sustainability

MDPI

Article

Collaborative Optimization of Storage Location Assignment and Path Planning in Robotic Mobile Fulfillment Systems

Jianming Cai [1,2,*], Xiaokang Li [1,2,*], Yue Liang [1] and Shan Ouyang [1]

[1] School of Traffic and Transportation Engineering, Central South University, Changsha 410075, China; LYLYLY33@csu.edu.cn (Y.L.); shanouyang@csu.edu.cn (S.O.)
[2] Smart Transport Key Laboratory of Hunan Province, Changsha 410075, China
* Correspondence: jmcai@csu.edu.cn (J.C.); lixiaokang@csu.edu.cn (X.L.); Tel.: +86-0731-8265-6626 (J.C.)

Abstract: The robotic mobile fulfillment system (RMFS) is a new automatic warehousing system, a type of green technology, and an emerging trend in the logistics industry. In this study, we take an RMFS as the research object and combine the connected issues of storage location assignment and path planning into one optimization problem from the perspective of collaborative optimization. A sustainable mathematical model for the collaborative optimization of storage location assignment and path planning (COSLAPP) is established, which considers the relationship between the location assignment of goods and rack storage and path planning in an RMFS. On this basis, we propose a location assignment strategy for goods clustering and rack turnover, which utilizes reservation tables, sets AGV operation rules to resolve AGV running conflicts, and improves the A-star(A*) algorithm based on the node load to find the shortest path by which the AGV handling the racks can complete the order picking. Ultimately, simulation studies were performed to ascertain the effectiveness of COSLAPP in the RMFS; the results show that the new approach can significantly improve order picking efficiency, reduce energy consumption, and lessen the operating costs of the warehouse of a distribution center.

Keywords: automatic warehousing system; green technology; robotic mobile fulfillment system (RMFS); storage location assignment; path planning; A-star algorithm

check for updates

Citation: Cai, J.; Li, X.; Liang, Y.; Ouyang, S. Collaborative Optimization of Storage Location Assignment and Path Planning in Robotic Mobile Fulfillment Systems. *Sustainability* **2021**, *13*, 5644. https://doi.org/10.3390/su13105644

Academic Editor: Sara Perotti

Received: 26 March 2021
Accepted: 4 May 2021
Published: 18 May 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The warehousing center is an important node in the logistics chain; its functions include goods storage, order picking, shipping, and goods transportation. Order picking is crucial for providing a quick response to users and is the most labor-intensive process: goods need to be picked from the current storage location according to customer orders. In a manual picking system, the picker must continuously access the storage location of the goods until the picking task is completed or the capacity of the picking device is full, and then return to the picking station to complete the follow-up work. This process accounts for approximately 60% of the labor in the entire warehousing operation and 30−40% of the operation time [1,2]. Therefore, the operational efficiency of order picking and operating costs have a critical impact on the overall performance of the logistics supply chain and sustainable development.

With the rapid development of Internet technology, the retail market, with e-commerce as the main channel, has driven the speedy growth of the logistics industry, accelerating its optimization and improvement, and provided a good external market environment for its sustainable development. The rapid increase in the number of orders in warehousing centers has increased operating pressure. Simply increasing the number of personnel will only increase the operating cost, and the efficiency of order picking will not be significantly improved. Manual operations cannot effectively promote the development of a sustainable economy due to factors such as long processing times and high cost. In this context, the application of sustainable green technologies (e.g., automated equipment) for warehousing

operations and order picking has become a trend in the promotion of sustainable social development, and green technology also facilitates higher productivity and lower labor costs. The three aspects of technology, organization, and environment are key factors for logistics enterprises to adopt automatic storage systems [3]. The application of automated equipment can reduce logistics costs and improve efficiency, which are important for the sustainable development of logistics and warehousing enterprises.

Manual picking is gradually being replaced by the green technology of robot picking. RMFSs, represented herein by the Amazon Kiva picking system, are a new type of order-fulfillment method and "goods-to-person" automatic warehousing system [4,5]: the AGV transports the requested rack where the ordered goods are stored to the picking station through the system's instruction, and the picker in the picking station then removes the target goods from those available according to the system's instructions (the RMFS job process is shown in Figure 1, and the warehouse layout is shown in Figure 2). The order picking efficiency of the RMFS is 2–3 times higher than that of the traditional picking system [6], which greatly improves the response to orders, thereby reducing storage operation and labor costs [7]. Due to the reduced logistics costs and improved efficiency of RMFSs, "goods-to-person" systems with robotic picking as the main technology are a new and globally expanding industrial field, and are regarded as a type of high-quality, high-efficiency, and low-pollution green technology.

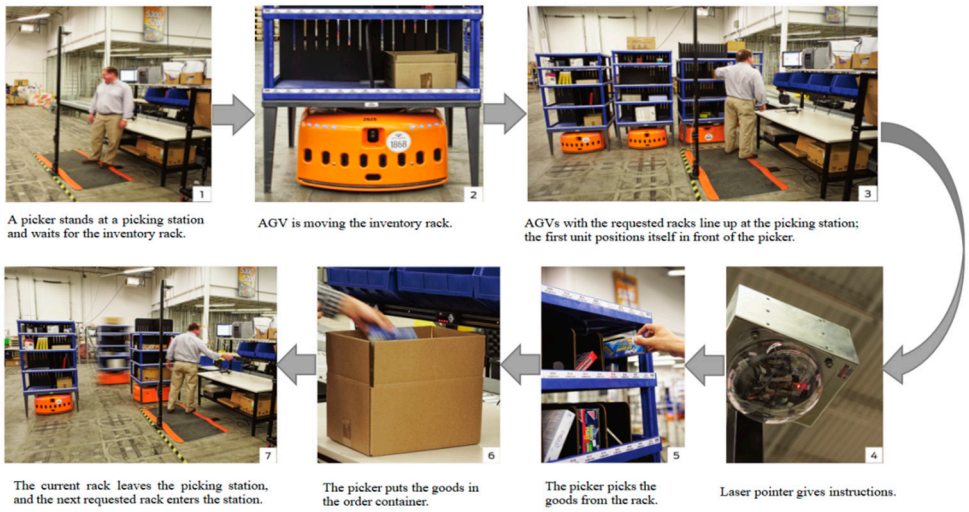


Figure 1. RMFS order picking process [6].

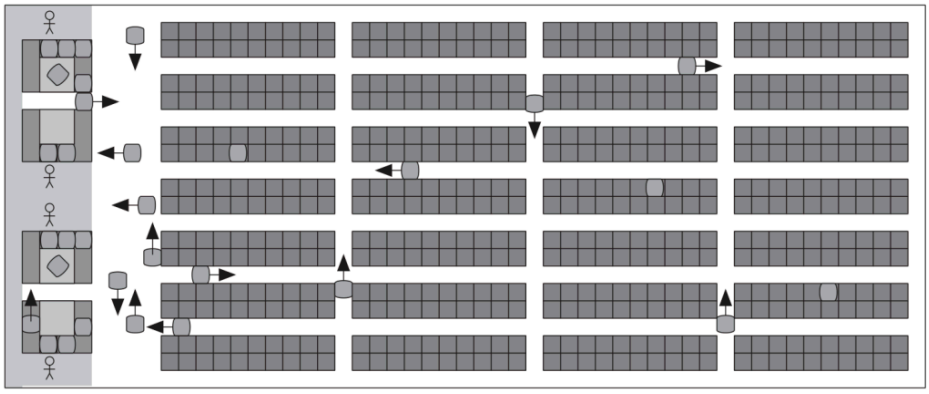
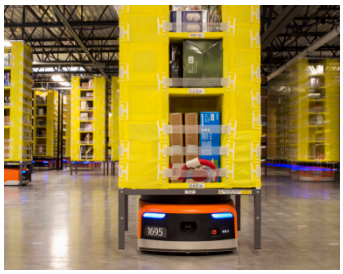


Figure 2. RMFS warehouse layout [7].

Adopting an appropriate green technical solution that is compatible with the operational features of an enterprise is not only an essential task for sustainability, but also a key process in the successful commercialization of any type of technology [8]. The core idea

of RMFSs is to use an AGV to transport the inventory racks storing goods to the picking station. After the pickers select the goods, the AGV returns the racks to the storage area. RMFSs have many advantages over manual and automated storage and retrieval system (AS/RS) picking systems, including picking efficiency and accuracy, and warehouse space utilization. They are highly flexibile and can adjust the warehouse layout dynamically in real-time according to changes in customer needs, and are especially suitable for the order picking requirements of e-commerce, supermarkets, factories, and other companies that experience large demand fluctuations and where rapid order processing is required [9]. RMFSs are also currently used by companies other than Amazon, including JD and Alibaba, as shown in Figure 3.



(**a**) Amazon Kiva Robot (Source: Amazon).



(**b**) Wolf robot (Source: JD).



(**c**) Cainiao handling robot (Source: Alibaba).



(**d**) A warehouse in Cainiao (Source: Alibaba).

Figure 3. RMFS for mature applications.

In actual application, many operation links affect the efficiency and cost of operation for an RMFS, including the location assignment strategy for goods or racks [10,11], task allocation [12–14], path planning [15–17], performance evaluation [18–20], AGV charging [5,21], and system design [22–24]. These operation link strategies affect the RMFS order throughput and flexibility, as well as the overall operating costs of the picking system. Among them, storage location assignment and path planning are important targets for optimization. Storage location assignment refers to the allocation of goods or racks to the appropriate locations in the warehouse, to minimize the time or distance for order picking. A scientific location assignment method can shorten the walking distance, reduce the search time, and improve the efficiency of warehouse picking [25]. Path planning determines a driving plan by which the AGV is to reach the requested rack, picking station, and then storage area after the system assigns tasks to the AGV, minimizing the path length while avoiding collisions.

Therefore, we took the RMFS of B2C e-commerce smart warehouse as the research object to study the COSLAPP and verify its theoretical feasibility.

2. Literature Review

Ever-growing globalization and industrialization have given rise to impending requirements for green and sustainable logistics [26]. Controlling energy consumption is an effective way to pursue sustainable logistics [27,28]. When considering the sustainability of warehousing, the optimization of warehouse operations should be understood

based on energy efficiency [29]. Bartolini et al. [30] analyzed the related literature on green storage and pointed out that storage energy saving is a hot spot in storage research, suggesting from a practical point of view that the waste of resources, such as fuel and land, should be reduced in the management of storage. With the upgrading and iteration of industrial and Internet technologies, lower-carbon automated warehousing technology is used to improve the energy efficiency of warehousing. Automated technology is vital for the survival and growth of enterprises in a green environment by creating sustainable value [3,31]. Nantee et al. [32] studied the economic, environmental, and social impacts of automated warehousing systems on corporate sustainability performance, and showed that after companies implement automation technology, they display significantly improved productivity, accuracy, worker safety, and air emissions; with the effective implementation of warehousing technology, these improvements will further increase, and the company's sustainable performance will also be higher. Tappia et al. [33] incorporated the environmental dimension into the assessment of automated warehouses, and proposed a model to evaluate the energy consumption and environmental impact of automated warehouse solutions, providing valuable support for enterprises to select advanced warehousing technologies. Lerher et al. [34] comprehensively considered factors such as the energy consumption, environmental impact, and driving speed of automated warehousing equipment, and proposed a small load AS/RS energy efficiency model, thereby reducing energy consumption. Fichtinger et al. [35] developed a structural framework to evaluate the environmental impact of automated warehousing solutions. The experimental simulations showed that the choice of inventory control strategy had a significant impact on the energy consumption and emissions of the warehouse; the larger the volume of automation equipment used in the warehouse, the higher the energy consumption. Compared with relatively large storage equipment, such as AS/RS and AVS/RS, small AGVs have more advantages in improving energy efficiency. Bechtsis et al. [36] studied the impact of AGV on sustainable supply chain management, and pointed out that the use of AGV can quickly respond to the dynamic changes of the market, so that the focus of supply chain management is consistent with sustainability. Witczak et al. [37] designed a multi-AGV system model predictive control algorithm, and showed through examples that the use of AGV in the warehouse can improve the sustainability and flexibility of the warehouse process. Kavakeb et al. [38] conducted research on the use of intelligent AGV in European ports for container handling and pointed out that AGV is a green technology that can effectively improve the efficiency of port operations. Considering this aspect, they further illustrated that automated warehousing technology is sustainable.

RMFS is representative in automatic warehousing systems, which helps to improve the efficiency of warehousing operations and reduce labor costs, and its optimization research has strong practical significance. At present, the theoretical research on RMFS is in its infancy, comprising mostly other automatic warehousing systems, such as the autonomous vehicle storage and retrieval system (AVS/RS) and Auto Store. However, for the entire automated warehousing system, the research strategies on storage location assignment and path planning are similar, because the optimization goals are basically the same. Additionally, the storage location assignment and path planning strategies can significantly affect the energy consumption of automated warehouses. Different operating strategies affect the cost and carbon emissions of the automated warehouse system, and reducing energy requirements during operation can have environmental benefits [28].

Hausman was the first to study the location assignment strategy of the traditional picking system [39]; early research on the location assignment strategy mainly concerned the characteristics of the goods themselves and rack characteristics. Storage location assignment based on empirical rules is the most commonly used method, including the random storage strategy, nearest available storage strategy, farthest available storage strategy, longest available storage strategy, and location storage strategy [40]. The random storage strategy is widely used, with the advantages of high storage space utilization and easy implementation [25]. Subsequent documents discuss the cube-per-order index (COI),

classified storage, and goods relevance, and more in-depth research has been carried out regarding other aspects. The COI rule location assignment strategy involves having a small ratio of the average space required to store the goods to the average daily order quantity for the goods in a location close to the In/Out; its advantage is that goods are assigned to more suitable locations [41]. Compared with the location assignment strategy under the COI rules, the classified storage strategy is easier to implement, the management of goods does not require a complete goods volume ranking table, and the time spent is relatively small. Under the classified storage strategy, the position of each category of goods is fixed [42]. Due to the complex dynamics of the external environment, goods cannot be smoothly turned around in accordance with the environment, in theory; goods lifecycles and the supply-and-demand relationships between upstream and downstream positions can affect their fluctuations. Therefore, COI rules and classified storage strategies do not make full use of the correlations between goods to allocate locations. Chiang et al. [43] used the association rules in data mining to obtain the strength of correlation between goods, and proposed an improved classification storage strategy algorithm; the results show that the method can greatly shorten the walking distance in picking compared with that in the general sorting and storage strategy, and it has a significantly positive effect on work efficiency. Zhang et al. [44] built a new model based on demand-related patterns to solve the storage location allocation problem.

Compared with the above-mentioned research into traditional storage location assignment, there is scarce investigation into RMFS storage location assignment, which is generally derived from traditional storage location assignment research. Roy [45], Onal [46], and Weidinger [47] studied the RMFS location assignment problem in two aspects: random assignment and decentralized assignment. Yuan et al. [48] used the partition storage strategy to study the RMFS location assignment problem, and through a simulation experiment, showed that the strategy can balance the picking workload in different areas and improve the picking efficiency. Then, they considered random, classification, and storage location assignment strategies based on the turnover rate; research shows that the use of classified storage strategies can effectively reduce the storage distance for racks [49]. Li et al. [11] used time correlation and goods cluster analysis methods to determine the goods stored on racks and then assigned the rack positions based on the rack decentralized storage strategy turnover rate; simulation shows that this method can significantly improve the efficiency of order picking. Krenzler et al. [50] established a deterministic model and designed a combination optimization algorithm to study the issue of storage location assignment after RMFS rack picking.

The RMFS path planning problem is the issue of path selection when the AGV moves a rack; the purpose is to enable each AGV to safely reach its destination while avoiding collisions. Therefore, AGV path planning not only establishes a suitable algorithm, but also requires the AGV to have a certain degree of intelligence, which is able to avoid obstacles and perform local dynamic path planning based on local environmental information [51]. At present, the heuristic algorithm on path planning more widely used is the A* algorithm, which is the most effective direct search method for finding the optimal path in a static road network. Kumar et al. [16] designed a conflict-free path planning algorithm to search for paths. Wang et al. [52] proposed an improved A* algorithm for AGV path planning, introducing a steering factor, and used the improved algorithm to remove edges, solving the k shortest path problem. They also proposed a conflict path planning method based on the A* algorithm, which can effectively search for the shortest path and avoid collisions. Zhang et al. [53] and Lee et al. [17] improved the Dijkstra and A* algorithms, respectively, set collision avoidance rules, and studied the problem of RMFS multi-AGV collision-free path planning. In the existing literature, there is scarce related research on RMFS storage location assignment and path planning, most of which comprises separate studies on optimization strategies for these two links; COSLAPP research for RMFS remains to be conducted. For the traditional picking system, Zuiga et al. [54] used mathematical planning methods to study the coordination problem of location assignment and path planning.

In the actual operation of the RMFS, the location assignments of goods and racks are interrelated and influence each other; there is a coupling relationship between the two processes of assignment and path planning. At the same time, the two links of storage location assignment and path planning constitute a large proportion of the workload and target for value enhancement.

Therefore, we consider the two issues of RMFS storage location assignment and path planning to improve the energy efficiency of RMFS operations. In theory, from the perspective of collaborative optimization, the two links of storage location assignment and path planning are combined into one optimization problem, and the influence of the two storage strategies for goods and racks assigned by location is considered, to achieve the coordination of the two branch problems of location assignment. This provides a theoretical basis for solving the COSLAPP. In application, by merging storage location assignment and path planning, the order picking efficiency of the RMFS is significantly improved, thereby reducing the operating costs for the warehouse of distribution center.

3. Mathematical Model

3.1. Problem Description

An RMFS mainly includes storage equipment (inventory racks), handling equipment (AGV), and workstations (manually operated picking stations). Its work is mainly completed by an AGV, which only handles one inventory rack at a time, and the picker selects orders according to the instructions of the system.

In an RMFS, goods are stored in the storage area according to the established rules, because the position of the inventory rack changes with order picking, resulting in non-unique storage locations for goods (Figure 4 is a schematic diagram of RMFS operations at a certain moment). According to the RMFS operation process, the COSLAPP can be described as follows: suppose that there are c different goods stored in a smart warehouse and m inventory racks, and each inventory rack has m' storage locations. Each type of good is stored in a different inventory rack according to the required number of goods. It must be decided which goods should be assigned to the rack to reduce the number of round trips for the AGV carrying rack, reduce the burden of AGV path planning, and improve the energy efficiency and order picking efficiency; that is, when receiving w goods orders, how to ensure that the goods in the order are stored on the same rack as much as possible without considering the batching of the order, and determine this rack as the requested rack during order picking? The above process is a matter of storage location assignment. When the requested rack is determined, the system assigns the AGV to the requested rack and transports it to the picking station. In the process for AGV carrying racks, how to integrate the starting point, target position, and end position under the constraints of the AGV driving rules are according to the environment of automatic storage; as well as how to avoid collisions and conflicts in the multi-AGV operating system and generate the best transportation path to minimize the total RMFS operation time, which is a path planning problem, should be determined.

In summary, we mainly used the coupling relationship between RMFS storage location assignment and path planning to conduct collaborative optimization research on the two. By adopting a suitable storage location assignment strategy, c different goods in the warehouse can be stored on m inventory racks, and then m racks can be stored in s positions in the warehouse. Next, according to the needs of the new order, the requested rack where the target goods are located is determined, and the AGV finds a reasonable path through a suitable path planning method, transports the requested rack to the picking station, and the picker completes the product picking. Assuming that the time spent on storage location assignment is T_{assign}, the time spent on path planning is T_{path}. Therefore, the problem studied in this paper is the minimization of the total time spent on the two processes of RMFS storage location assignment and path planning; that is, by considering the COSLAPP problem in RMFS, the aims were to reduce the AGV's moving distance and the number of times the racks were carried, and complete the order picking task in a

shorter time, thereby improving the overall efficiency of the RMFS system, expressed by the following mathematical formula: $\min DT = T_{assign} + T_{path}$.



Figure 4. RMFS running at a certain moment.

3.2. Model Assumptions

Based on the practicality and ease of model construction, in order to simplify the collaborative optimization problem of RMFS location assignment and path planning, the following assumptions were made:

(1) The original state of the warehouse is empty, and the inventory racks are all homogenized racks; the size, specification, and number of goods in each inventory rack are the same;
(2) The order information for each time period is roughly the same and is regular;
(3) Each storage space can only store one type of good, regardless of the storage impact of the volume and weight of the goods;
(4) An AGV cannot perform multiple tasks at the same time and can only carry one inventory rack at a time;
(5) The AGV runs at a constant speed, regardless of the impact of acceleration and deceleration, and ignores the turning time;
(6) The operation of the AGV is a complete handling process; the AGV moves the requested rack to the picking place according to the order requirements and waits for the picker to complete the picking operation, and then moves the rack to the storage area for storage;
(7) Each order contains a limited variety of goods, and a certain good stored on a rack that is moved at a certain time must meet the demand for the quantity of the goods in the order;
(8) In the same operation cycle, goods are picked in order each time, regardless of the order of batching and order placement time; the priority of each order task is the same;
(9) The situation of insufficient power and failure of the AGV is not considered.

3.3. Parameter Setting

There are c types of goods ($C = \{c_1, c_2, c_3, \ldots c_c\}$ representing a collection of goods), l picking stations p_k ($k = 1, 2, 3, \ldots, l$), m inventory racks s_i ($i = 1, 2, 3, \ldots, m$), and n AGVs a_j ($j = 1, 2, 3, \ldots, n$) in the warehouse. $A = \{0, 1, 2, \ldots, m\}$ represents the collection of all the points in the coordinate system, $M = \{0, 1, 2, \ldots, m\}$ represents the collection of the points of all the inventory racks, $N = \{0, 1, 2, \ldots, n\}$ represents the collection of the points of all the AGVs, and $M \subset A, N \subset A$. The basic parameter settings are shown in Table 1, and the decision variable settings are shown in Table 2.

Table 1. Basic parameters.

Symbol	Meaning	Value
(x_i, y_i)	The current position of the inventory rack i	$i = 1, 2, 3, \ldots, m \quad \forall i \in A$
(ax_k, ay_k)	AGV's current location	$k = 1, 2, 3, \ldots, l \quad \forall k \in N$
DT	The total time to complete the order task in period t	$DT \geq 0$
T_{path}	Total time for the AGV to complete rack handling	$T_{path} \geq 0$
T_{assign}	The total time cost of completing the location assignment	$T_{assign} \geq 0$
α, β	The influence coefficient for storage location assignment and path planning	$\alpha + \beta = 1 \quad \alpha, \beta \geq 0$
T_{ij}^m	Goods location assignment system decision time cost	$T_i^s > 0$
T_i^k	The total time taken by the AGV to move the rack i	$T_i^k \geq 0$
T_i^p	The time that rack i spends when picking goods at the picking station	$T_i^p \geq 0$
T_i^q	The time it takes for the AGV to transport the rack i from the storage location to the picking station	$T_i^q \geq 0$
T_i^r	The time taken by the AGV to transport the rack i from the picking station to the storage area via the shortest path	$T_i^r \geq 0$
T_{ij}^k	The time it takes for AGV k to move from rack i to the shortest path taken by rack j	$T_{ij}^k > 0$
c	Number of goods	$c = 1, 2, 3, \ldots$
c_i	Current goods number	$i = 1, 2, 3, \ldots, c$
λ_i	Current goods quantity	$\lambda_i = 1, 2, 3, \ldots$
m	Number of inventory racks	$m = 1, 2, 3, \ldots$
m_i	Current rack	$\forall m_i \in M$
w	Quantity of order	$w = 1, 2, 3, \ldots$
m′	Number of goods on each rack	$m\prime = 1, 2, 3, \ldots$
u	The maximum number of goods stored in each location	$u = 1, 2, 3, \ldots$
C_{ij}	The correlation coefficient for goods i and j	$C_{ij} \in [0, 1] \quad \forall i, j \in C$
g_i, g_j	Only include the number of orders for goods i or j	$g_i, g_j = 1, 2, 3, \ldots$
g_{ij}	The number of orders containing both goods i and j	$g_{ij} = 1, 2, 3, \ldots$
f_m	Rack turnover rate	$f_m \in [0, 1]$
v_k	Driving speed of AGV k	$v_k > 0$
n	Number of AGVs	$n = 1, 2, 3, \ldots$
a_i	AGV in operation	$\forall a_i \in N$
p	Number of picking stations	$p = 1, 2, 3, \ldots$
s	Number of rack storage locations	$s = 1, 2, 3, \ldots$
s_i	Current storage location of the rack	$\forall s_i \in S$

Table 2. Decision variables.

Symbol	Meaning	Value
X_{ij}^k	Whether AGV k transports rack i and then rack j	$X_{ij}^k \in \{0, 1\}$
X_i^k	Whether the rack i is handled by AGV k	$X_i^k \in \{0, 1\}$
Y_i^m	Whether goods i assigned to rack m	$Y_i^m \in \{0, 1\}$
Z_m^s	The rack m is stored in the s position in the warehouse	$Z_m^s \in \{0, 1\}$

3.4. Model Establishment and Analysis

The location assignment focuses on the storage of the goods and ultimately determines the location of the requested rack for order picking, so as to reduce the burden of path planning. The cost is the decision time of the picking system. The more efficient the goods

storage location assignment, the less time spent on path planning, and the higher the efficiency of RMFS order picking. Path planning focuses on optimizing the path taken by the AGV in carrying the racks. The cost is the actual operating time for the picking system. The shorter the actual working time, the more efficient the system's decision making. In this regard, we considered the coupling relationship between storage location assignment and path planning, and proposed a collaborative optimization model involving them, realizing the shortest total time for responding to orders and completing order picking tasks in period t. The objective function is as follows:

$$minDT = \alpha T_{assign} + \beta T_{path} \quad \alpha + \beta = 1 \tag{1}$$

among them:

$$T_{assign} = max\Sigma_{i=1}^{c}\Sigma_{j=1}^{c} Y_i^m Z_m^s T_{ij}^m \quad \forall i, j, c \in C \tag{2}$$

$$T_{path} = \underset{k\in N}{max}\left[\Sigma_{i\in M} X_i^k T_i^k + \Sigma_{i\in A}\Sigma_{j\in A, j\neq i} X_{ij}^k T_{ij}^k\right] \quad \forall k \in N \tag{3}$$

Equation (2) is the time cost of the goods location assignment, which is the system decision cost; it indicates that the sum of the correlations between the goods on each inventory rack is the largest. Equation (3) indicates the time for AGV k to complete the requested rack handling task. The actual operating time reflects the pros and cons of the system's decision making. Therefore, when solving the collaborative model, minimizing the actual operating time of path planning means the coordinated optimization of both storage location assignment and path planning. Therefore, the solution objective function (1) is converted to the solution objective function (3), which represents the shortest total time to complete the order picking operation in the period t.

The position assignment constraints are as follows:

$$T_{ij}^m = C_{ij} f_m \quad \forall i, j \in C; m \in M \tag{4}$$

$$C_{ij} = \begin{cases} \frac{g_{ij}}{g_i + g_j + g_{ij}} & i \neq j \\ 0 & i = j \end{cases} \quad C_{ij} \in [0, 1] \tag{5}$$

$$\Sigma_{s=1}^{m} Y_i^m = 1 \quad \forall m \in M \tag{6}$$

$$\Sigma\, \lambda_i \geq c \quad c \in C \tag{7}$$

$$u \cdot m \cdot m\prime \geq \Sigma\, \lambda_i \tag{8}$$

$$\Sigma_{s=1}^{m} Z_m^s = 1 \quad \forall m \in M \tag{9}$$

$$\Sigma_{s=1}^{m} Z_m^s \leq 1 \quad \forall s \in S \tag{10}$$

Equation (4) is the time cost of goods location assignment, expressed by the product of the goods correlation coefficient and the rack turnover rate, reflecting the high frequency of goods and rack storage and maximizes the satisfaction of orders. Among them, the turnover rate of the rack is equal to the mean value of the turnover rate of each good stored on the rack. Equation (5) is the correlation coefficient for the goods, which is the implicit relationship between the two goods, indicating their tendency to appear on the same order at the same time, according to B2C e-commerce warehousing. The historical order data can be calculated. The higher the correlation coefficient for goods i and j, the greater the probability that the two are in the same order. Therefore, the two goods should be stored on the same rack, as shown by Equation (5). The correlation matrix for all the goods can be obtained as follows:

$$R = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1c} \\ c_{21} & c_{22} & \cdots & c_{2c} \\ \vdots & \vdots & \ddots & \vdots \\ c_{c1} & c_{c2} & \cdots & c_{cc} \end{bmatrix}$$

Equation (6) signifies that each good will be assigned to the inventory rack. Formulas (7) and (8) represent the capacity constraint of the rack, indicating that the total number of locations on the inventory rack is greater than the total number of goods, and the total number of goods is greater than the number of types of goods. Equations (9) and (10) are the capacity constraints of the storage area, where Equation (9) indicates that a rack can only be stored in one location, and Formula (10) indicates that each storage location can store a maximum of one rack.

The path planning constraints are as follows:

$$T_i^k = T_i^p + T_i^q + T_i^r \qquad \forall i \in M \tag{11}$$

$$T_{ij}^k = \frac{|x_i - x_j| + |y_i - y_j|}{v_k} \qquad \forall k \in N; \forall i, j \in M \tag{12}$$

$$T_{0i}^k = \frac{|ax_k - x_i| + |ay_k - y_i|}{v_k} \qquad \forall k \in N; \forall i \in M \tag{13}$$

$$T_{j0}^k = \frac{|x_j - ax_k| + |y_j - ay_k|}{v_k} \qquad \forall k \in N; \forall j \in M \tag{14}$$

$$\Sigma_{i \in M} X_{0i}^k = 1 \qquad \forall k \in N \tag{15}$$

$$\Sigma_{j \in M} X_{j0}^k = 1 \qquad \forall k \in N \tag{16}$$

$$\Sigma_{k \in N} \Sigma_{i \in A, i \neq j} X_{ij}^k = 1 \qquad \forall i \in M \tag{17}$$

$$\Sigma_{k \in N} \Sigma_{j \in A, j \neq i} X_{ij}^k = 1 \qquad \forall j \in M \tag{18}$$

$$P(X_{ig}^k) = P(X_{gj}^k) \qquad \forall k \in N; \forall i, g \in A \tag{19}$$

Equation (11) represents the time it takes for AGV k to transport rack i to complete the picking task. Equation (12) is the time that AGV k takes to transport from rack i to j, which means that after AGV k completes the task of transporting rack i, it immediately executes the task of transporting rack j. Equation (13) is the time for the AGV to move from the initial point to rack i, while Equation (14) represents the time that the AGV takes to return to the initial point after completing the handling of rack j. Equations (15) and (16) indicate that the AGV starts from the initial point and returns to the initial point after completing the task. Equations (17) and (18) indicate that each rack will be visited and can only be visited once. Equation (19) indicates that each point on the map has the same probability of being visited.

The variable constraints are as follows:

$$X_{ij}^k \in \{0, 1\} \qquad \forall k \in N; \forall i, j \in A \tag{20}$$

$$X_i^k \in \{0, 1\} \qquad \forall k \in N; \forall i \in A \tag{21}$$

$$Y_i^m \in \{0, 1\} \qquad \forall i, j \in C; m \in M \tag{22}$$

$$Y_j \in \{0, 1\} \qquad \forall j \in C \tag{23}$$

$$Z_m^s \in \{0, 1\} \qquad \forall m \in M \tag{24}$$

Formulas (20)–(24) are the variable constraints of the synergy model; if yes, the value is 1; otherwise, it is 0.

By analyzing the coupling relationship between RMFS storage location assignment and path planning, and fully considering the interrelationship between the various subsystems of the RMFS, a mathematical model for the COSLAPP is established. Taking into account the actual operation of the RMFS, due to the strong cohesion of its various links, a single problem and optimization cannot address the practical issues of the automatic storage system effectively. An RMFS not only needs to store the goods on the racks in

the warehouse, but also needs an AGV to transport the racks where the goods are located according to order requirements. Combining the two can further improve the efficiency of order picking. For the model established in this paper, how to eliminate local optima and avoid the occurrence of optimal storage location assignment and failure to achieve optimal routes must be considered. In the actual situation of the warehousing operation, goods with a high degree of correlation will appear on the same order with a high probability of delivery. In the storage process, such goods will also be stored close to the picking station. Generally speaking, the goods shipment rate and the correlation between the goods are positively correlated. Therefore, the product between the goods correlation coefficient and the turnover rate of the rack is used in the model to represent the time cost of the RMFS location assignment system decision, which directly reflects the pros and cons of the storage location assignment. In addition, when fully considering conflict and obstacle avoidance in AGV path planning, it is also directly related to the advantages and disadvantages of storage location assignment. Thus, we adopt the idea of collaborative optimization to link storage location assignment with path planning, regarding the pros and cons of the location assignment strategy as the main factor for AGV path planning to resolve conflicts and other issues. By solving the transformed objective function, the unit measurement of the system's decision making and actual operation is unified, so as to achieve the goal of COSLAPP.

4. Algorithm Design

4.1. RMFS Warehouse Model Design

The overall storage environment of B2C e-commerce warehouses is constantly changing, and the storage model needs to be refactored frequently; we used the grid map method [55] to model the storage environment and abstract the storage environment as a grid map. For the RMFS warehouse, it is known that there are p picking stations, m inventory racks, n AGVs, and s storage locations ($s \geq m$). Considering the entire smart storage area as a two-dimensional plane, this plane is denoted as O. With the upper left corner as the coordinate origin O, the horizontal axis as the X axis, and the vertical axis as the Y axis, a rectangular coordinate system O_{XY} is established for the plane area O.

The walking unit for each AGV in the RMFS in the horizontal and vertical directions is d, and the maximum values of the plane O on the X and Y axes are Xmax and Ymax, respectively; then, the number of grids in each row is $n_X = X_{max}/d$, and for the grid in each column, the number is $n_Y = Y_{max}$. The picking station (p_i), inventory rack (s_i), AGV (a_i), and rack storage location (s_i) in the system each occupy a grid. We define the coordinate of the first grid in the upper left corner as (0, 0), and in the system, each grid has corresponding coordinates (x, y), where the coordinate position of the dynamically changing inventory rack i is (x_i, y_i), and the coordinate position of AGV k is (ax_k, ay_k). Figure 5 shows the constructed RMFS storage environment model.

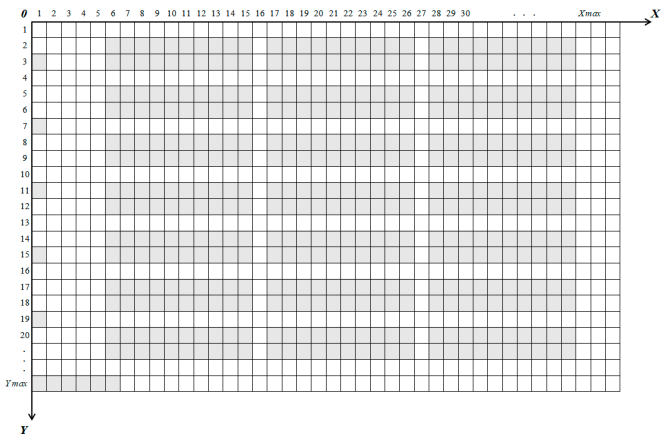


Figure 5. RMFS warehouse environment model.

4.2. Problem Solving Framework Design

For the purpose of improving picking efficiency, the collaborative optimization model is considered from two aspects: One is storing relevant goods in the same rack according to historical order data, so that picking is performed in one rack as much as possible. The goods in the order are then placed on the racks with high frequencies of delivery to a position close to the picking station to reduce the burden of AGV path planning. The second is that, in the AGV path planning, the actual operation of multiple AGVs in the integrated RMFS automatic warehouse is considered. Under the circumstances, the optimal path minimizing the moving distance of the AGV during the operation is output to achieve the optimal coordination of storage location assignment and path planning. Consequently, this paper proposes a two-stage optimization method for RMFS location assignment and multi-AGV path planning (as shown in Figure 6). Time is divided into different intervals, thereby transforming dynamic demand into static demand. Knowing the order demand in each interval, the order demand in the previous interval is the historical order demand; the correlation between the two goods is obtained based on the historical order. Finally, the matrix of correlation between the goods and the goods in the smart warehouse can be obtained. According to the value of the matrix, a goods group (that is, the type of goods stored in a rack) can be obtained, and then, the rack storage can be determined by considering the turnover rate of the rack. A set of rack combinations is then formed. The new orders generated in the next time stage determine the rack requested for order picking based on the known rack combination set, and the path is planned according to the actual order picking situation, comprehensive collisions, conflicts, and other issues, to obtain a more efficient AGV handling path. The efficiency of the whole process of order picking is improved.

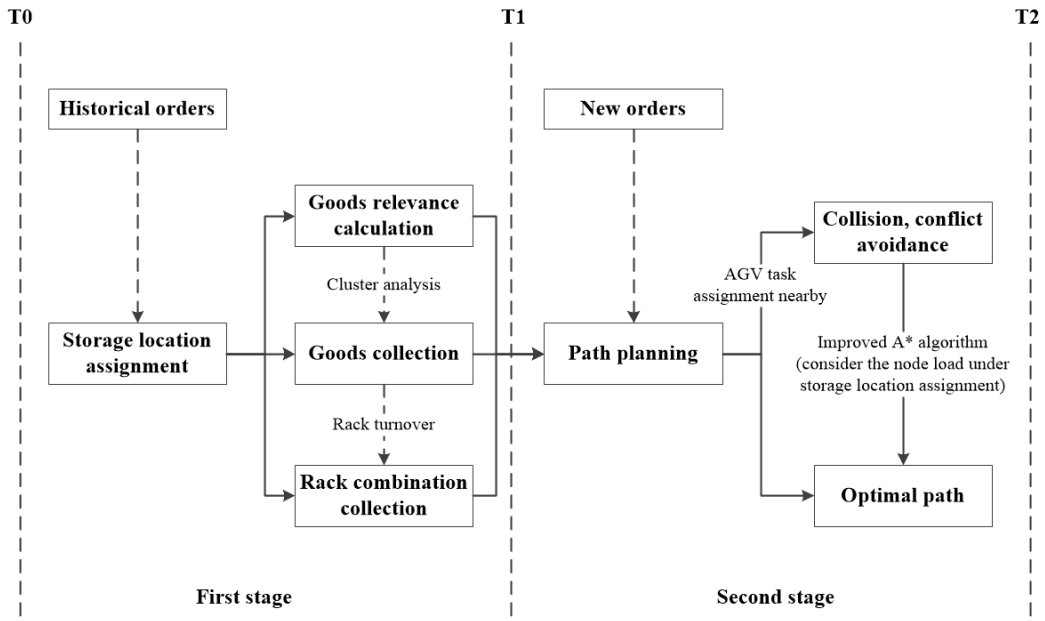


Figure 6. Problem solving framework.

4.3. Storage Location Assignment Strategy

Step 1: Data abstraction. Count the key values of the goods in historical orders (the number of goods types, and the quantities and frequency of each type of good out of the warehouse); according to the correlation between the goods, transform the goods information into a correlation matrix R, and add the corresponding quantity relations of the goods. In the correlation matrix R, the goods information matrix λR containing the quantity of goods is formed.

Step 2: Calculate and update the goods information matrix. Find the maximum correlation in the goods information matrix λR, obtain the two related goods corresponding

to the value, and reassign the correlation value to 0 to obtain the updated RR. Find the goods in the λR that are the most relevant to the above two goods, classify the goods into the same category, store them on the same rack, and update the λR; when goods are all stored on the rack, in the next goods correlation calculation, the correlation between the goods and other goods is 0, and the λR is updated.

Step 3: Calculate the rack turnover rate. Determine whether to add the m' secondary number to a certain rack. If so, calculate the sum of the inventory requirements of all the goods stored on each rack after the allocation of the storage space according to the shipping frequency of each type of good in the historical order, and take the average value. The turnover rate of the rack forms the rack shipment frequency vector α_1, etc., to form the vectors α_2, α_3, etc.; otherwise, execute Step 2.

Step 4: In the updated λR, determine whether all the goods are stored in the rack. If so, arrange the rack shipment frequency vector α in descending order; otherwise, determine whether the relevance of all the remaining goods is 0. If so, store the remaining goods randomly until they are available. Move the racks, and calculate the rack turnover rate to form the shipping frequency α_i; otherwise, go to Step 2.

Step 5: According to the layout of the automatic warehouse, calculate the average shortest distance from each rack storage location to the picking station (expressed by the Manhattan distance) to form a vector β, and arrange it in ascending order according to the distance of each location.

Step 6: Store the arranged racks in the corresponding storage layout, specify that the racks with high turnover rates are preferentially stored in a location close to the picking station, and output the combination set of merchandise racks storing merchandise and inventory rack positions.

4.4. Path Planning Algorithm Design

The core problem in AGV path planning is that, when the requested rack is determined, the handling task is assigned to an AGV, while the rules of collision and conflict are considered, and the route for the handling rack is planned; then, the AGV completes the rack handling task in the shortest time. Ensuring high efficiency for the path planning algorithm is the key to solving the problem. The A* algorithm is a heuristic algorithm, which determines the search direction of the path and finally selects the optimal path by selecting the appropriate cost function. Additionally, it has the characteristics of real-time operation and a high speed, and is widely used in the field of AGV path planning. Its cost function is expressed as follows:

$$f(n) = g(n) + h(n) \qquad h(n) \leq h*(n) \tag{25}$$

where n represents a grid node in the grid map that needs to be the estimated path cost, $g(n)$ refers to the true cost of moving from the starting point to grid node n, and $h(n)$ refers to the grid node n. The heuristic estimation cost of moving to the target node represents the shortest distance from n to the target node. $h^*(n)$ represents the true optimal cost of moving from grid node n to the target node. This cost can estimate its range before the AGV reaches the target node but cannot calculate an accurate value. The selection principle for $h(n)$ is that the value of $h(n)$ is not greater than $h^*(n)$, and the value of $h(n)$ is usually expressed in Manhattan distance (Equation (26)), Chebyshev distance (Equation (27)) or Euclidean distance (Equation (28)).

$$h(n) = |x_n - x_m| + |y_n - y_m| \tag{26}$$

$$h(n) = max(|x_n - x_m| + |y_n - y_m|) \tag{27}$$

$$h(n) = \sqrt{(x_n - x_m)^2 + (y_n - y_m)^2} \tag{28}$$

In an RMFS, the positions of racks and picking stations are fixed and placed in the warehouse according to certain rules. When multiple AGVs are in operation, the racks and

picking stations can be regarded as static obstacles relative to the AGV. When the AGV is carrying inventory racks, in order to ensure safety, it is necessary to maintain a certain safe distance from the obstacles in the environment. It is stipulated that the AGV can only move in four forwards directions—east, west, south, and north (E, W, S, and N)—in RMFS, and the grid environment information with the AGV as the center and d as the radius can be detected at each moment (as shown in Figure 7), so in RMFS path planning, the Manhattan distance is used as the estimation function.

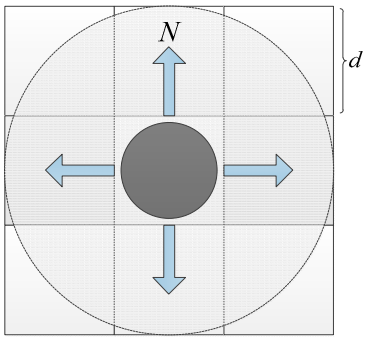


Figure 7. Schematic diagram of AGV movement direction.

After determining the search area, the traditional A* algorithm introduces the open list and the closed list to the node search of the path, and scores the path through the evaluation function, continuously selecting the node with the lowest $f(n)$ value until the target node is searched and the estimated value is found. The path with the lowest value is a static path-finding method at this point; that is, the static path of the AGV from the starting point to the target point is obtained. The AGV drives on a prescribed route. If there is a dynamic obstacle in the middle of the path, the obstacle cannot be avoided. According to the storage strategy adopted by the goods location assignment, in actual application scenarios, the starting points of the AGV are relatively concentrated in the AGV unified stop (charging area) or high-frequency rack storage area, and the target nodes are relatively concentrated in the high- and intermediate-frequency rack storage areas. It may occur that the probability of intersection points for the paths planned by AGVs performing different tasks is greatly increased, so that the AGV traffic in the meeting node area is increased, in addition to the corresponding situation in which the AGV traffic in the node area decreases in other areas. A node area with large traffic has a large load, and there are often delayed or stranded AGVs, which increases the burden of path planning and reduces the overall efficiency of the RMFS. Next, the A* algorithm is improved by considering the load of grid nodes.

4.4.1. Improved A* Algorithm Based on Grid Node Load

The idea for improving A* in this paper is as follows: First, under the rules of storage location assignment, considering the situation of the node load, dynamic node load is introduced into the heuristic evaluation function of the A* algorithm, and a search based on the load situation of each grid node regarding AGVs is performed. The possibility of AGV conflict and the path optimization time are reduced. Second, considering the shortest selection time, in the case of relative measurement, there are still conflicts. At this point, the conflict avoidance rules are determined according to the attributes of the AGV, so the process of path planning is optimal.

As shown in Formula (29), in the A* algorithm evaluation function, the node load is introduced by improving the actual coordination relationship of storage.

$$f(n) = g(n) + h(n) + \alpha L_n \tag{29}$$

where n represents the nth grid node (current point) expanded in the AGV path optimization process, and $f(n)$ is an estimation function that represents the priority of the

grid node to be expanded; the larger the value of $f(n)$, the lower the priority of the grid node; the smaller the value of $f(n)$, the higher the priority of the grid node. $g(n)$ is the shortest distance from the starting grid node to the current grid node; $h(n) + \alpha L_n$ is the node heuristic function considering the load of the grid node; and α is the influence coefficient for the storage location assignment, indicating the influence of the location assignment strategy on the load situation of the grid node, so that the location assignment algorithm and the path planning algorithm can achieve collaborative optimization, to achieve the overall coordinated optimization of RMFS storage location assignment and path planning. $h(n)$ is the traditional heuristic function of the A* algorithm. Based on the previous analysis, this paper uses the Manhattan distance to express $h(n)$. Ln is the load value of the current grid node n, stored in a two-dimensional matrix ($L \times N$), through the dynamic update of the grid node load value, to maintain a two-dimensional matrix ($L \times N$); the calculation formula is as follows:

$$l_i = \begin{cases} l_{i-1} + \frac{T_i}{t_i - t_{i-1}} - G & l_i \geq 0 \\ 0 & l_i < 0 \end{cases} \tag{30}$$

$$T_l = \sum_{i=0}^{l} t_i \tag{31}$$

In the equation, i represents the number of iterations of the grid node load, l_i represents the load value of the grid node after the i-th iteration, t_i represents the time of the i-th iteration, the iteration starts at t_0, and the $t_0, t_1, \ldots, t_{i-1}, t_i, \ldots t_l$ time intervals are equal. T_i represents the total time spent by all the AGVs passing the grid node from t_{i-1} to t_i. G is the grid node cooling constant. If there is no AGV or a small number of AGVs pass through the node from t_{i-1} to t_i, the load of the grid node is reduced accordingly, and the system updates $t_i - t_{i-1}$ at every time interval. A two-dimensional matrix ($L \times N$) and the grid node load value are always greater than or equal to 0.

The load of the grid node is added to the evaluation function, and the load value of the grid node is used as a reference to affect the selection of the grid node in the AGV path optimization process. When the load value of the node is high, the corresponding $f(n)$ value increases, and the corresponding grid priority decreases; when the load value of the node is low, the corresponding $f(n)$ value decreases, and the corresponding grid priority increases. Then, the AGV gives priority to grids with low load values and high priority to the path optimization process, so that the load distribution of each grid node is balanced, reducing the time for multiple AGV path optimizations and improving the operating efficiency of the RMFS.

4.4.2. Reservation Table Mechanism

Maintaining the two-dimensional matrix ($L \times N$) requires dynamically updating the load value of the grid node. The more AGVs a grid node passes in a certain period of time, the longer the load calculation time of the node, and the lower the overall efficiency of the path optimization. To ensure the effectiveness of the improved A* algorithm based on the grid node load, we used the reservation tables for AGV conflict detection and grid node load calculation. On the one hand, a grid node that has an AGV conflict is detected through the reservation table and responds in advance to avoid it, reducing the load of a particular grid node to a certain extent; on the other hand, the load value of the grid node is calculated by counting the number of AGVs that pass a certain grid node at a certain time, and the update of the two-dimensional matrix ($L \times N$) is improved.

In the grid map, when a certain AGV selects the grid node n that will move next time, other AGVs need to take corresponding conflict avoidance measures according to the current situation of the AGV in the process of path optimization. In this regard, this study used the reservation table mechanism to record the number of AGVs passing by a grid node, dynamically detecting the conflict of a grid node and forming a conflict avoidance response in advance. A three-dimensional time reservation table to mark each conflict node in the grid map is created in advance. The reservation table is composed of a data structure,

including the horizontal and vertical coordinates and the three dimensions of time. It represents the one-to-one correspondence between the conflicting nodes in a certain time node. A simplified three-dimensional time reservation table contains the horizontal and vertical coordinates in a certain time interval, in two-dimensional form. When a certain AGV moves to a certain grid node n at the next moment, the corresponding position of the reservation table is queried; if the reservation table indicates that the grid position is not occupied, then the AGV moves to the grid node, and the corresponding reservation table position marks the occupancy of the AGV. After the AGV passes the grid node, the corresponding position of the reservation table deletes the AGV information; when an AGV moves to a certain grid node n at the next moment, the position is displayed in the reservation table. If it is occupied, it means that there is a conflict. At this point, which AGV passes first is judged according to the AGV priority. An AGV with a low priority responds according to the conflict avoidance rules, and the system updates the reservation in real-time according to the movement and location of multiple AGVs. Table 3 shows an example of the reservation table at time T_i $(t_{i-1} - t_i)$. In the RMFS, each AGV has its own identity. When an AGV moves to a grid node in the grid map, the AGV's exclusive identity is used; the identifier marks the location of the corresponding reservation table, so the corresponding grid node is recorded according to the route by which the AGV is about to travel; the number of AGVs recorded by a grid node at a certain moment may be greater than one.

Table 3. T_i $(t_{i-1} - t_i)$ time reservation table.

$x - y$	x_1	x_2	$\cdots$	x_i	$\cdots$	x_n
y_1			$\cdots$			
y_2		a_1, a_4	$\cdots$		$\cdots$	
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$
y_i			a_i			
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$	$\vdots$	$\vdots$
y_n		a_2	$\cdots$		$\cdots$	a_n

4.4.3. AGV Conflict Types and Avoidance Rules

The RMFS is a storage system operated by multiple AGVs, and the actual running space for an AGV is relatively narrow. Some warehouses have a single AGV with one-way traffic in the racking lanes. In addition, in multiple AGV operations, AGVs are constantly running and executing order tasks, so conflicts are inevitable. The following proposes an AGV conflict avoidance rule to reduce the impact of conflicts on the picking efficiency.

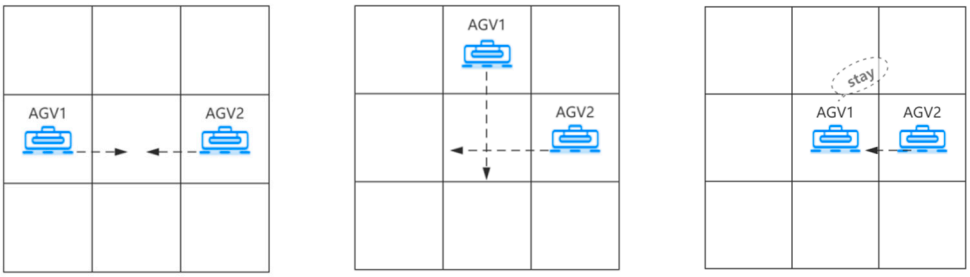
(1) Types of conflict

A conflict between multiple AGVs is actually a combination of conflicts between pairs of AGVs, so it is sufficient to analyze the types of conflict between two AGVs. Combined with the operation of multiple AGVs in the actual storage grid environment, there are three types of conflict:

① Opposite conflict: When multiple AGVs meet head-on during operation, the two AGVs collide with each other (Figure 8a).

② Cross conflict: When multiple AGVs meet at a corner during operation, the AGV has a cross conflict. Figure 8b shows a cross conflict of two AGVs.

③ Stay conflict: When an AGV temporarily stops to avoid conflict, it creates a stay conflict with the AGV behind it (Figure 8c).



(**a**) Opposite conflict. (**b**) Cross conflict. (**c**) Stay conflict.

Figure 8. Types of conflict.

(2) Conflict avoidance rules

In RMFS, the corresponding driving rules are set according to the different working conditions of the AGV, which are specifically divided into the following four categories:

① The AGV is moving the rack to the picking station;
② AGV is heading to the requested rack;
③ The AGV is carrying the rack and returning to the storage area;
④ The AGV has no task and returns to the waiting area (charging area).

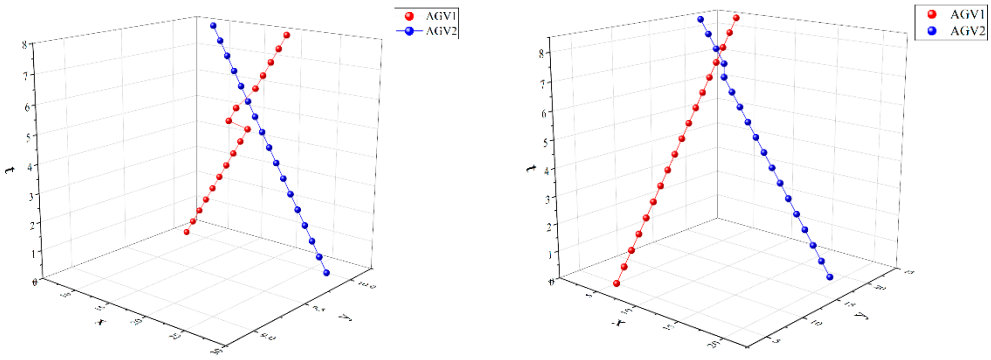
Based on the four types of attributes of the AGV, the priority of the goods is determined according to the rack frequency and the relevance of the goods, and the corresponding priority is assigned to the AGV to achieve conflict avoidance. The AGV priority is divided into 11 levels, as shown in Table 4.

Table 4. Comparison of AGV priority classification.

AGV Attributes	Rack Frequency	Goods Relevance	Goods Priority	AGV Priority
Moving the rack to the picking station	High-frequency rack	Large relevance	1	1
		Little relevance	3	3
	Low-frequency rack	Large relevance	2	2
		Little relevance	4	4
Going to the requested rack	High-frequency rack	Large relevance	5	5
		Little relevance	7	7
	Low-frequency rack	Large relevance	6	6
		Little relevance	8	8
Moving the rack back to the storage area	High-frequency rack	–	–	9
	Low-frequency rack	–	–	10
No task currently	–	–	–	11

Take the working status of AGV as the standard, the priority of the AGV passing the collision point is judged. When two AGVs conflict, according to the priority rules in Table 3, the conflict avoidance rules are determined by combining task, rack, and goods factors. The AGV with the higher priority passes first through the conflict point. There are different collision avoidance rules for different types of conflict. There are four types of rules, as follows:

Rule 1: When AGVs are in conflict, an AGV with a low priority judges the situation of the surrounding grid nodes, treats the AGV with the higher priority as an obstacle, and searches for the next optimal grid node using the improved A* algorithm and drives to it. At this node, the AGV has a high priority, in order to avoid obstacles. After passing the conflicting node, the AGV with higher priority travels along the originally determined route, and the AGV with lower priority travels according to the latest optimization route (Figure 9a).



(**a**) Rule 1 conflict avoidance. (**b**) Rule 2 conflict avoidance.

Figure 9. A schematic diagram of the three-dimensional path of conflict avoidance between two AGVs.

Rule 2: When AGVs are in a cross conflict, the AGV with the lower priority waits in place, and after the AGV with high priority has passed the conflicting node, it passes through the conflict node; both vehicles then drive along the initially determined paths (Figure 9b).

Rule 3: When AGVs are in a stay conflict, the following AGV treats the preceding AGV as an obstacle, finds a new optimal path according to the improved A* algorithm, and drives along this path.

Rule 4: When an AGV at a conflict point is unloaded, one of the AGVs is randomly determined to pass first.

4.4.4. Improved A* Algorithm Steps

Through the reservation table mechanism combined with the improved A* algorithm based on grid node loads, the improvement of the operating efficiency of an RMFS multi-AGV system can be achieved. The specific steps of the improved A* algorithm are as follows:

Step 1: The RMFS updates the reservation table in real-time according to the current position of each AGV.

Step 2: Take the current grid node of the AGV as the starting point, and check the $f(n)$ values of the grids that can pass through the four adjacent grids around the starting point according to the improved evaluation function $f(n)$.

Step 3: Expand the grid node:

(1) When the value of $f(n)$ is different, select the grid node n with the smallest value of $f(n)$ as the current grid; the AGV moves to the current grid and updates the reservation table.

(2) When the value of $f(n)$ is the same, it means that the surrounding grid nodes have the same load. According to the reservation table, check the number of AGVs reserved by adjacent grid nodes a, take a as the number of obstacles, and select the grid with the smallest value of a. The node is the current node, and the AGV moves to the current grid and updates the reservation table.

(3) When the values of $f(n)$ and a are the same, a grid node is randomly selected as the current grid, and the AGV updates the reservation table in the current grid.

Step 4: Judge whether the grid node n is the target end point; if so, stop the search, save the path, and update it in the reservation table at each moment; if not, execute Step 5.

Step 5: Perform conflict detection at the current position of each AGV and detect the surrounding conditions. If no dynamic obstacles are encountered, go to Step 2; otherwise, compare AGV priorities according to the conflict avoidance rules, form a conflict avoidance response, and go to Step 2.

5. Simulation Experiment and Result Analysis

5.1. RMFS Simulation Implementation

This study programmed the RMFS simulation experiment in MATLAB. The essence of simulation is using a computer to simulate the order picking process in an RMFS; it can achieve the following two functions:

(1) It can simulate the order picking process for the RMFS system and dynamically show that multiple AGVs carry out rack handling according to the optimized path of the improved A* algorithm.

(2) The main purpose of the simulation was to study the implementation and operating efficiency of the algorithm. Therefore, in the simulation experiment, the warehouse environment map, the number of AGVs, the number of orders, the number of picking stations, and other parameters could all be changed to verify, in different situations, the reliability and effectiveness of the coordinated optimization method for storage location assignment and path planning proposed in this article.

The grid map shown in Figure 10 is the RMFS simulation environment after setting the map value of the logistics facility. A map value of "1" indicates an inventory rack, "2" indicates an AGV, and "3" indicates a picking station.

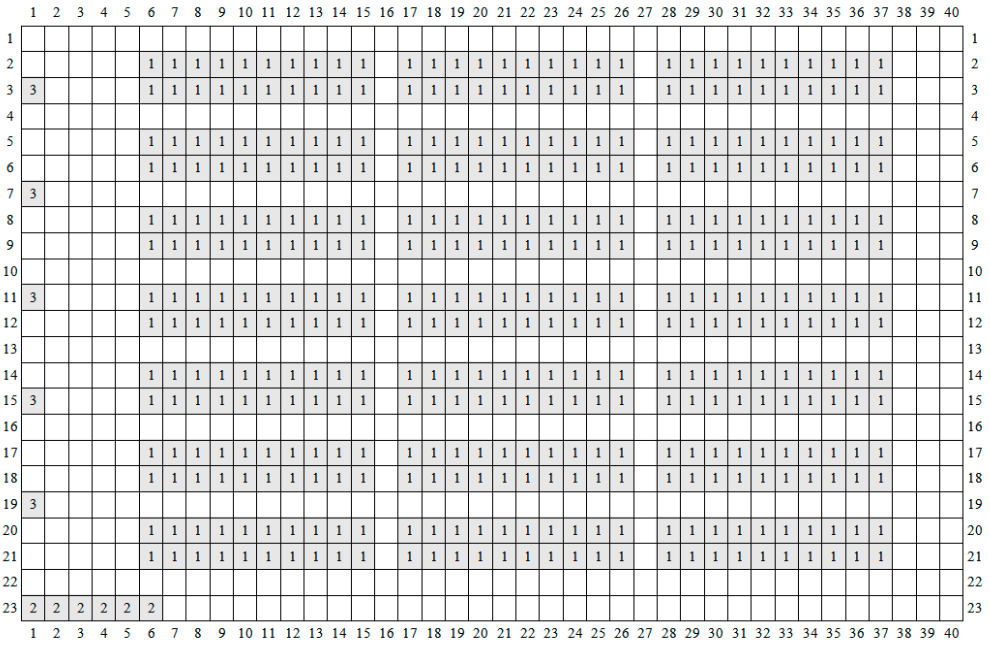


Figure 10. RMFS simulation warehouse environment map.

The adjacency matrix that stores the accessibility between adjacent path points was used to realize map storage. The raster conversion matrix is shown in Figure 11.

In the built model of the warehouse environment for the RMFS simulation experiment, the racks in the system were arranged according to the specifications of 2 × 10 as a group, a total of 21 rack groups, and 420 inventory racks, and task racks are randomly assigned to the picking station (using a station picking time of 10 s/vehicle). After the rack picking was completed, it was returned to the original location for storage. The AGVs were independent of one another and moved forward at a constant speed (v_k = 1 m/s), not considering AGV turning, charging, and failure. According to the description of the above simulation conditions, we designed two groups of comparative experiments. The time and distance to complete 200 order picking tasks were used to verify the effectiveness of the COSLAPP.

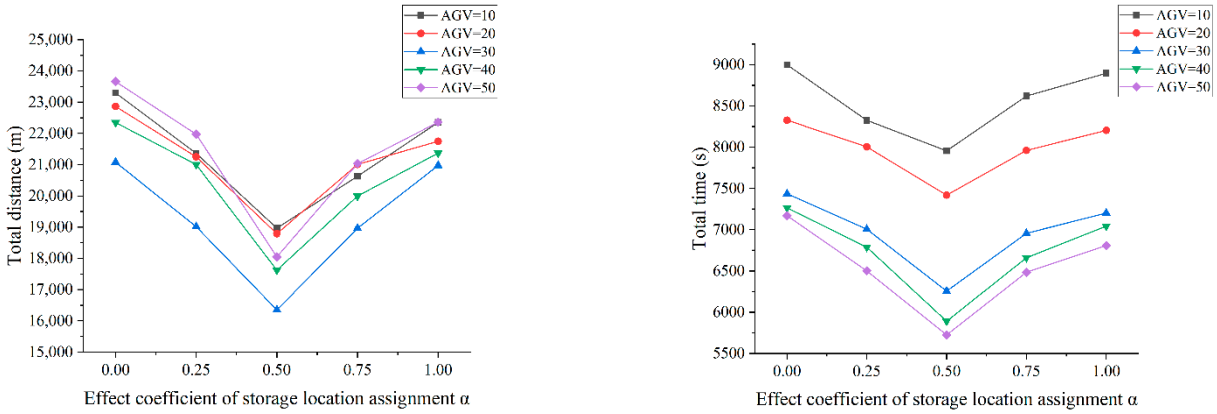
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
3	3	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
6	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
7	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
9	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	3	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
12	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
15	3	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
18	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
19	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
21	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	2	2	2	2	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 11. RMFS warehouse environment map conversion matrix.

5.2. Simulation Results and Analysis

5.2.1. Comparative Analysis of Individual Optimization and Collaborative Optimization

When the two links of storage location assignment and path planning were optimized separately, there were two situations: In one case, the influence of the storage location assignment strategy was not considered, and the influence coefficient of storage location assignment $\alpha = 0$. In this situation, the A* algorithm did not consider the load situation in the path optimization process, and only performed A* algorithm path optimization based on the reservation table and obstacle avoidance rules. The other case was that the full load situation was considered, and the influence coefficient of storage location assignment $\alpha = 1$. Under these circumstances, the A* algorithm path optimization was performed according to the full load, the reservation table, and the obstacle avoidance rule. From an overall point of view, the comparative analysis of separate optimization and collaborative optimization can be transformed into the influence of storage location assignment on path planning. For this, we set α to 0, 0.25, 0.5, 0.75, and 1, and the test was repeated five times, taking the average. The final results are shown in Table 5 and Figure 12.



(**a**) α–s (**b**) α–t

Figure 12. The influence of storage location assignment influence coefficient α on the total distance (s) and total time (t).

Table 5. Itinerary and time according to the coefficients of influence of different storage location assignments.

Number of AGVs	The Value of α	Total Distance (m)	Total Time (s)
10	0	23,298	8997
	0.25	21,362	8326
	0.5	18,966	7955
	0.75	20,627	8620
	1	22,353	8896
20	0	22,865	8327
	0.25	21,251	8003
	0.5	18,790	7418
	0.75	21,006	7961
	1	21,748	8204
30	0	21,077	7436
	0.25	19,014	7006
	0.5	16,350	6255
	0.75	18,963	6956
	1	20,974	7202
40	0	22,348	7265
	0.25	21,001	6787
	0.5	17,622	5890
	0.75	19,994	6660
	1	21,370	7043
50	0	23,659	7169
	0.25	21,973	6501
	0.5	18,048	5724
	0.75	21,034	6484
	1	22,361	6807

From Table 5 and Figure 12, it can be seen that, for the same AGV quantity, when the storage location assignment influence coefficient $\alpha = 0.25, 0.5, 0.75$, the total distance and total time are significantly improved compared to those in the case of $\alpha = 0$ or $\alpha = 1$, which indicates that the difference in the value of the influence coefficient α affects the total distance and total time to complete the order picking; when the location assignment influence coefficient $\alpha = 0.5$, the COSLAPP has the best effect in the simulation. Taking AGV = 30 as an example, the total improvement times of the COSLAPP ($\alpha = 0.5$) are 15.9 and 13.15% lower than those of the independent optimization methods ($\alpha = 0$ and $\alpha = 1$). This shows that the collaborative optimization of storage location assignment and path planning is more effective than the separate optimization of the two problems.

In addition, when the number of AGVs is constant, RMFS handles the same number of order picking tasks, and the time and distance of the AGV handling racks to complete the picking tasks change within a certain scale; that is, when the number of rack handling tasks is constant, the application of COSLAPP can effectively reduce the total distance of AGV handling racks and the total time of order picking when RMFS completes the order picking task. Therefore, it also shows that RMFS COSLAPP is more effective than the separate optimization of the two problems.

The main reason for the higher efficiency of the collaborative optimization method compared to the separate optimization method is that, under the rules of storage location assignment, high-frequency shelves are stored close to the picking station. When RMFS processes a large number of orders at the same time, it is easier to cause problems at each node. The load is too large, and AGV conflicts occur. In this regard, the method of RMFS COSLAPP fully considers the impact of node load caused by the location assignment strategy, and adds the dynamic load of the grid node to the evaluation function. The load value is a reference and affects the grid node selection in the AGV path optimization process; that is, the AGV prioritizes the grid with a low load value and high priority during

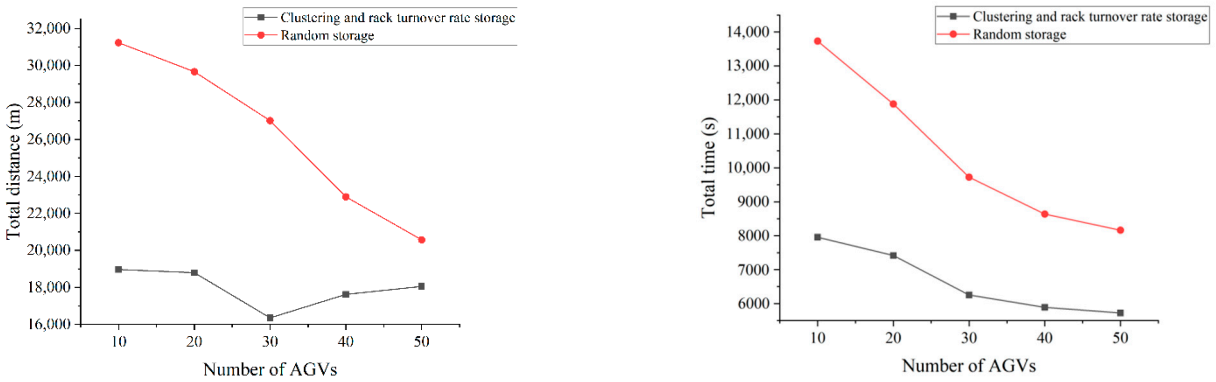
the path optimization process, and the load of each grid node achieves a dynamic balanced distribution, thereby reducing the duration of AGV path optimization and the actual time of rack transportation, effectively improving the efficiency of RMFS picking operations.

5.2.2. Comparative Analysis under Different Storage Location Assignment Strategies

In order to verify the influence of different location assignments on path planning, under the parameter settings of $\alpha = 0.5$ and AGV = 30, the location assignment strategy using goods clustering and the rack turnover rate and the random storage location assignment strategy were examined. The effect of the strategy on order picking is shown in Table 6 and Figure 13.

Table 6. Total distance and total time with different AGV quantities.

Number of AGVs	Clustering and Rack Turnover Rate Storage		Random Storage		Total Time Reduction (%)
	Total Distance (m)	Total Time (s)	Total Distance (m)	Total Time (s)	
10	18,966	7955	31,231	13,733	42.07
20	18,790	7418	29,660	11,880	37.56
30	16,350	6255	27,014	9726	35.69
40	17,622	5890	22,897	8638	31.81
50	18,048	5724	20,571	8161	29.86



(**a**) AGV-s (**b**) AGV-t

Figure 13. The total distance and total time to complete the picking task under different AGV quantities.

Under the goods clustering and rack turnover rate storage assignment strategy, highly correlated goods are stored on one shelf (highly correlated goods indicate that two goods tend to appear on the same order at the same time), and the high turnover racks are stored close to the picking station. When RMFS processes new orders, AGV gives priority to move these racks to complete order picking. From the simulation results shown in Table 6 and Figure 13, we can see that, at the scale of the system simulation, the location assignment strategy using goods clustering and the rack turnover rate is significantly more effective than the random storage location. The storage assigning strategy reduces the total time by approximately 35.4% on average, effectively improve the efficiency of RMFS operations.

However, in the case of a certain warehouse scale, as the number of AGV increases, the probability of AGV conflicts in the warehouse increases, and the time for AGV to avoid conflicts increases. When the number of AGVs in the RMFS matches the size of the warehouse, increasing the number of AGVs cannot effectively reduce the total time of order picking. At this time, as the number of AGVs increases (AGV $>$ 50), the storage location assignment strategy based on goods clustering and shelf turnover is not necessarily more effective than the random storage location assignment strategy. Therefore, it is necessary to set an appropriate number of AGVs for order picking according to the actual order

situation and warehouse scale, so as to achieve an improvement in RMFS picking efficiency and a reduction in warehousing operation costs.

6. Conclusions

The rapid growth of new retail has accelerated the development of the logistics industry and led to higher requirements with regard to the degree of automation and operational capabilities of logistics warehousing to adapt to the economic changes in the new situation. As a new type of "goods-to-person" automatic warehousing system, the RMFS provides a green technology comprising an automatic solution for order picking. The application of sustainable green technology using robots for order picking cannot only promote the sustainable development of the economy, but also promote environmental protection [56], such as avoiding the noise generated by warehousing operations late at night, increasing the energy efficiency of automated storage, and reducing the energy consumption of AGV in RMFS. This paper analyzes the optimization methods and objectives of RMFS storage location assignment and path planning, clarifies the coupling relationship between the two links, transforms the collaborative optimization problem of the two into mathematical problems, and establishes a COSLAPP mathematical model. The location assignment strategy and path planning are the focus of this paper. A goods clustering and rack turnover rate location assignment strategy is proposed, the reservation table mechanism and node load are utilized to improve the A* algorithm and determine the quickest path for order picking tasks.

The main contributions of this article are as follows:

(1) From the perspective of collaborative optimization, the RMFS's storage location assignment and path planning are combined into one optimization problem. At the same time, the impact of the two storage strategies for goods and racks assigned by the storage location is considered. While planning collaborative optimization, coordination between the two subproblems of storage location assignment is achieved, which provides a theoretical reference for solving problems of the COSLAPP.

(2) The coefficient of the influence of RMFS location assignment and path planning are introduced, and a mathematical model for the COSLAPP is established. In the process of designing the algorithm to solve the model, the characteristics of the B2C e-commerce warehouse are considered, and the cluster analysis of the relevance of goods, to enable the storage of strongly-related goods in a rack, is performed. Then, the turnover rate of the rack is obtained according to the shipping frequency of the goods, and the racks with high turnover rates are stored in a location close to the picking station. Under this location assignment strategy, the energy consumption of the automated warehouse is decreased, and the cost is reduced. This achieves an improvement in the storage location assignment; then, based on the influence of the storage location assignment strategy, a reservation table mechanism is used, and AGV conflict avoidance rules are set. The storage location assignment influence coefficient is added to the evaluation function of the A* algorithm as a grid coefficient of the node load, to achieve synergy between the AGV path optimization and storage location assignment. Finally, simulation experiments show that the COSLAPP designed in this paper can effectively improve the efficiency of RMFS order picking and reduce the operating costs of the warehouse of the distribution center.

The RMFS, a new green technology, provides a flexible business process model, using low energy consumption and flexible AGV to complete order picking and help companies quickly respond to new customer needs, new business opportunities, and competitive threats. Since the order picking for RMFS is a combination of multiple subproblems, its difficulty increases with increases in warehouse scale, the number of orders, and the number of AGVs. Although the research in this paper achieved positive results, there are still many aspects that have not been considered or studied in depth. In future research, order batching and task allocation can be considered on the basis of the COSLAPP, and multi-factor and multi-issue collaborative optimization can be carried out to improve the

RMFS order picking efficiency, to achieve the global optimum for the RMFS. Furthermore, in order to make the algorithm more practical, the kinematic constraints of the AGV could also be studied, considering the AGV's acceleration and deceleration, turning, failure, and charging.

Author Contributions: Conceptualization, J.C. and X.L.; methodology, J.C. and X.L.; software, X.L.; validation, J.C. and Y.L.; formal analysis, J.C. and S.O.; investigation, X.L.; resources, J.C.; data curation, X.L.; writing—original draft preparation, J.C., X.L., Y.L., and S.O.; writing—review and editing, J.C. and X.L.; visualization, X.L.; supervision, J.C.; project administration, J.C. and X.L.; funding acquisition, J.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Key Research and Development Project of China (No. 2018YFB1201601).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bassan, Y.; Roll, Y.; Rosenblatt, M. J Internal Layout Design of a Warehouse. *AIIE Trans.* **1980**, *12*, 317–322. [CrossRef]
2. Tompkins, J.A.; White, J.A.; Bozer, Y.A.; Tanchoco, J.M.A. *Facilities Planning*; John Wiley & Sons: Hoboken, NJ, USA, 2010.
3. Hao, J.; Shi, H.; Shi, V.; Yang, C. Adoption of Automatic Warehousing Systems in Logistics Firms: A Technology–Organization–Environment Framework. *Sustainability* **2020**, *12*, 5185. [CrossRef]
4. Mountz, M. Kiva the Disrupter. *Harv. Bus. Rev.* **2012**, *90*, 74.
5. Zou, B.; Xu, X.; Gong, Y.; De Koster, R. Evaluating battery charging and swapping strategies in a robotic mobile fulfillment system. *Eur. J. Oper. Res.* **2018**, *267*, 733–753. [CrossRef]
6. Guizzo, E. Three Engineers, Hundreds of Robots, One Warehouse. *IEEE Spectr.* **2008**, *45*, 26–34. [CrossRef]
7. Lamballais, T.; Roy, D.; De Koster, M. Estimating performance in a Robotic Mobile Fulfillment System. *Eur. J. Oper. Res.* **2017**, *256*, 976–990. [CrossRef]
8. Xia, D.; Zhang, M.; Yu, Q.; Tu, Y. Developing a framework to identify barriers of Green technology adoption for enterprises. *Resour. Conserv. Recycl.* **2019**, *143*, 99–110. [CrossRef]
9. Wurman, P.R.; D'Andrea, R.; Mountz, M. Coordinating Hundreds of Cooperative, Autonomous Vehicles in Warehouses. *AI Mag.* **2008**, *29*, 9–20.
10. Zou, B.; Gong, Y.; Xu, X.; Yuan, Z. Assignment rules in robotic mobile fulfilment systems for online retailers. *Int. J. Prod. Res.* **2017**, *55*, 6175–6192. [CrossRef]
11. Li, X.; Hua, G.; Huang, A.; Sheu, J.-B.; Cheng, T.; Huang, F. Storage assignment policy with awareness of energy consumption in the Kiva mobile fulfilment system. *Transp. Res. Part E Logist. Transp. Rev.* **2020**, *144*, 102158. [CrossRef]
12. Li, Z.; Li, W.; Jiang, L. Research on the Task Assignment Problem of Warehouse Robots in the Smart Warehouse. In Proceedings of the 12th International Symposium on Operations Research and its Applications in Engineering, Technology and Management (ISORA 2015), Luoyang, China, 21–24 August 2015; pp. 29–33. [CrossRef]
13. Valle, C.A.; Beasley, J.E. Order allocation, rack allocation and rack sequencing for pickers in a mobile rack environment. *Comput. Oper. Res.* **2021**, *125*, 105090. [CrossRef]
14. Zhang, J.; Yang, F.; Weng, X. A Building-Block-Based Genetic Algorithm for Solving the Robots Allocation Problem in a Robotic Mobile Fulfilment System. *Math. Probl. Eng.* **2019**, 1–15. [CrossRef]
15. Merschformann, M.; Xie, L.; Erdmann, D. Path planning for Robotic Mobile Fulfillment Systems. *arXiv* **2017**, arXiv:1706.09347.
16. Kumar, N.V.; Kumar, C.S. Development of Collision Free Path Planning Algorithm for Warehouse Mobile Robot. In *Proceedings of the International Conference on Robotics and Smart Manufacturing*; Muthuswamy, S., Zoppi, M., Eds.; Elsevier Science Bv: Amsterdam, The Netherland, 2018; pp. 456–463. [CrossRef]
17. Lee, C.; Lin, B.; Ng, K.; Lv, Y.; Tai, W. Smart robotic mobile fulfillment system with dynamic conflict-free strategies considering cyber-physical integration. *Adv. Eng. Inform.* **2019**, *42*, 100998. [CrossRef]
18. Yuan, Z.; Gong, Y.Y. Bot-In-Time Delivery for Robotic Mobile Fulfillment Systems. *IEEE Trans. Eng. Manag.* **2017**, *64*, 83–93. [CrossRef]
19. Hanson, R.; Medbo, L.; Johansson, M.I. Performance Characteristics of Robotic Mobile Fulfilment Systems in Order Picking Applications. *IFAC-PapersOnLine* **2018**, *51*, 1493–1498. [CrossRef]
20. Merschformann, M.; Lamballais, T.; de Koster, M.; Suhl, L. Decision rules for robotic mobile fulfillment systems. *Oper. Res. Perspect.* **2019**, *6*, 6. [CrossRef]

21. Keung, K.L.; Lee, C.K.M.; Ji, P. Mobile Robots Charging Assignment Problem with Time Windows in Robotic Mobile Fulfilment System. In Proceedings of the 2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Macao, China, 15–18 December 2019; pp. 1329–1333.
22. Gong, Y.; Jin, M.; Yuan, Z. Robotic mobile fulfilment systems considering customer classes. *Int. J. Prod. Res.* **2020**, 1–18. [CrossRef]
23. Jin, G.; Yang, P.; Duan, G. Multiple Deep Layout of Robotic Mobile Fulfillment System. In Proceedings of the 2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA), Bangkok, Thailand, 16–21 April 2020; pp. 230–234.
24. Keung, K.L.; Lee, C.K.M.; Ji, P.; Ng, K.K.H. Cloud-Based Cyber-Physical Robotic Mobile Fulfillment Systems: A Case Study of Collision Avoidance. *IEEE Access* **2020**, *8*, 89318–89336. [CrossRef]
25. Koster, R.B.M.D.; Duc, T.L.; Roodbergen, K.J. Design and Control of Warehouse Order Picking: A Literature Review. *Eur. J. Oper. Res.* **2007**, *182*, 481–501. [CrossRef]
26. Ren, R.; Hu, W.; Dong, J.; Sun, B.; Chen, Y.; Chen, Z. A Systematic Literature Review of Green and Sustainable Logistics: Bibliometric Analysis, Research Trend and Knowledge Taxonomy. *Int. J. Environ. Res. Public Health* **2020**, *17*, 261. [CrossRef] [PubMed]
27. Meneghetti, A.; Monti, L. Multiple-weight unit load storage assignment strategies for energy-efficient automated warehouses. *Int. J. Logist.* **2014**, *17*, 304–322. [CrossRef]
28. Antonella, M.; Eleonora, D.B.; Luca, M. Rack shape and energy efficient operations in automated storage and retrieval systems. *Int. J. Pro. Res.* **2015**, *53*, 7090–7103. [CrossRef]
29. Meneghetti, A.; Monti, L. Sustainable storage assignment and dwell-point policies for automated storage and retrieval systems. *Prod. Plan. Control* **2013**, *24*, 511–520. [CrossRef]
30. Bartolini, M.; Bottani, E.; Eric, H. Green warehousing: Systematic literature review and bibliometric analysis. *J. Clean. Prod.* **2019**, *226*, 242–258. [CrossRef]
31. Hristov, I.; Chirico, A.; Appolloni, A. Sustainability Value Creation, Survival, and Growth of the Company: A Critical Perspective in the Sustainability Balanced Scorecard (SBSC). *Sustainability* **2019**, *11*, 2119. [CrossRef]
32. Nantee, N.; Sureeyatanapas, P. The impact of Logistics 4.0 on corporate sustainability: A performance assessment of automated warehouse operations. *Benchmarking Int. J.* **2021**. (ahead-of-print). [CrossRef]
33. Tappia, E.; Marchet, G.; Melacini, M.; Perotti, S. Incorporating the environmental dimension in the assessment of automated warehouses. *Prod. Plan. Control* **2015**, *26*, 824–838. [CrossRef]
34. Lerher, T.; Edl, M.; Rosi, B. Energy efficiency model for the mini-load automated storage and retrieval systems. *Int. J. Adv. Manuf. Technol.* **2014**, *70*, 97–115. [CrossRef]
35. Fichtinger, J.; Ries, J.M.; Grosse, E.H.; Baker, P. Assessing the environmental impact of integrated inventory and warehouse management. *Int. J. Prod. Econ.* **2015**, *170*, 717–729. [CrossRef]
36. Bechtsis, D.; Tsolakis, N.; Vlachos, D.; Iakovou, E. Sustainable supply chain management in the digitalisation era: The impact of Automated Guided Vehicles. *J. Clean. Prod.* **2016**. [CrossRef]
37. Witczak, M.; Majdzik, P.; Stetter, R.; Lipiec, B. Multiple AGV fault-tolerant within an agile manufacturing warehouse. *IFAC-PapersOnLine* **2019**, *52*, 1914–1919. [CrossRef]
38. Kavakeb, S.; Nguyen, T.T.; Mcginley, K.; Yang, Z.; Murray, R. Green vehicle technology to enhance the performance of a European port: A simulation model with a cost–benefit approach. *Transp. Res. Part C Emerg. Technol.* **2015**, in press. [CrossRef]
39. Hausman, W.H.; Schwarz, L.B.; Graves, S.C. Optimal Storage Assignment in Automatic Warehousing Systems. *Manag. Sci.* **1976**, *22*, 629–638. [CrossRef]
40. Gu, J.; Goetschalckx, M.; McGinnis, L.F. Research on warehouse operation: A comprehensive review. *Eur. J. Oper. Res.* **2007**, *177*, 1–21. [CrossRef]
41. Malmborg, C.J. Optimization of cube-per-order index warehouse layouts with zoning constraints. *Int. J. Prod. Res.* **2007**, *33*, 465–482. [CrossRef]
42. Pan, J.C.-H.; Shih, P.-H.; Wu, M.-H. Storage assignment problem with travel distance and blocking considerations for a picker-to-part order picking system. *Comput. Ind. Eng.* **2012**, *62*, 527–535. [CrossRef]
43. Chiang, D.M.-H.; Lin, C.-P.; Chen, M.-C. Data mining based storage assignment heuristics for travel distance reduction. *Expert Syst.* **2012**, *31*, 81–90. [CrossRef]
44. Zhang, R.-Q.; Wang, M.; Pan, X. New model of the storage location assignment problem considering demand correlation pattern. *Comput. Ind. Eng.* **2019**, *129*, 210–219. [CrossRef]
45. Roy, D.; Nigam, S.; de Koster, R.; Adan, I.; Resing, J. Robot-storage zone assignment strategies in mobile fulfillment systems. *Transp. Res. Part E Logist. Transp. Rev.* **2019**, *122*, 119–142. [CrossRef]
46. Onal, S.; Zhang, J.R.; Das, S. Modelling and performance evaluation of explosive storage policies in internet fulfilment warehouses. *Int. J. Prod. Res.* **2017**, *55*, 5902–5915. [CrossRef]
47. Weidinger, F.; Boysen, N. Scattered Storage: How to Distribute Stock Keeping Units All around a Mixed-Shelves Warehouse. *Transp. Sci.* **2018**, *52*, 1412–1427. [CrossRef]
48. Yuan, R.; Cezik, T.; Graves, S.C. Stowage decisions in multi-zone storage systems. *Int. J. Prod. Res.* **2018**, *56*, 333–343. [CrossRef]
49. Yuan, R.; Graves, S.C.; Cezik, T. Velocity-Based Storage Assignment in Semi-Automated Storage Systems. *Prod. Oper. Manag.* **2019**, *28*, 354–373. [CrossRef]

50. Krenzler, R.; Xie, L.; Li, H. Deterministic Pod Repositioning Problem in Robotic Mobile Fulfillment Systems. *arXiv* **2018**, arXiv:1810.05514, preprint.
51. Hosseininejad, S.; Dadkhah, C. Mobile robot path planning in dynamic environment based on cuckoo optimization algorithm. *Int. J. Adv. Robot. Syst.* **2019**, *16*, 172988141983957. [CrossRef]
52. Wang, C.; Wang, L.; Qin, J.; Wu, Z.; Duan, L.; Li, Z.; Cao, M.; Ou, X.; Su, X.; Li, W.; et al. Path Planning of Automated Guided Vehicles Based on Improved A-Star Algorithm. In Proceedings of the 2015 IEEE International Conference on Information and Automation, Yunnan, China, 8–10 August 2015; pp. 2071–2076.
53. Zhang, Z.; Guo, Q.; Chen, J.; Yuan, P. Collision-Free Route Planning for Multiple AGVs in an Automated Warehouse Based on Collision Classification. *IEEE Access* **2018**, *6*, 26022–26035. [CrossRef]
54. Zuiga, J.B.; Saucedo Martinez, J.A.; Salais Fierro, T.E.; Marmolejo Saucedo, J.A. Optimization of the Storage Location Assignment and the Picker-Routing Problem by Using Mathematical Programming. *Appl. Sci.* **2020**, *10*, 534. [CrossRef]
55. Moravec, H.; Elfes, A. High Resolution Maps from Wide Angle Sonar. In *Proceedings of the 1985 IEEE International Conference on Robotics and Automation, St. Louis, MO, USA, 25–28 March 1985*; IEEE: New York, NY, USA, 2005. [CrossRef]
56. Fujii, H.; Managi, S. Decomposition analysis of sustainable green technology inventions in China. *Technol. Forecast. Soc. Chang.* **2019**, *139*, 10–16. [CrossRef]