Automated warehouse systems: Finding blanks

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Abstract. E-commerce companies are facing a challenge in terms of customer service experience: faster and more frequent deliveries. Therefore, order picking productivity becomes a critical factor to establish a competitive advantage and, as a consequence, automation has been being incorporated into more warehouse systems, primarily to help order pickers to improve process performance. In addition, new automated picking systems have not yet been addressed or have received little attention from academia.

Then, this project addresses the problem by doing research about automated configurations and, as its main contribution, offers a new proposal to categorize these systems. Furthermore, a list of relevant topics to be studied is listed for any researcher who is interested in the subject, and, finally, a focus on the Robotic Fullfillment Mobile Systems (RFMS) is presented in order to understand a very complex problem to optimize and to define a baseline configuration to serve as a parameter for future research.

Keywords: Warehouse, Order Picking, Automated Systems, RMFS, E-commerce.

1 Introduction

E-commerce company's fulfillment processes are dealing with an accelerated commerce environment and shifts in consumer behaviour trends. According to Euromonitor (2021), two of the most critical customer needs are as convenience and faster services. Furthermore, the e-commerce pace is pushing companies' boundaries in terms of scale, volume, and speed of operations. Then, its aim is to improve the process productivity of their logistics facilities in order to cope with the effects of their rapid growth.

Besides the peak of 17% in 2021, e-commerce sales worldwide have increased 7.7% per year on average and are expected to continue their upward trend at 8.6% per year on average (Insider Intelligence, 2023). Literature agrees that there will be at least 50% growth against pre-pandemic trends of technology-based tools usage for shopping habits (Boston Consulting Group, 2021).

This trend is pushing for faster last-mile delivery and reconfiguring inner processes to gain more productivity while maintaining (or even improving) costs. This affirmation is consistent with previous studies' conclusions on how order fulfillment has become more critical for e-commerce companies (Lee & Whang, 2001; Xu et al., 2009;

Azadeh et al., 2019a; Jaghbeer et al., 2020). As a result, warehouses have incremented the handling of a more significant number and variety of orders, while the time available for preparing the order has been shortened dramatically (van Gils et al., 2018a). Therefore, order-picking productivity has become the main goal to meet customer expectations and keep relevant in this fiercely competitive business environment.

One of the fundamental order fulfillment processes is order picking which, whether it is performed manually or automatically, carries high costs for companies (Marchet et al., 2015). Order picking can account for more than 50% of the operating costs of a warehouse, which is mainly due to the large amount of manual human work involved in this process (Grosse & Glock, 2015). In addition, it is mainly performed manually, with little automation. These are the picker-to-parts configurations, in which the picker walks around the warehouse looking for the SKUs. For example, 80% of western European warehouses do so, even though there are systems available on the market for partially automate this process (De Koster et al., 2007).

With the advancement of technology (particularly in robotics), warehouses are establishing systems that combine robots and human labor, called parts-to-picker systems, in which the SKUs are removed from their position and are brought to the picker's position (Benavides-Robles et al., 2024). In comparison with picker-to-parts configuration, they can save time and space and significantly increase the performance of storage and recovery systems for different SKUs (Pinto et al., 2023). However, high investment costs and the risk of interruptions in the order picking process during the implementation phase of automated systems still discourage the use of these systems in practice (Briant et al., 2020; Vanheusden et al., 2023). Furthermore, picker-to-part systems still outperform robots on flexibility as humans prove to react better to unexpected changes in the process, are flexible with respect to capacity, and can retrieve a wide variety of products (van Gils et al., 2019; Vanheusden et al., 2023).

What has not been considered in the previous paragraph is that, on the one hand, order picking is not only the most labor-intensive and expensive process in warehousing, but it is also repetitive, often suffers from poor ergonomics, and requires high-quality labor willing to work in shifts, which is often difficult to achieve. It is therefore not surprising that warehousing systems and processes are key candidates for automation. In addition, available land for warehouses (which should preferably be close to the demand points) has become scarce, and many warehouses have to operate 24/7. Taken together, these factors have provided a major impetus for warehouse automation (Azadeh et al., 2019a).

Finally, in the academic field, the majority of warehouse research still focuses on conventional storage and order picking methods; then, automated systems have not yet been adequately studied: they have many areas that require more attention from researchers (Azadeh, 2021).

Therefore, this article examines various order picking configurations described in the literature and highlights the warehouse configurations considered most promising for study. It provides a detailed overview, focusing especially on the Robotic Mobile Fulfillment System (RMFS), recognized as one of the most intricate optimization challenges faced by researchers (Benavides-Robles et al., 2024). Moreover, this system is the main object of analysis of the author's doctoral path.

More specifically, it responds to the following questions:

- Which are the different picking systems you can find in a warehouse nowadays?
- Which warehouse configurations have been less studied by the academia so far?
- RMFS is a complex optimization problem with many variables to tackle (Benavides-Robles et al., 2024), could it be defined a list of assumptions in order to define a baseline configuration/scenario?

Hence, the sections of this work address the steps undertaken to develop this research and answer the above questions. In Section 2, the project reviews the relevant literature regarding automated warehousing configurations and offers a new classification. After that, in Section 3, it explains research opportunities arising from the development of new technologies. Then, in Section 4, the author makes focus on the RMFS, describing it and some future research topics related to this configuration. Finally, he states his conclusions in the fourth section.

2 Classification according to automation methods

The order-picking process has been in the spotlight over recent years, and, in particular, studies have been focused on the effectiveness of the process and on different ways to improve it.

Based on De Koster et al. (2007), Yu (2008) and Pinto et al. (2023), order-picking processes are divided into two groups: "Employing Humans" and "Employing Machines". The question that is answered with this division is "Who does pick goods?". Therefore, when talking about the first configuration, technology can be added to the process, by moving goods to picker's locations (parts-to-picker systems) or using a conveyor to connect picking zones, among others. However, in Employing Machines systems, everything is done with automation, without human intervention (Dallari et al., 2009). Below, in Figure 1, different configurations are classified within the two groups.

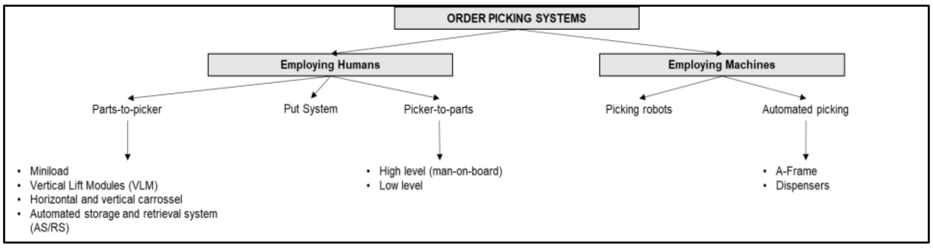


Fig. 1. Classification of order picking systems.

Note. Source: Author's elaboration, based on the works of De Koster et al. (2007), Pinto et al. (2023) & Yu (2008).

Related to the categories, "Employing Humans" configurations are mainly three:

- Parts-to-picker: Stock-keeping units (SKUs) are removed from boxes and taken to picker's picking locations through automatic or semi-automatic Storage/Retrieval (S/R) machines. Finally, at the picking location, the picker is the responsible of collecting the required quantities to fulfil the order (or the order line) and later, the remaining SKUs are returned to their warehouse locations (De Koster et al., 2007; Pinto et al., 2023; Yu, 2008).
- Picker-to-parts: As described in the previous section, order pickers walk or drive along the aisles to pick items (De Koster et al., 2007) and two types of picker-to-parts systems can be determined: low-level picking and high-level picking. In low-level order picking systems, pickers collect the requested items from storage racks or bins (bin-shelving storage), while travelling along the storage aisles. In the others, high storage racks are employed; so, order pickers go to the pick locations on board of a crane or a lifting order-pick truck. The crane halts automatically at the designated pick spot, ready for the order picker to execute the pick. This type of system is called a high-level or a man-aboard order picking system (De Koster et al., 2007; Yu, 2008).
- Put System: This type of configuration combines the two previous ones. First, items are collected from their location using parts-to-picker or picker-to-parts systems; and, then, these SKUs are offered to an order picker who distributes them over different orders (De Koster et al., 2007; Yu, 2008).

As mentioned before, picker-to-parts systems, in particular the low-level ones, are the most common order picking configuration in warehouses (De Koster et al., 2007). Furthermore, parts-to-picker systems are receiving more attention from academia, because S/R machines have become very popular in practice (Azadeh et al., 2019a) and Put systems, which are recommended when many orders must be picked in a short time by each picker, are widely used in e-commerce (Pinto et al., 2023).

About "Employing Machines" systems, Figure 1 shows two:

- Automated picking: These configurations, that combine computational systems, algorithms and equipment, include the storage, transport, and shipping of SKUs. A-frame and dispensers are examples of these systems that divide the items using conveyor belts such as: i) unit-load Automatic Storage and Retrieval Systems (AS/RS); ii) horizontal case flow systems iii) vertical case dispensers; iv) cylindrical case dispensers; v) horizontal item dispensers; vi) dense matrix array dispensers (Pinto et al., 2023).
- Robotized picking: Robots move independently or on rails in various directions to perform picking with high speed and precision. They are normally used to handle valuable and delicate materials and to work in toxic and hazardous environments (Pinto et al., 2023).

Selecting and deploying technology hinges on the company's nature, chosen methodology, and a thorough assessment of financial feasibility, weighing the costs of technological options against the performance achieved (Azadeh et al., 2019a; Pinto et al., 2023). Warehouse robots are gaining traction as they reduce human labor, driving a surge in research exploring their utilization, alongside numerous optimization strategies (Pinto et al., 2023).

At this point, it is important to highlight that the classification in Figure 1 was first defined in De Koster et al. (2007), based on De Koster (2004), and, practically, it has remained unchanged until now (the latest paper reviewed in which this division persists was Pinto et al. (2023)). However, warehouse automation has developed rapidly since 2007, and the picking systems, particularly the automated ones, required an update, as the one made by Azadeh et al. (2019a).

Therefore, in Figure 2, it is shown a new division of picking systems, updating the previous of 2007, which is presented in Figure 1, with the contribution of Azadeh et al. (2019a).

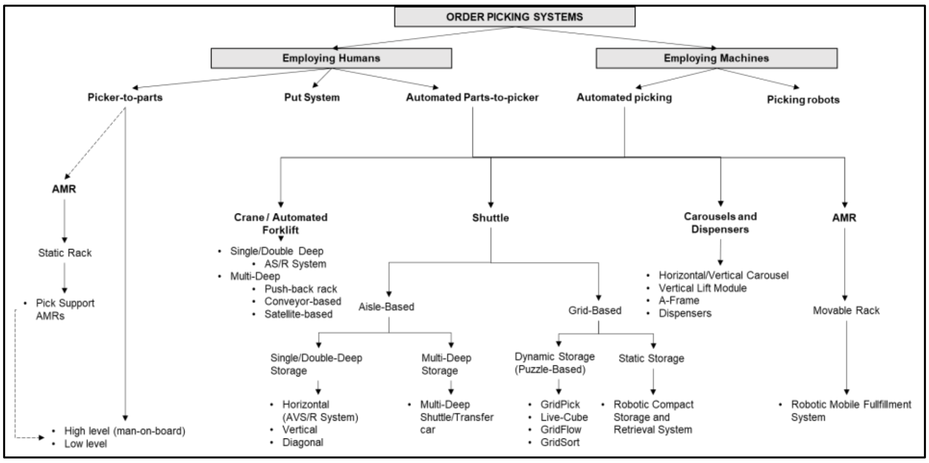


Fig. 2. A new proposal for the classification of order picking systems

Note 1. Source: Author’s elaboration, based on the work of Azadeh et al. (2019a), De Koster et al. (2007) & Yu (2008)

Note 2: The dotted lines mean that the relation is optional.

Note 3: Carousels and Dispensers may also be used for final disposal, without any human or machine intervention.

As it can be seen by comparing Figure 1 with Figure 2, the barrier between Manual and Robot Picking systems is becoming increasingly blurred, sharing more and more configurations, which also demonstrates that humans have become accustomed to working with new technologies for improving the order picking process. As workers increasingly collaborate with automated and robotized systems in many tasks related to picking activities, new models, frameworks, concepts, and systems are needed to efficiently manage human–machine interactions (Lorson et al., 2023; Olsen & Tomlin, 2020).

New systems will then appear because, as noted before, humans have distinctive characteristics, skills and capabilities that robots are not able to replicate or perform cost efficiently. Since automated picking solutions are often tied to a specific capacity, human operators compensate for various fluctuations that may occur and continue to play a critical role in aligning supply and demand (Lorson et al., 2023).

In conclusion, companies are introducing changes in picking processes, in order to rapidly improve its operations, forced by different features: orders must be processed faster, customer impatience puts pressure to reduce lead times, and the error rate must be kept as close as possible to zero (Lamballais, 2019). New automation solutions will then appear and at a faster pace, despite the fact that their implementation entails high investments and the possibility of interruptions. Therefore, professionals need academy to work on the systems that are already in place and those that are going to appear, with the aim of improving them, rather than always looking for new disruptive solutions that only create new uncertainties and possibly lead to taking wrong decisions at the business level.

As a consequence of this last point, this study continues with the following section, which reviews the main research opportunities within automated picking systems.

3 Research opportunities within automation methods

With the rapid development of e-commerce, the B2C environment has changed. Its main characteristics are: small orders (very few items in each demanding order), large assortment (a wide variety of products), varying workloads, and tight delivery schedules (Boysen et al., 2019). Therefore, distribution centers need to manage a considerable number of very small and heterogeneous orders. In addition, companies competing in the retail e-commerce market accept more late orders from customers while promising quick delivery. By doing this, the remaining time to pick an order is reduced (Marchet et al., 2015; van Gils, Ramaekers, Caris, et al., 2018), forcing companies to improve their order picking effectiveness if they want to survive. Improvements in order picking systems in warehouses are mainly realized by automatizing hardware (e.g., using a rack as a device or a pick-by-voice solution or a picking workstation) (Boysen et al., 2017, 2018, 2019; Zaerpour et al., 2015, 2017), supporting what has been described until this point of this work.

On these initiatives, including automation and intelligent planning approaches, Boysen et al. (2019) reveal in their survey study that these investments are not suitable for the tight delivery schedules and vast assortments that companies in the e-commerce retail market must manage. In addition to the investment, there is also the risk of disruptions in picking operations, and firms do not want to expose themselves to failures that could put them out of business.

Then, the best way to incorporate automated improvements is to work together with academia in the study of these new emerging solutions and improve them together, instead of thinking about coming up with new ideas. Furthermore, emerging technologies (those incorporated in Figure 2) have not received sufficient attention in the literature, considering the need with which it is required in the new context in the warehouses of e-commerce companies (Azadeh, 2021; Azadeh et al., 2019a).

In Azadeh et al. (2019a), a comprehensive review of the new automated systems listed in Figure 2 is included. This review, which is incorporated in Azadeh (2021), as its chapter 2, has an interesting section on topics that have not yet been considered by academia and that open up new lines of research. Then, these research opportunities are described in Table 1.

Table 1. Description of research opportunities

System	Topic	Description
Shuttle	Multiple Input/Output (I/O) Points	The majority of the literature, when analyzing these systems, assumes a single I/O point. Then, new research is needed to tackle questions like: What is the effect of having multiple I/O points on the design and operational choices, such as depth-to-width ratio and storage policies?
	Automated Replenishment	Certain systems integrate automated storage and replenishment of the pick system alongside manual picking. Particularly, in scenarios where the number of pick slots is fewer than the number of products available, scheduling retrievals to minimize picker wait times poses a challenge. Some researchers have explored this issue to a limited extent, mainly in conjunction with manual pick processes (Füßler & Boysen, 2017, 2019; Ramtin & Pazour, 2015, 2014; Schwerdfeger & Boysen, 2017; Yu & De Koster, 2010). Further investigation is warranted, especially for systems incorporating automated picking and across various storage and retrieval systems.
Shuttle / Aisle-Based / Single/Double-Deep Storage	Diagonal and Vertical Systems	The diagonal system has not yet been studied while the vertical system has been studied in only one paper (Azadeh et al., 2019b). These configurations have roaming flexibility in the robots, in comparison to the horizontal system. Then, studying routing trajectories is a key subject.
Shuttle / Grid-Based / Dynamic Storage (Puzzle-based)	Grid-Sort	GridSort fundamentally deviates from conventional conveyor-based sorters, necessitating new models to assess its performance. For instance, in GridSort, the movements of the shuttles, which transport the loads, are contingent on the vacant spaces on the grid. Thus, a pertinent research query arises: How can the unoccupied spaces on the grid be leveraged to efficiently move multiple loads in the system simultaneously?
Shuttle / Grid-Based / Static Storage	Robotic Compact Storage and Retrieval (RCSR) System	Zou et al. (2018) stand out as the sole researchers to explore the RCSR system. The distinguishing feature of RCSR systems, unlike others, is the stacking of items atop one another. Consequently, it becomes imperative to consider reshuffling and congestion effects when scrutinizing the system.

AMR / Movable Rack / Robotic Mobile Fulfillment Systems	Storage Decisions	Two storage decisions have to be taken in this configuration: how pods should be stored in the storage area, and how the items should be divided over the pods. Then, understand order patterns over time may be one of the lines that this topic brings.
	Replenishment Policy	The pod replenishment policy in RMFS deviates from other systems due to the storage of multiple SKUs in each pod. Hence, determining the ideal timing for pod retrieval for replenishment poses a challenging inquiry. Thus, the research question arises: What is the optimal inventory threshold for pod replenishment?
AMR / Static Rack	Pick Support AMRs	The parallel movement of pickers and AMRs introduces a distinctive dynamic to the modeling, analysis, and optimization of this system, setting it apart from any manual or robotic picking system depicted in Figure 2. Assessing the performance of these systems presents an intriguing avenue for future research.

Note. Source: Author’s elaboration, based on the work of Azadeh (2021) and Azadeh et al. (2019a).

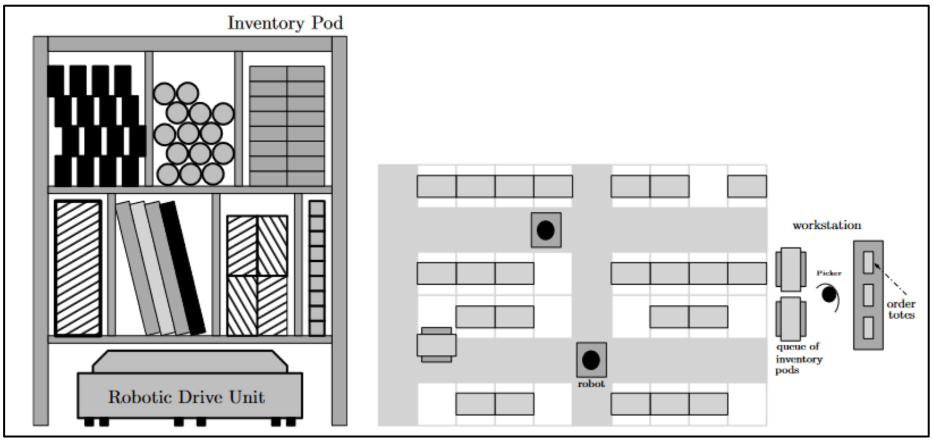
In summary, automated picking systems bring new challenging topics for researchers mainly arising from what practitioners and companies have been developing. Thus, the previous non-exhaustive list in Table 1 offers new perspectives and lines to explore. Specifically, the author’s interest is focused on RMFS. This is the reason why in the next section this configuration is presented in detail. In addition, a baseline framework is defined in order to establish some assumptions to initiate future research, primarily utilizing analytical models, in particular simulations, which is the second most relevant to date, after hybrid methods (Benavides-Robles et al., 2024).

4 Robotic Mobile Fulfillment Systems: defining a baseline framework

As highlighted in the previous sections, e-commerce has not only driven a shift toward greater automation, but more specifically, it has promoted a shift toward automated systems with greater degrees of flexibility. In particular, an automated parts-to-picker system that eliminates picker walking time may therefore improve performance, but only if such a system has the flexibility to handle sharp demand fluctuations, even upscaling or downscaling the system at any time (Lamballais, 2019).

The Robotic Mobile Fulfillment System (RMFS) involves robots equipped with lifting and carrying capabilities that retrieve storage pods (i.e., movable shelf racks) and deliver them to pickers stationed at ergonomically designed workstations (Azadeh et al., 2019a). On the one hand, with respect to the first requirement, bringing the inventory to the picker instead of having the picker travelling to the inventory can potentially double productivity of the picker (Azadeh et al., 2019a; Wurman et al., 2008). On the other hand, the system boasts high flexibility in throughput capacity, with the ability to increase capacity by integrating additional robots and pods into the warehouse (Azadeh et al., 2019a; Lamballais, 2019), covering the second necessity.

The RMFS comprises three key elements: 1) Robotic Drive Units: These robots receive instructions from the central computer to transport inventory pods to workstations for restocking or picking. Additionally, there are decentralized (or locally) controlled systems available nowadays. 2) Inventory Pods: These movable shelf racks hold stored products and come in two standard sizes. Smaller pods accommodate weights up to 450 kg, while larger pods can handle weights up to 1300 kg. 3) Workstation: These areas are ergonomically designed for human workers (or potentially robots) to carry out tasks such as pod replenishment, picking, and packing (MWPVL International, 2012). Figure 3 presents a scheme of the system, extracted from (Azadeh et al., 2019a).



a) Robot and inventory pod b) Schematic of the RMF system with one workstation

Fig. 3. Elements and layout of the RMF system

Note. Source: Extracted from Azadeh (2021)

To fulfill an ordered item using the RMFS, the process unfolds as follows (Azadeh et al., 2019a; Enright & Wurman, 2011; Wurman et al., 2008):

1. The order is initially assigned to one of the workstations.
2. Subsequently, the item is designated to a pod and a robot.
3. The robot proceeds from its stationary position to retrieve the designated pod. During this phase, the robot moves without a load, allowing it to traverse beneath the pods, circumventing the designated travel aisles.
4. Upon reaching the targeted pod, the robot positions itself beneath it, lifts the pod, and transports it to the workstation through the travel aisles.
5. Upon arrival at the workstation buffer, the robot awaits its turn.

6. The picker retrieves the requested products and places them into the customer order bin, located in a separate rack.
7. Following this, the robot returns the item pod to a storage location that takes into account the frequency of requests for that particular pod. These storage locations are dynamically adjusted to optimize efficiency.

Then, RMFS is a complex problem for optimizing due to the interaction of multiple variables, including robots, pods, products, and/or humans. However, this complexity can be addressed by breaking down the problem into simpler components. These components resemble Combinatorial Optimization Problems (COPs), where a finite number of candidate solutions exist, and combinations of variable values represent potential solutions (Benavides-Robles et al., 2024).

Lamballais (2019) outlines five key concepts pertaining to operational issues in RMFS:

1. Pile-on: This refers to the quantity of units that can be retrieved from a single pod during its visit to the pick station.
2. Well-sortedness: This concept evaluates the distance between pods and pick stations, factoring in "pod popularity," which is a weighted total across all products on a pod, considering the frequency with which a product is ordered multiplied by the quantity of units of that product on the pod.
3. Priority zoning: It entails categorizing storage locations into zones based on priority, housing pods required at pick stations in the near future.
4. Dynamic resource allocation: With RMFS allowing swift reallocation of resources between picking and replenishment tasks, dynamic resource allocation emerges. This capability facilitates quicker responses to fluctuations in demand.
5. Centralization-decentralization trade-off: This concept involves deciding between a centralized system, where decisions are made by a central computer, and decentralization, where robots have autonomy in decision-making processes.

In particular, Lamballais (2019) works focused on the concepts of Pile-on and Dynamic resource allocation, giving some opportunities to do research about the other points.

About Well-sortedness, it can be used to comprehend to what degree continual pod repositioning supports sorting inventory according to popularity. It is challenging, because it could be difficult to measure, as pods may contain many different SKUs and popularity may fluctuate due to volatile demand during operations (Lamballais, 2019).

Concerning Priority zoning, establishing these zones in proximity to picking stations serves to decrease travel times and their variability. This, in turn, can lead to more meticulous planning and scheduling regarding robot queuing at the pick station, potentially reducing queueing and idle time. However, unintended consequences may arise, such as increased travel times elsewhere, as pods also need to be transported between priority zones and other areas of the storage facility, including replenishment stations. Ultimately, priority zones can be dynamically adjusted in real-time by reassigning storage locations to different priority areas (Lamballais, 2019).

Regarding the final concept, decentralization reduces the time required to recover from unforeseen events and lowers the chances of such events disrupting the system. Distributing decision-making processes may be essential in certain scenarios. For operational decision problems resolved in real-time, the window for finding solutions is typically brief, while the scope of potential solutions is extensive (Lamballais, 2019).

Lamballais (2019) utilizes simulation to examine the different decisions he makes during his study. In fact, a technique to analyse the effects of the improvement that is widely used in research is simulation (van Gils, Ramaekers, Caris, et al., 2018). Moreover, as described above, the simulation method is the second most important approach to solve RMFS case studies so far. Benavides-Robles et al. (2024) justify this by saying that papers are still defining the system structure within warehouses, because the development of the system is at an early stage. In addition, it is important to note that the main methods used are the hybrid ones, which combine different approaches, also including simulation.

Then, at this point, it is necessary to define a baseline list of assumptions for a RMFS configuration in order to serve as a benchmark for any research modification. Specifically, the author adopts the one defined by Benavides-Robles et al. (2024):

1. Policy for pod relocation after its usage: Static (remains in the same location) or dynamic (relocated to a new position after each use).
2. Nature of robot displacement: Ideal (robots teleport), constant (robots move at the same speed all the time), or variable (speed adjusts based on conditions).
3. Policy for product replenishment: Ideal (infinite stock), static (products are refilled at fixed time intervals or item levels), or dynamic (system decides when to replenish based on conditions).
4. Conditions of the warehouse layout: Which zones are included or omitted, as well as a scheme with the distribution.
5. Policy for distributing SKUs into pods: Ideal (each pod contains all SKUs), static (products are distributed once at the beginning), or dynamic (products are redistributed based on warehouse conditions).
6. Policy for assigning orders to workstations: Static (a given scheme is always used, e.g., first-come, first-serve basis into a free workstation), dynamic (an order is selected with some criteria, even if it is not the first one in the queue), whole (full orders are assigned to a single workstation), or split (an order is distributed across multiple workstations).

In conclusion, various avenues for future research have been outlined, establishing a baseline of assumptions for comparison with any forthcoming decisions.

5 Conclusions

This study initially arose to deepen the knowledge of automated picking systems, a topic that the author wishes to explore in order to find a research opportunity for his doctoral career. However, the results exceeded initial expectations.

First of all, the main contribution of this work is a new proposed classification of the order picking systems. This categorization incorporates emerging technologies that have been shaping new schemes of the picking processes in warehouses.

Secondly, from these new systems, new problems and, consequently, new research opportunities are emerging. Then, a non-exhaustive list of topics to be addressed, which have not yet been explored or have received little attention from academia, is provided. This summary is worthwhile because the study of these emerging technologies needs attention from researchers, as described, taking into account the need for improvement in picking processes in the warehouses of e-commerce companies.

Finally, a description of the Robotic Mobile Fulfillment System (RMFS) is presented. In addition, based on current literature, a baseline list of assumptions is defined in order to establish a benchmark for new studies about this complex system.

What is expected for the future is that the author will begin to tackle some of the problems shown in this paper, in particular those related with the RMFS, considering the new trends in the e-commerce business and in automated picking systems.

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