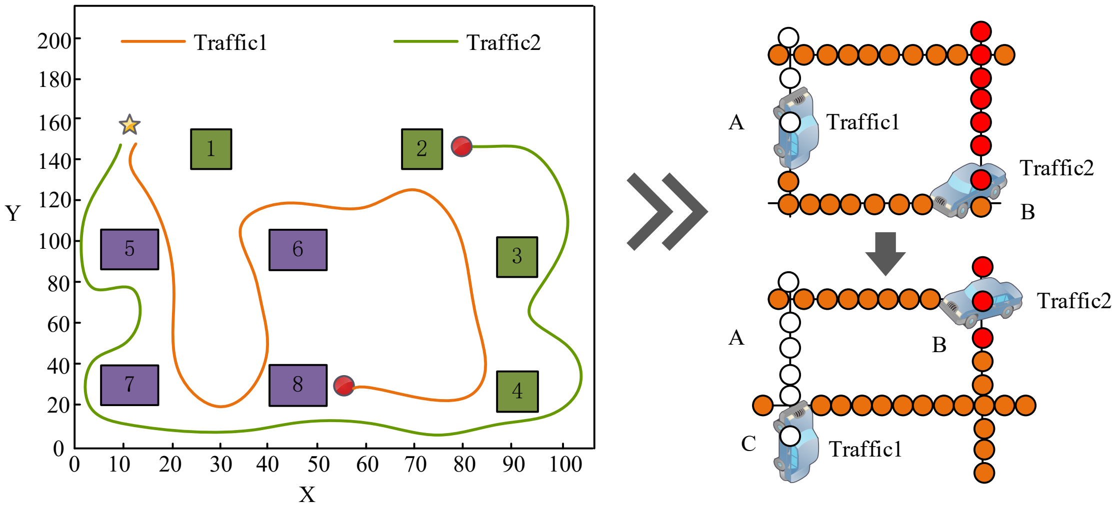
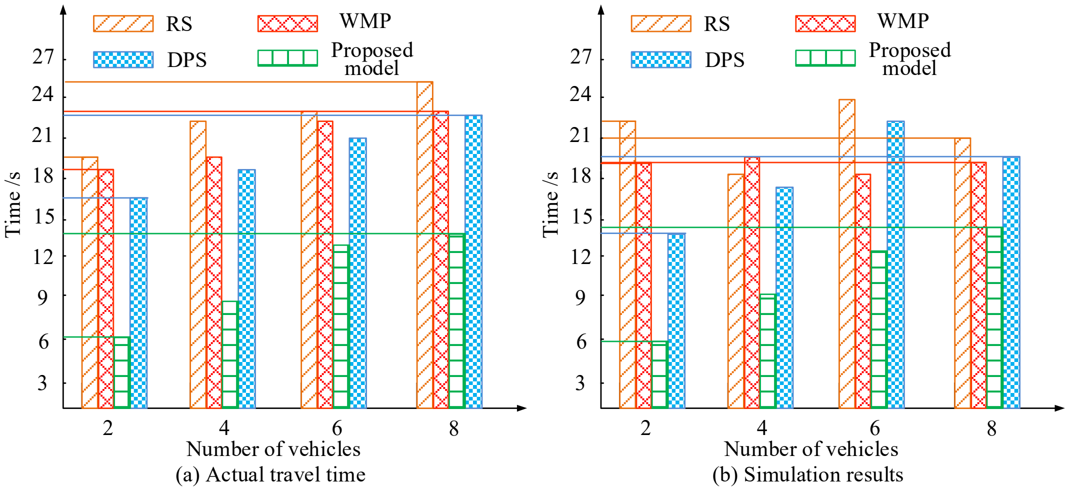


Fig. 10. Route trajectory effect diagram during vehicle scheduling process

Fig. 10(a) shows the obstacle grid map trajectory routes of two vehicles in the e-commerce logistics warehouse scheduling optimization decision model. Fig. 10(b) displays the anti-collision test results of the two vehicles in the e-commerce logistics warehouse scheduling optimization decision model. In Fig. 10(a), the yellow star signifies the initial point, and the red circle signifies the endpoint. From Fig. 10(a), the scheduling path of the two vehicles perfectly bypassed the narrow obstacle while maintaining a certain distance from its edge. According to Fig. 10(b), vehicle 2 waited at node B until vehicle 1 passed through node A ahead and reached point C. At this time, node A was released. Once node A was available, vehicle 2 passed smoothly, avoiding collision with vehicle 1. The above data indicates the effectiveness of the proposed model in avoiding collisions when multiple automatic vehicles are driving simultaneously. Finally, the study also introduces similar warehouse scheduling models, namely the Warehouse Management Problem (WMP) model (Stanisław et al., 2022), the Dynamic Picking System (DPS) model (Serhat et al., 2023), and the Random Storage (RS) model (Keung et al., 2022), for comparison. All models are run under the same hardware configuration (Intel i5 2.7GHz, 16 GB RAM) and the same software environment (MATLAB R2022a simulation platform), ensuring the rationality and interpretability of the simulation time comparison. The weight parameter of the WMP model is set to 0.6, and the iteration step size is 0.01. The scheduling priority coefficient of the DPS model is set to 0.8, and the task switching threshold is 5s. The RS model adopts a uniformly distributed random scheduling strategy, with the random seed fixed at 2023. The test results are shown in Fig. 11.



(a) Actual travel time
(b) Simulation results

Fig. 11. Performance effects of different storage scheduling models

Fig. 11(a) shows the actual travel time comparison results of different warehouse scheduling models. Fig. 11(b) shows the simulation time comparison results of different warehouse scheduling models. In Fig. 10, the proposed model had the minimum travel time, with actual travel times of 6.1s, 8.8s, 12.4s, and 14.2s for vehicles 2, 4, 6, and 8, respectively. There was almost no error compared with the simulation test results. The RS model has the longest time consumption, as the warehouse scheduling process is susceptible to various interferences from complex environments, resulting in vehicle congestion and collisions, and leading to longer travel time. From this, the proposed model not only avoids vehicle collisions but also has enhanced operational efficiency.

4. Conclusion

With the development of e-commerce logistics automation and intelligent services, improving warehouse scheduling efficiency and reducing transportation costs have become hot topics. To improve the transportation efficiency of warehouse scheduling in complex environments, the study first adopted the A* to select the shortest path. The improved A* algorithm was combined with a CAHA to propose a CAHA-IA* path planning model. Second, based on the CAHA-IA* path planning model, adjustments were made to the vehicle scheduling mode. Finally, a novel e-commerce logistics warehouse scheduling optimization decision model was designed. From the results, the CAHA-IA* path planning model had better comprehensive performance, with the best performance of 94.26% in the Solomon dataset and 95.53% in the ABEFMP dataset. Each module component proposed in the study had a positive impact on the final model, which effectively improved the success rate of the path planning. Its planned shortest path was only 14m. Simulation experiments showed that the proposed e-commerce logistics warehouse scheduling optimization decision model could effectively avoid collisions when multiple automatic vehicles were driving simultaneously, with the least travel time. Its actual travel time under the number of vehicles 1, 2, 3, and 4 was 17.7s, 18.2s, 21.1s, and 22.1s, respectively. The final e-commerce logistics warehouse scheduling optimization decision model can adapt to the current needs of the logistics industry. The innovation of the research lies in the ability to effectively avoid the A* algorithm falling into a local optimal solution prematurely by introducing an equalization factor and dynamically adjusting the task weights. This approach allows the algorithm to intelligently optimize the task execution order and resource allocation based on the reward information obtained by the nodes after completing the tasks. In the field of path planning, the improved A* algorithm can select a path that performs best in terms of cost-effectiveness by accurately calculating the cost function of each node, thereby reducing the overall travel distance and cost. This design not only improves the decision quality but also enhances its adaptability and efficiency in complex environments. However, this study does not give much consideration to the impact of the real-time transportation environment on warehouse scheduling. In the future, more comprehensive scheduling factors can be fully considered to develop more comprehensive scheduling commands.

Author Contributions

Shizheng Liu contributed to conceptualization, validation, analysis, manuscript editing, visualization, supervision and project administration. Xinnan Ji contributed to conceptualization, methodology, data collection, draft preparation and manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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Declaration of Artificial Intelligence (AI) Tools

The authors used DeepSeek solely for language editing and readability improvement. The authors reviewed and verified all content and take full responsibility for the accuracy and integrity of the manuscript.

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