Improving Robotic Mobile Fulfillment System Efficiency

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Abstract: A Robotic Mobile Fulfillment System (RMFS) is a novel "parts - to - picker" automated order picking system. In this system, robots are responsible for transporting movable shelves to picking stations for pickers. It is particularly suited for e - commerce distribution centers that handle a vast array of small products and experience strong demand fluctuations. This system plays an essential and decisive role in enhancing logistics efficiency and reducing warehouse costs significantly. This paper reviews the optimization studies on RMFS from 2017 to 2023. By adopting the three - level framework of "strategy - tactical - operational" to conduct this research, the strategic level decision involves the layout of the warehouse, like determining the placement of picking station. The tactical level decision focuses on resources allocation, such as robots and inventory. The operational level deals with the actual order picking task, like optimizing the picking sequence. Through this approach, decision - making at different levels can be better and more precisely clarified. and we summarize the key factors influencing the efficiency at each level. Eventually, this paper discovers that the decisions within these three levels are mutually influential. Hence, an in - depth analysis of their impacts is carried out, and detailed future research directions are proposed.

Keywords: Robotic Mobile Fulfillment System; RMFS; Order Picking; Automatic Warehousing System; Order Picking Efficiency

1. Introduction

The rise of e-commerce has created the need for new warehousing systems to handle the increase in orders efficiently [1]. Traditional manual picking becomes inefficient due to the small size and large variety of e-commerce orders [2]. To overcome this, warehouses are turning to automation, with the Robotic Mobile Fulfillment System (RMFS) emerging as a key solution [3,4]. RMFS, featuring mobile robots, movable shelves, picking stations, and pickers, streamlines the picking process and enhances efficiency [5]. Despite growing interest and research, comprehensive reviews on RMFS remain limited.

We found 4 review articles related to RMFS, Da Costa Barros and Nascimento reviewed seven aspects of RMFS, including its system architecture, scheduling, path planning, and performance improvement by considering the different functions and technologies of RMFS [6]. However, that classification method may cause different aspects to intersect with other aspects of research at the same time, such as performance improvement and the path planning or scheduling. Indeed, Azadeh et al.[7] mentioned the summary of RMFS in their review of automated warehouses, which classifies the literature into three aspects using the perspectives of system design: system analysis, design optimization, and operations planning and control. That research perspective is similar to the classification perspective used in this paper, but still ignores the interrelationships between the various levels, The part of RMFS mentioned by Jaghbeer et al. [8] in their review of automated order picking systems also does not classify them, but rather treats the system as a whole entity, only focusing on the design and performance optimization of RMFS, and the studied links between design and performance. Benavides-Robles et al. [9] classified the Robotic Mobile Fulfillment System (RMFS) into three subproblems: path planning, zoning, and assignment, and summarized the techniques currently applied to these problems. Then compared to the reviews of the above three cited scholars, this current paper has three significant focuses and differences as follows:

(1) Classifies the research on RMFS systems into three levels: the strategic (warehouse

layout), the tactical (resource allocation), and the operational (order picking).
(2) Summarizes the influencing factors of each level about the operation efficiency of RMFS.
(3) Explores the interrelationships among these levels, and how they influence each other.
The rest of the paper is structured as follows: Section 2 discusses the data collection, Section 3 review the literature and analyzes the strategic, tactical, and operational factors related to RMFS use and reveals the interrelationships and links between the three levels, Section 4 concludes with a summary, Section 5 proposes the future research directions.

2. Research Methods

To achieve our research goals, we conducted a targeted search for RMFS-related studies. We used "Robotic mobile fulfillment system" and "RMFS" as keywords, searched in Scopus and Google Scholar, and yielding 552 studies. We then filtered these by focusing on English-language, peer-reviewed journal articles from 2017 to 2023. After reviewing titles, abstracts, and keywords, we narrowed down to 302 documents from Scopus and 75 from Google Scholar. After removing duplicates and less relevant documents, we selected 46 high-quality papers closely related to RMFS performance studies.
To achieve our research goals, we conducted a targeted search for RMFS-related studies. We used "Robotic mobile fulfillment system" and "RMFS" as keywords, searched in Scopus and Google Scholar. Eventually, 302 articles were found on Scopus and 75 articles on Google Scholar. First, 116 duplicate articles were deleted. Secondly, 56 articles that were not relevant to the theme and theoretical articles were deleted. Finally, after titles, abstracts, and keywords, and entire articles, 12 articles were deleted. In the end, we selected 46 high-quality papers closely related to RMFS performance studies. (Figure 1 notes the process of searching and filtering these studies).

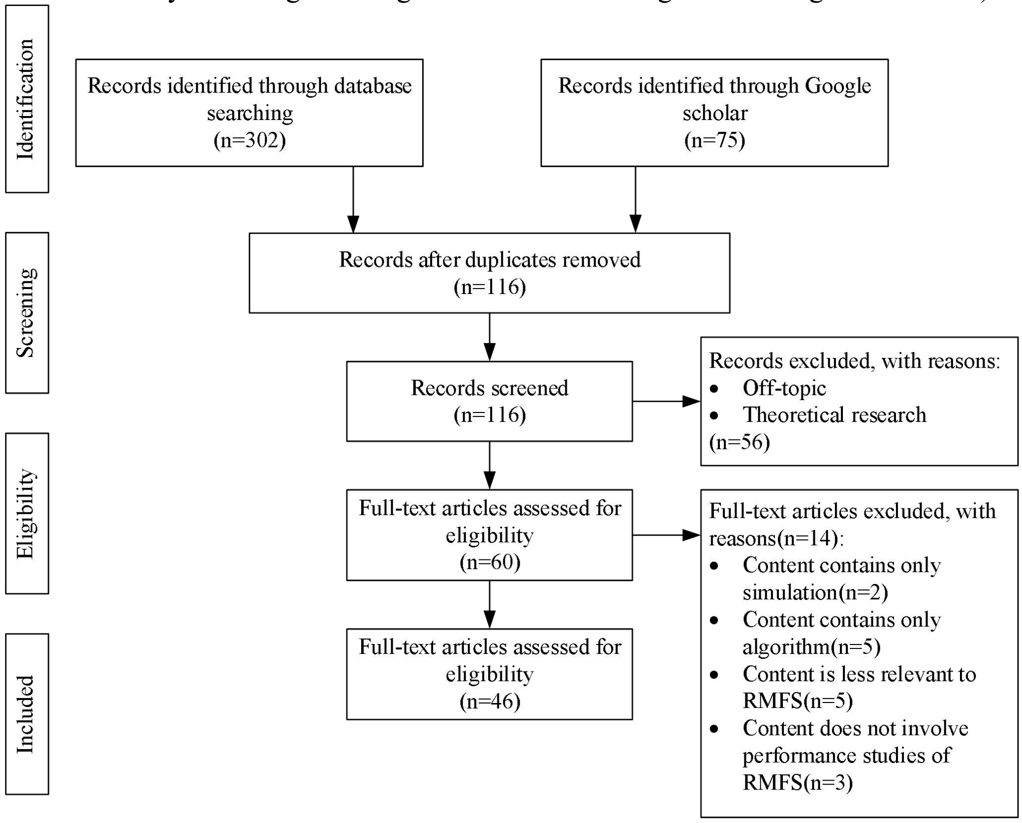

Figure 1. The Collection Process Used for Article Searching and Selection in this Study

3. Results Analysis

Based on the classification methods mentioned in Li et al. [10] and Merschformann et al. [11], we categorized RMFS decision-making into strategic, tactical, and operational levels. This novel classification is based on decision timeframes: strategic for long-term planning over years to decades, tactical for medium-term plans of months to a year, and operational for daily system management, the overall framework of the article is shown in Figure 2.

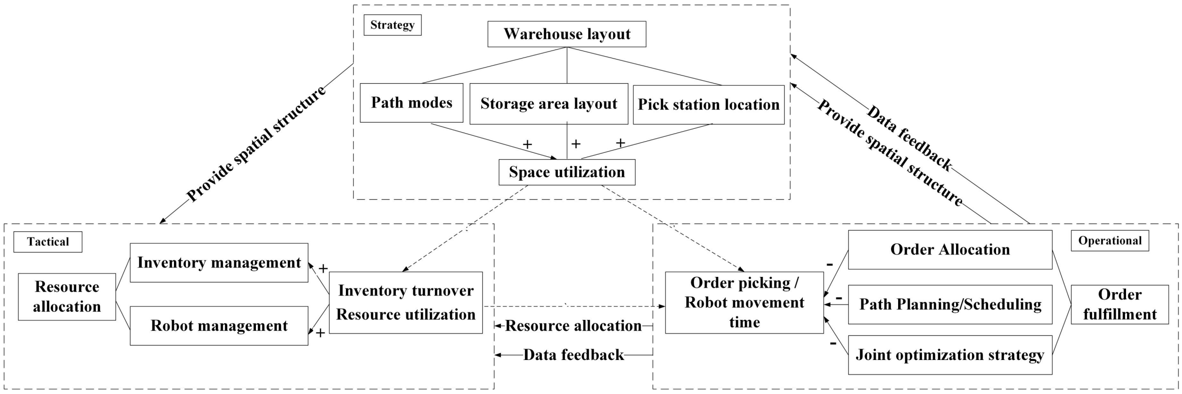

Figure 2 Framework for Robotic Mobile Fulfillment System (RMFS) Research Categories

3.1 The Strategic Level

The layout of the RMFS is mainly considered at the strategic level, three aspects are summarized: the picking station location, the storage area layout and the aisle deployment, the specific contents of the summary are shown in Table 1.

Table 1. Summary of Literature Related to the Strategic Level

Reference	Objective	Problem solved	Influencing factors
[10]	Maximize space utilization	Low warehouse utilization	Storage area layout
[12]	Maximize order throughput	Unreasonable warehouse layout	Pick station location
[13]	Minimize task completion time	Order arrival rates are uneven	Pick station location
[14]	Turnover time of order, system throughput	Low warehouse utilization	Storage area layout
[15]	Maximize order throughput	Unreasonable warehouse layout	Pick station location
[16]	Maximize order throughput	Poor space utilization of single-level RMFS	Storage area layout
[17]	Maximize order throughput	Unibidirectional path for warehouses with low throughput	Path mode
[18]	Minimize the distance the robot movement	Excessively long picking paths	Storage area layout

3.1.1 Picking station location

The location of the picking station significantly impacts the robot's travel time and the overall efficiency of RMFS operations. Lamballais et al. [12] found that the position of the picking station on both sides of the storage area affects system throughput differently, with zoning making a significant difference. They discovered that placing workstations on the two long sides outperforms other layouts, and a width-to-length ratio of 0.5 seems optimal for order throughput time with various workstation configurations [13]. Setting more picking stations in the direction of more aisles facilitates robot access and reduces travel time [14]. These studies indicate that locating picking stations closer to the aisles enhances RMFS operational efficiency. To minimize robot travel distance and processing time, a layout plan was proposed with picking stations placed inside the storage area [15].

3.1.2 Storage area layout

To enhance space utilization in RMFS, vertical storage area types, such as multi-level RMFS, have been introduced [16]. In this system, each layer uses conveyor belts to transport picked items and consolidate split orders from multiple picking stations, significantly improving space utilization. Additionally, a puzzle-based storage system (PBS) has been proposed, where shelves are adjacent to the aisles for direct item retrieval, using only half the storage area for aisles. Experiments show that the RMFS with a PBS layout can save an average of 10% of storage space [10].

3.1.3 Aisle deployment

Research on picking station location and storage area layout in RMFS has predominantly focused on unidirectional aisle patterns to prevent deadlocks. Luo and Zhao introduced a bidirectional RMFS mode, which achieves peak output with fewer robots [17]. Traditionally, RMFS aisles are straight and parallel with right-angle intersections.

However, Yang et al. [18] proposed a 'flying-v' layout to reduce the total robot travel distance, which was shown to save 8%-26% of travel distance.

3.2 The Tactical Level

At the tactical level, the decisions are primarily about resource allocation, including storage allocation and robot management, the specific contents of the summary are shown in Table 2.

Table 2. Summary of Literature Related to the Tactical Level

Reference	Objective	Problem solved	Influencing factors
[19]	Maximize SKU similarity	Unreasonable item storage location	Inventory turnover
[20]	Minimize task completion time	Unreasonable item storage location	Inventory turnover
[21]	Minimize task completion time	Unreasonable item storage location	Inventory turnover
[22]	Minimize robot movement time	Unreasonable item storage location	Inventory turnover
[23]	Maximize SKU similarity	Unreasonable item storage location	Inventory turnover
[24]	Maximize SKU similarity and order similarity	Unreasonable item storage location	Inventory turnover
[25]	Minimize task completion time	Picking lane congestion	Robot utilization
[26]	Maximize order throughput	Order prioritization management	Robot utilization
[27]	Minimize system operating costs	human picking error	Inventory turnover

3.2.1 Storage allocation

To minimize shelf movements and robot travel distance, it is essential to establish rules for item storage allocation, which determine the placement of shelves and areas for items. Ma et al. [19] introduced a scattered storage policy for RMFS, taking into account SKU classification, correlation, and inventory dispersion. Keung et al. [20] proposed a data-driven approach for RMFS region allocation using clustering and storage location assignment. Lamballais et al. [21] suggested dispersing inventory across multiple shelves to locate items closer to picking stations. Cezik et al. [22] modelled policies based on unit velocity, stowing higher velocity units on higher velocity pods, which resulted in significant travel-time reduction. Kim et al. [23] recommended placing frequently ordered items on the same shelf to reduce shelf movements. Additionally, some scholars conduct research by comprehensively considering multiple factors. Yang[24], for instance, studied the combined optimization strategy of item storage and order batching, aiming to minimize the robot's movement time by leveraging the similarity of items and orders in experiments. Overall, these joint research strategies offer a more comprehensive and efficient solution for RMFS by holistically considering multiple factors.

3.2.2 Robot management

For the robot's management, the main attention is paid to the determination of their number and battery management. The optimal number of robots in RMFS is key to balancing operational efficiency and costs. Chi et al. [25]suggest that the ideal number of AGVs should match task demands and arrival rates. Gong et al. [26] categorized orders into expedited and standard deliveries to determine the minimum robot requirement. In recent years, there have been few studies on the charging strategy of robots in RMFS. Zou et al. [2]compared the three strategies of battery swapping, inductive charging, and plug-in charging, and concluded that for system throughput time and performance indicators, inductive charging had the best performance, and the battery swapping strategy was better than automatic plug-in charging. Still, the annual cost of inductive charging was also cost-effective than the cost of the other two strategies [27].

3.3 Operational Level

The decision-making problems at the operational level are divided into single optimization strategy research and joint optimization strategy research. Single optimization focuses on improving one aspect, while joint optimization aims to enhance overall performance by considering multiple factors simultaneously, the specific contents of the summary are shown in Table 3.

Table 3. Summary of Literature Related to the Operational Level

Reference	Objective	Problem solved	Influencing factors
[3]	Minimize task completion time	Changes in order volume	The length and height of the order volume

[28]	Minimize task completion time	Uneven task distribution	Relevance of the task
[29]	Minimize the distance the robot movement	Dynamic changes in orders	Order picking time
[31]	Maximize robot utilization	Storage area partitions	Order picking time
[32]	Minimize task completion time	Crowded roads inside warehouses	Order picking time
[33]	Minimizes the energy consumption of the robot	Energy-consuming robots	Robot movement time
[34]	Minimize the probability of deadlocks	Traffic jams on picking roads	Robot movement time
[35]	Minimize task completion time	Inefficient order picking	Order picking time
[36]	Minimize the number of shelves	Inefficient order picking	Order picking time
[37]	Minimize task completion time	Inefficient order picking	Order picking time
[38]	Minimize task completion time	Inefficient order picking	Order picking time
[39]	Minimize task completion time	Long decision-making time	Order picking time
[41]	the number of pod visits	Robots operate inefficiently	Robot movement distance
[42]	Mining the total operation cost	Local optimization efficiency cannot be maximized	Robot movement distance

3.3.1 Order allocation

In RMFS, order allocation is crucial for fulfillment efficiency and impacts robot scheduling. Yuan et al. [28] studied a task allocation method applicable to small and medium-sized e-commerce enterprises, and proposed a task time cost model that considers task relevance and can significantly improve the task allocation efficiency. However, dynamics and uncertainties should be taken into account for task assignment in large-scale and variable application scenarios. Therefore, to be more realistic, many scholars add more uncertainties to the comprehensive analysis. Lamballais et al. found that dynamically reallocating resources based on workload outperforms traditional strategies under varying demand [3]; Li et al. [29] developed a model where robots can participate in task allocation, enhancing the number of orders picked and reducing travel when idle.

3.3.2 Path planning/scheduling

The aim of this research is to ensure that the robot has no collisions during driving. In order to find the movement path of the robot more quickly, Luo et al. proposed an AG-DQN algorithm that can find the shortest path in less time based on the changing scenes and narrow spaces of RMFS. Gharehgozli and Zaerpour [30] investigated robot scheduling for fulfilling multiple customer orders from a single picking station, prioritizing tasks based on order urgency. Roy et al. [31] compared dedicated and pooled robots, finding that pooled robots reduce order-picking throughput time but may affect replenishment times. Sun et al. [32] proposed an interference-free, bidirectional AV scheduling approach using the A* algorithm, which was more efficient than unidirectional paths for small RMFS. Zhou and Zhu[33] focused on green scheduling for mobile robots, aiming to minimize energy consumption. Li and Fan[34] developed a cellular automata-based RMFS simulation framework (SFRMFSCA) to improve picking efficiency by reducing the risk of large-scale deadlocks with adaptive traffic light control strategies.

3.3.3 Joint optimization strategy

In order to obtain the global optimal order picking scheme, many scholars have begun to jointly optimize multiple aspects. For example, Xie et al. [35] focus on decisions about order and shelf allocation, and proposed a new MIP model to integrate both decision problems; Valle and Beasley[36] incorporated shelf sequencing to the previous two research areas, and divided the problem into two sub-problems, still the split order was not considered. Wang et al. [37] extended Valle's research to allow shelves to be accessed at multiple picking stations during the picking process and proposed a two-stage hybrid heuristic algorithm framework to solve this problem; Boysen et al. [38] then studied the order and shelf sequencing problems, providing a decomposition program for simulated annealing to solve these two problems, respectively. Justkowiak[39] and Pesch introduced a mixed integer programming model with a polyhedral heuristic for medium-sized instances. Building on this foundation, Yang et al. [40] combined shelf allocation into a MIP model, and found that joint optimization can reduce the robot task by 50.8% and 32.0%, respectively. Teck and Dewil[41] conducted more research, considering the above problems and robot scheduling, finding that joint optimization can save 10% of the operating cost. However, this proposed model is only applicable to small-scale examples and is not feasible for practical application. Zhang et al. [42] studied the joint optimization problem of order sequencing and robot scheduling, and numerical experiments showed that the MINLP model is helpful for saving costs. It can be seen that the order picking sequence and robot scheduling are interrelated.

3.4. Connection Between the Three Level

After conducting a literature review on the strategic, tactical, and operational levels of RMFS, we learned that these three levels are indeed closely interconnected. Therefore, we will further analyze their interplay.

3.4.1 Strategic level → Tactical level, Operational level

At the strategic level, the overall layout of the warehouse is planned. This process provides the basis for a spatial structure at the tactical level, allowing for a more efficient deployment of resources. For example, the RMFS fishbone layout proposed by Wang et al. allows robots to travel not only through vertical and horizontal aisles but also through diagonal aisles, effectively reducing the travel distance for shelf allocation optimization by 20% [43]. Yang et al. [14] analysed the impact of the number of robots on system performance in single-depth and multi-depth compact layouts, and believe that under the premise of meeting the requirements of the shelf layout, setting up more vacancies can improve the utilization rate of robots. The above two studies have shown how the tactical level affects the system performance from a strategic level; The layout also has a direct impact on the efficiency and process of order picking. Li et al. [44] studied the influence of different warehouse layouts on the path optimization problem in the case of warehouse layout based on bidirectional channel and cross channel. Luo et al applied the proposed algorithm to 5 different RMFS model layouts for simulation operations when exploring the shortest path of the robot [4]. Based on the multi-layer RMFS layout, Tadumadze et al. studied the joint optimization of order arrangement and shelf arrangement [16].

3.4.2 Tactical Level → Operational Level

Inventory management and robot management decisions at the tactical level ensure that there are sufficient resources at the operational level to carry out the tasks. For example, when Bolu and Korcak[45] studied order assignment, they considered the robot's battery level and inventory status; Merschformann et al. evaluated the impact of these operational-level decisions on the system throughput by changing the number of robots and the number of SKUs when studying the joint optimization of order scheduling and shelf scheduling [11]; Li et al. mentioned in their study that in the case of a high-density warehouse layout, the higher the warehouse utilization rate would be, and a certain level of efficiency would be maintained [10].

3.4.3 Operational Level → Strategy Level, Tactical Level

The operational level in RMFS oversees order fulfilment and provides critical data and feedback to strategic and tactical decision-making. Real-time data generated includes robot travel distances and order picking times. Zhu and Li[46] emphasize the importance of managing the number of robots to match operational performance and order arrival rates, thereby reducing maintenance costs. Yang et al. [18] used travel distance to optimize picking station positions between layouts, while Yuan et al. [28] determined optimal robot numbers and capacities based on order urgency. Kim et al. [23] proposed storage plans based on item similarity to minimize robot movement and shelf interactions. Chi et al. [25] stress the need to consider task arrival rates when determining the number of robots. This data facilitates flexible adjustments and optimizations across all levels, reflecting the operational impact on strategic and tactical planning.

4. Conclusions

This paper examines RMFS in e-commerce warehouses by reviewing 46 articles from 2017 to 2023. It reveals the multi-level decision-making structures and their interconnections within RMFS, through a framework of strategy, tactics, and operations. The goal is to optimize tasks and environments within RMFS, enhancing operational efficiency and customer satisfaction.

In this system, information flows among the strategic, tactical, and operational levels to create a dynamic feedback loop. The strategic

level offers a spatial structure for the other two levels. Meanwhile, the allocation of resources at the tactical level guarantees the successful execution of specific picking tasks at the operational level. This operational level, in turn, influences the adjustment and optimization at the strategic and tactical levels through the utilization of real-time data and process feedback. This combination forms a decision-making chain that extends from long-term planning to medium-term resource allocation and then to specific implementation. The establishment of this decision-making chain endows managers with the ability to respond to change more rapidly and more flexibly. Real-time data and feedback from the operational level enable managers to make practical and effective decisions in a shorter period of time. This rapid feedback loop helps reduce risk, optimize resource utilization, and enhance the adaptability of the entire system.
The multi-level decision-making structure is not limited to RMFS. It offers managers a reference for applying it across different environments and industries to enhance their systems' responsiveness to complex challenges.

5. Future Research Directions

Future research in RMFS should focus on:
(1) Given the interconnection between strategic, tactical, and operational levels, joint optimization is of crucial importance for cost reduction and efficiency enhancement. Future studies can explore multi-objective optimization methods to balance system performance and coordinate different optimization objectives across levels to achieve the best combined benefits.
(2) Future algorithmic solutions could combine deep learning models, which can understand problem structures and features, with optimization algorithms for global search and efficient convergence. This hybrid approach may improve algorithmic performance and adaptability.
(3) Despite the focus on automation, the human role in the picking process is significant. Research should explore closer collaboration between AI systems and human operators, particularly in scenarios requiring direct human-robot interaction.

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