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SURVEY

Robotic Mobile Fulfillment System: A Systematic Review

MARIA TORCOROMA BENAVIDES-ROBLES, (Student Member, IEEE), GERARDO HUMBERTO VALENCIA-RIVERA, JORGE M. CRUZ-DUARTE, (Senior Member, IEEE), IVAN AMAYA, (Senior Member, IEEE), AND JOSÉ CARLOS ORTIZ-BAYLISS, (Member, IEEE)

School of Engineering and Sciences, Tecnologico de Monterrey, Monterrey 64700, Mexico

Corresponding author: Maria Torcoroma Benavides-Robles (A00836554@tec.mx)

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ABSTRACT The Robotic Mobile Fulfillment System (RMFS) is a method for handling products, in which a Line Follower Robot (LFR) transports products to a human workstation for packing. In this systematic review, we delve into the current state of RMFS research using data sourced from Scopus. After a comprehensive search, we found 264 manuscripts, which we filtered to 76 relevant articles. Our analysis covers several variables, from basic metadata to manuscript impact and specific conditions the authors consider. We discovered that there needs to be more focus on the pod allocation problem, despite its potential, with the majority of the emphasis on LFR displacement. We created a detailed diagram that outlines the essential elements and subproblems associated with RMFS. As the interest in RMFS continues growing, our study provides crucial insights and direction for future research efforts.

INDEX TERMS Automated warehouses, e-commerce, Kiva system, RMFS, robotic mobile fulfillment system.

I. INTRODUCTION

The last three years have been full of challenges in different disciplines. One is the sudden rise in the demand for online shopping services due to the pandemic. For some companies, this meant migrating to a new business scheme. For others, which were already engaged in e-commerce, this conveyed a sudden increase in the number of orders and a reduced possibility of raising the (human) staff needed to meet it.

Product delivery services are something familiar nowadays. There are several well-known companies around the world, such as Amazon, eBay, AliExpress, and Mercado Libre. Companies like these have spent years improving their systems to the point that today it is possible to receive products on the same day we order them [1], [2]. However, how was e-commerce before the pandemic? Initially, products were manually handled. Nevertheless, with the advancement of technology (especially in robotics), it has migrated to systems that combine robots and human labor [3], [4].

The first automated warehouse was created in 1960 [5], and since then, it has been evolving alongside robotics. In 2008, Wurman et al. presented a paramount work with a new proposal for automated warehouses [6]. Their objective was to optimize the automated warehouses, using an autonomous vehicle to move the shelves with products to different points where a person would complete the orders. These products and points received the well-known terms of pods and workstations, respectively. Moreover, some authors initially referred to this idea as the *Kiva system* [7], [8]. However, later on, the term evolved into the name of *Robotic Mobile Fulfillment Systems (RMFS)*.

The relationship between the components of the system is intertwined and complex. Hence, although this new idea significantly improved traditional warehouses, it also brought some decision-making problems. A few examples of such problems can be stated as follows:

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- Order assignment to workstations: The system must decide which order to assign first and how to distribute them to the various workstations available at any given time [9], [10], [11].
- Pod assignment to storage locations: Choosing a proper storage location for the pods is critical. Since the pods are coming and going between the workstations and their storage, selecting one or another location could make a difference [12], [13].
- Pod assignment to replenishment stations: Many jobs simplify the system with infinite products and no replenishment stations. A decision that the system must make is to send the pods to replenish products; it is barely studied but does not make it less important than the other decision-making problems [14].

Research on RMFS has taken different paths. Some authors have researched the sensitivity to changes in one or several parts of the system, such as the location of workstations [15], the pod allocation [16], or the distribution of Stock Keeping Units (SKUs) [17]. Another approach is the application of Artificial Intelligence (AI) techniques to specific subproblems within warehouses [18], [19]. Some of the reported works have compared several techniques. For example, Luo et al. compared discrete-event system simulation versus queuing networks [20]. Similarly, Douchan and Kaminka compared Q-learning and reinforcement-learning [21]. Even so, they all have a common goal: to optimize warehouses that incorporate RMFS.

Additionally, the literature contains two reviews about warehouses that mention RMFS. Azadeh et al. reviewed robotized and automated warehouse systems, as a whole [5]. Although they dedicated a subsection to RMFS, the topic was relegated to a brief mention. In contrast, Da Costa Barros et al. dedicated their survey entirely to RMFS [22]. They analyzed a total of 75 publications, and their work offers a broad description of how RMFS work, their design, and their planning and control. The authors also highlighted the difficulty of comparing studies about RMFS. In fact, it is impossible to determine the current state of this application by glancing at the literature. The main reason is that the problem is so complex that authors cannot cover it entirely, forcing them to subdivide it into smaller components. Although this is not bad by itself, it does hinder the comparison across multiple works. However, it has the benefit of allowing to focus on specific issues and proposing better alternatives for tackling them.

As one may notice, literature lacks a comprehensive review that covers other aspects, such as those techniques that have been already explored, and the categorization of RMFS into subproblems. For example, the survey from Da Costa Barros et al. [22] focuses on how the RMFS works and on its taxonomy. In contrast, we analyze what other authors have worked on. So, our focus is on discovering the current state of the studies carried out since the creation of the RMFS. Hence, we offer a three-fold contribution:

- A synthesis of the works on RMFS with the highest impact, as well as the most relevant actors.
- An analysis about the way in which research efforts for the RMFS have been distributed. This includes information about the subproblems that have been studied the most, and those where more study is needed. It also covers the kind of techniques that have been applied to the subproblems, and which ones have been the most fruitful ones. Similarly, it spans over simulation considerations, including the kind of metrics that have been analyzed.
- Some ideas that shall enhance cooperation, or at the very least, facilitate comparisons across different works. Undoubtedly, these shall enhance research in the area.

This paper consists of five more sections. Section II explains the main concepts addressed in this work, especially those about the RMFS. Later on, Section III details our research questions, as well as the methodology we followed for gathering and processing the data. Subsequently, Section IV presents the results of our research, which we discuss in Section V. Finally, Section VI contains the most relevant conclusion of this systematic review.

II. BACKGROUND ON ROBOTIC MOBILE FULFILLMENT SYSTEMS

A Robotic Mobile Fulfillment System (RMFS) is a complex optimization problem where several variables interact, like robots, pods, products, and humans. Following, we provide a brief overview of the system and its components, and then we talk about some of the of Combinatorial Optimization Problems (COPs) that we may find when dealing with an RMFS.

A. OVERVIEW

Throughout the years, progress in diverse areas of engineering has led to new and improved materials, enhancing the mechanic and electronic systems of Line Follower Robots (LFRs). Currently, LFRs stand as quite the robust devices [23], [24]. Therefore, the research focus has migrated towards improving their performance and expanding their applications. Kumar described some of such applications inside and outside the industry [24]. The former includes transporting materials for manufacturing processes or within product warehouses. The latter relates to serving robots in hotels or medicine delivery robots to improve service quality in public healthcare systems. Since automation emerged, companies have been interested in reducing processing times and increasing efficiency. This represents an opportunity to interconnect robots, employees, and orders, controlling all variables simultaneously.

Currently, the world is most connected than ever. It is possible to find a product online, in a store on the other side of the world, and buy it immediately. Because of this enhanced and straightforward approach, more stores are offering their products online through websites like Amazon, eBay, AliExpress, and Mercado Libre, to mention some famous examples. These websites send products to many countries and handle many Stock Keeping Unit (SKUs). So, they have many big warehouses. Managing all the orders implies a considerable effort for the companies. As explained by Wurman et al., Kiva proposed a new system to answer this need [6]. Initially, the literature referred to this system as the *Kiva system*. However, some time later, the term RMFS was coined. Figure 1 shows a simplified view of such a system.

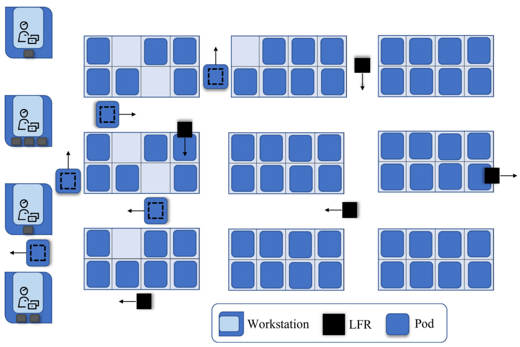


FIGURE 1. **A simplified layout of the *Kiva system*. Based on [6].**

Since the problem is complex, there are many details to consider when dealing with RMFS. For instance, a pod and an LFR can only be in one place simultaneously in a real-life system. So, one must consider possible conflicts when dealing with resource allocation. Plus, an order may or may not be required to be fulfilled at a single workstation, so this must be considered and included in the model. For example, one may consider that each order must be processed at a single workstation to guarantee that the order is properly fulfilled (with no repetitions or omissions) at the expense of processing time. However, one may also consider that different workstations can tackle different parts of an order (*e.g.*, a large and complex order) so that it can be completed faster. This would require additional processing to merge the partial orders into a completed one, so that is also something to ponder.

One may be interested in considering some other elements, such as constraints and performance metrics. In the first case, constraints could include time windows for order fulfillment since different orders may be set up with different delivery dates. Similarly, pods can be replenished when they run out of SKUs or reach a threshold. This may even be set at different levels for each SKU within the pod. Moreover, performance metrics vary depending on the focus of the research. A couple of metrics that come to mind are the number of orders processed in a time frame or the average time required for fulfilling an order. However, one may also account for other variables, such as the amount of LFR movement, which could help improve energy consumption.

An RMFS uses LFRs to pick a pod with different SKUs and take it to a workstation where a human gathers the product for fulfilling a particular order. All processes within an RMFS involve many engineering challenges, and we are especially interested in the one related to using AI for coordinating the allocation of pods.

After the Kiva system was released, some researchers began working on this topic. For example, Yuan et al. worked on the study of Multi-Robot Task Allocation (MRTA) in e-commerce [25]. They considered both the task correlation and the balance across picking stations. They used the former to create a task time cost model for the picking system to achieve this balance. Another example is the work from Xie et al., who developed a Genetic Programming-based Hyper-Heuristics (GPHH) approach and proposed a method for solving the storage allocation problem [26]. Additionally, Zhuang et al. formulated a comprehensive multi-workstation order and pod sequencing problem as a mixed integer programming model that accounts for workload balancing and pod conflicts [11]. Although they all work on the pod allocation problem, the works differ. For starters, they do not consider the same relationships between variables, nor even the same variables. Other differences arise as authors assume that the problem behaves more and more ideally. For example, some authors leave aside the conflict that arises when a pod under use is called to another station. The aforementioned jobs found good results but also left room for improving efficiency, since they only addressed the optimization of one part of the problem.

Some companies have already implemented an RMFS. For example, Amazon focuses on making work safer for employees and has different LFRs according to the load they need to transport [27]. In contrast, FedEx is testing the sorting of letters and small packages. Although the system recurrently has difficulty deciding correctly, it remains a promising prototype [28]. Plus, Walmart uses palletizing robots to optimize product storage according to the needs of store resupply [29].

B. COMBINATORIAL OPTIMIZATION PROBLEMS

Optimization problems are diverse in nature. Among them, we can find a subset of problems in which the number of candidate solutions is finite and where a combination of values for the variables represents a solution. These problems are known as Combinatorial Optimization Problems (COPs). Although the number of solutions is finite, for most COPs of interest, this number grows exponentially w.r.t. the input size. Precisely, it is because of this combinatorial explosion that such problems become intractable. Then, solutions based on enumeration techniques fall out of scope. Hence, it is customary to use approximate solvers for tackling COPs, although they do not guarantee optimality. The following section has some examples of COPS that can be found in an RMFS.

1) ILLUSTRATIVE EXAMPLES

When reviewing the literature, we found many examples of COPs. However, for brevity we only mention three of them, which are related to RMFS. The first one corresponds to the

Knapsack problem (KP), where we have a set of items and a knapsack with a limited capacity. Packaging an item into the knapsack provides a fixed profit and takes up some of its capacity. The objective when solving a KP is to identify and select the items that maximize the profit without exceeding the total capacity.

The second example is the **Job Shop Scheduling problem (JSSP)**, which integrates more variables and conditions. In the JSSP, we deal with several tasks that must be scheduled across different machines, requiring several operations to complete. Moreover, these operations are usually performed in different machines with a fixed order that must be preserved. There are additional constraints, such as the machine's capacity, which assumes that any given machine can only process one operation at a time. Another common constraint is that operations cannot be interrupted, meaning that they must be completed once assigned to a machine. The goal when dealing with a JSSP is to minimize the makespan, which represents the total time required to complete all tasks.

Lastly, we must mention the **Vehicle Routing Problem (VRP)**. In this problem, a vehicle must go from point A to point B, visiting several points along the way. Since there are several paths to accomplish the task, the goal is to select the shortest one that meets the requirements.

As one may see, COPs are diverse, so there are different approaches to solving them. Although having an exact solver for this problem would be ideal, the available ones fail when dealing with larger instances. The main reason is the combinatorial explosion of the candidate solutions, which may lead to unfeasible computing times or excessively high memory requirements.

2) RELATIONSHIP BETWEEN RMFSS AND COPS

An RMFS represents a big optimization problem that we can divide into simpler components. Such components resemble COPs and so can be modeled as one of them. Let us start with the diverse route planning processes that a Line Follower Robot (LFR) requires. Such a robot must travel to the workstations, replenishment stations, and pods. Hence, at least three kinds of routes must be planned. Do note that, additionally, one might consider all of them as a single route planning with different kinds of locations.

Figure 2 provides an example of the required routing (indicated in red), where workstations at locations **B** and **C** need products from the selected pod at **A**. So, the challenge is to plan which station to visit first and how to complete the route until point D, *i.e.*, the storage location for the pod. We can solve this as a VRP (*cf.* Section II-B1), by considering the LFR as the vehicle and the route from A to D as the routing problem. In this way, a solver for the VRP would prefer a route given by points A, B, C, and D, rather than one given by A, C, B, and D, as the latter retraces part of the path.

Another COP related to RMFS is JSSP, which consists of scheduling tasks to minimize the time required for fulfilling them. Several subproblems within RMFS can be interpreted this way, such as pod allocation [7] or order assignment.

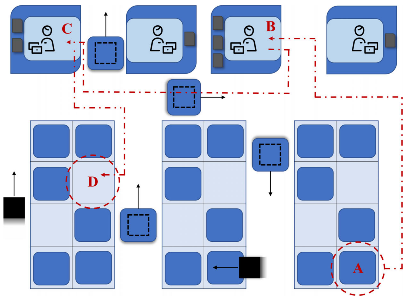


FIGURE 2. Vehicle Routing Problem inside a Robotic Mobile Fulfillment System.

For example, when solving the assignment of orders to workstations, it can be done on a first-come, first-served basis. However, this is not necessarily efficient nor represents the best approach for all scenarios. Suppose the first order in the queue is enormous and distributed across the available workstations. In that case, the whole warehouse will be blocked until such an order is processed, which may delay upcoming orders. Figure 3 shows an example where orders are assigned considering the SKUs required to complete each order and their availability. Lastly, some aspects considered when solving the Knapsack Problem can also be useful when selecting the pod with the largest number of SKUs needed to complete the order. To illustrate that, the setting depicted in Figure 3 has two options for the pod. However, only one of them has the two products needed to complete Order # 2, so we prefer Pod 1, which lets us complete the order with only one travel.

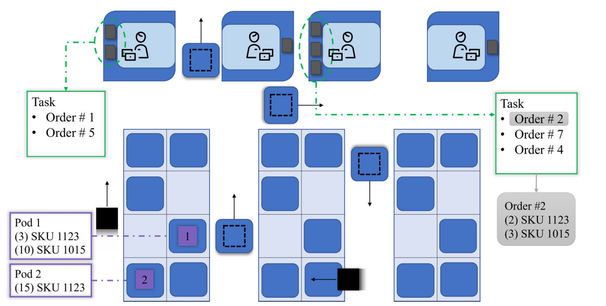


FIGURE 3. Job Shop Scheduling problem and Knapsack problem inside a Robotic Mobile Fulfillment System.

C. SOLUTION APPROACHES

The literature contains a plethora of alternatives for tackling COPs. A relatively straightforward example is to use **heuristics**, which directly represent tools that solve a problem instance. They are usually crafted from existing knowledge about a problem domain. So, in most cases, they are problem dependent. Albeit approximate, they allow for a fast solution to each problem instance. Hence, it is customary to find them in complex problems. In some cases, this solver is equivalent to rules-of-thumb or policies for taking actions.

Metaheuristics (MHs) are another widespread alternative. Roughly speaking, MHs are techniques inspired by the behavior of natural phenomena. There are many of them, and their popularity is due to their straightforwardness and performance [30]. MHs have been mixed with other techniques [31]. Moreover, new MHs have been created very quickly, sometimes haphazardly. This has even led to an intense discussion about the novelty of recent approaches [32]. So, works have been striving to formalize and provide a systematic structure for generating MHs [33]. The goal is to make them more transparent by discarding the need for metaphors. Some examples used in RMFS include Genetic Algorithms [34], Adaptive Large Neighborhood Search and Simulated Annealing [11], and Multi-Objective Disturbance and Repair Strategy Enhanced Cohort intelligence [35].

Additionally, authors have widely used **simulation techniques**. In these cases, the objective is to test the response of efficiency metrics when varying one or multiple parts of the system. The idea of the simulation techniques is to test the system's sensitivity to changes in aspects such as the distribution of the pods, and the location of the workstations, to mention a couple of examples. This process allows for a first approximation of the optimum values for these variables. In that lane, Lienert et al. used a time window routing method to study the blocking effects between vehicles when the number of vehicles in the system increases [36]. Merschformann et al. analyzed the order assignment, pod selection, and pod storage issues and tested multiple decision rules per problem [37].

III. METHODOLOGY

In this work, we aimed to identify the current state of studies related to the Robotic Mobile Fulfillment System (RMFS). Likewise, we wanted to identify critical points, such as the methods that have been traditionally used, the research problems that compose an RMFS, and some of the typical assumptions that authors have considered for the warehouse simulation, among others. Hence, we pursued the following research questions:

1) What are the most relevant entities (*e.g.*, authors, institutions, countries) in RMFS?
2) How many documents study the RMFS application, and what features do such documents have?
3) What is the maximum number of workstations the authors have analyzed?
4) What methods have been used to tackle the RMFS?
5) How many restrictions have authors considered in their simulations?

To answer these questions, we generated a Scopus search based on the following query:

```
TITLE-ABS-KEY (
 ``Robotic Mobile Fulfillment System'' OR
  rmfs OR
 ``Kiva system'' OR
 ``kiva warehouse-management system'' OR
 ``kiva warehouse management system''
)
```

This preliminary search was carried out in July 2022 and returned 264 results. This dataset underwent a three-stage filtering process, as we show in Figure 4. We manually inspected the title and abstract to detect those manuscripts unrelated to RMFS. This reduced the dataset to 90 entries. Afterward, we removed the manuscripts that were not written in English and those for which the full-length manuscript was unavailable. This left us with 76 manuscripts. A further inspection revealed that there were two surveys within the dataset. However, such surveys did not contain data about the questions we have formulated for this work. Hence, we removed them from the dataset, as we show in the first line of the third block of Figure 4. So, by this point our dataset contains 74 manuscripts. In order to avoid losing information during the search, we randomly selected some articles and validated that the related references were included in our results. This revealed two manuscripts that had been omitted, so we manually incorporated them, as we show in the last line of Figure 4. Thus, the final dataset contains 76 manuscripts. Moreover, we tested different combinations and variants of the search equation and detected the same number of results or even fewer. We omit such equations for the sake of brevity. Afterward, we analyzed each manuscript and tabulated relevant data for each question. Then, we imported these data into MATLAB through a comma-separated file. Finally, we processed the information and separated the resulting insights into three research stages, as follows.

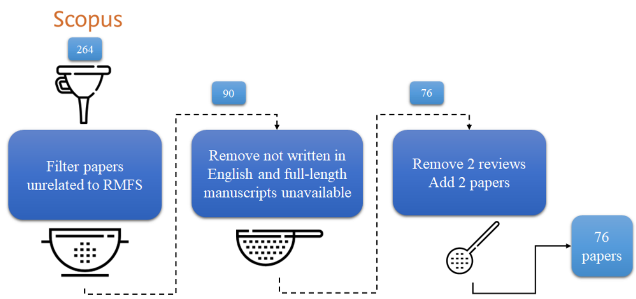


FIGURE 4. Three-stage filtering process applied to the initial dataset for selecting the manuscripts analyzed in this work..

A. GENERAL INFORMATION

We employed all the information related to the authors to summarize and identify the most relevant works, countries, and institutions. We also analyzed the most prolific authors and the overall testing conditions they have incorporated. Additionally, we determined the citation density (ρ_c) per year because newer papers generally exhibit fewer citations, such as

$$\rho_c = \frac{N_c}{2023 - t_y}, \tag{1}$$

where N_c is the number of citations achieved in the year t_y. If we only considered the raw number, it would be hard to distinguish between relatively recent works with a high impact and older works with less impact. Additionally, to avoid divisions by zero, we assumed that the year has already finished, *i.e.*, manuscripts from 2022 are one year old, those from the previous year are two years old, and so forth. Moreover, we only present the resulting data for the top 10 documents since there are no significant changes in the data, and they quickly tend towards 1 or 0 (see Section IV-A). We applied the same reasoning to data related to authors, countries, and institutions. Plus, we analyzed where authors prefer to publish, be it journals or conferences, and how accessible the information is. To count affiliations, authors and countries, we relied on the search tools that Scopus offer. Do note that Scopus provides the number of articles in which at least one author belongs to a country or institution. Hence, a manuscript may count more than once. Similarly, Scopus considers all authors from a manuscript as equals. So, the same manuscript counts towards the total of all the involved authors.

B. SIMULATION CONDITIONS

After studying the general information, we analyzed the authors' assumptions when researching the RMFS. Since this is a complex problem, authors usually simplify some components or assume that other parts of the problem are constant. This, however, dislocates the problem from reality, thus limiting the applicability of the results. So, we defined the following simulation perspectives and analyzed how each paper handles them:

- **Number of workstations**. To consider a single workstation is the most basic assumption for this perspective. Nonetheless, Zhuang et al. highlighted the importance of simulating with over one workstation [11]. The reason is that one cannot simply search for a solution with a single workstation and then hope to extrapolate it to multiple workstations, as new conflicts emerge. Even so, analyzing multiple workstations involves additional challenges. Hence, at this perspective we analyze the maximum number of workstations that authors have considered. This means that whenever authors consider multiple scenarios, we only count the scenario with the highest number of workstations.
- **Number of assumptions**. It is normal to find a list of testing conditions the authors assumed, such as specific variables or given simulation conditions. This list can include information about the type of LFR movement, quantity of workstations, and distributions of SKUs, to mention a few. For this perspective, we target the number of constraints each work assumes.
- **Subproblems of interest**. The RMFS has many components that must be analyzed. However, our primary motivation for pursuing this systematic review is to identify three of those components so that we can delve into them in more detail. One is the movement of the LFR within the warehouse. Another one relates to the replenishment policy. The final one deals with how pods are allocated within the warehouse. Additionally, we defined three categories to try and unify the analyses: "optimized", "simplified", and "Not Applicable (N/A)". The first one indicates that the authors implemented a technique for enhancing performance, *i.e.*, they focused on improving that variable. We use the second category to designate an idealization or simplification of the process, *i.e.*, some assumption made by the authors to reduce the complexity of the problem. Finally, the last category indicates either that the authors did not provide any information related to this variable, or that the subproblem is not relevant to them.

C. TECHNIQUES

Research is quite a diverse process. Hence, it is customary for authors to incorporate different techniques and variations or even combinations of such techniques. For this reason, we decided to assign a representative family depending on the type of technique the authors used in their work. First, we read each manuscript to identify the precise technique that the authors used. Whenever authors compared several techniques, we only consider the one that they report as the best approach. Then, we grouped similar techniques into a single and representative family name, as we show in Section IV-C. Do note that we also considered a label called "hybrid methods". We used this label whenever the authors combine techniques from two or more different families, *e.g.*, Semi-Open Queuing Networks (SOQN) with Markov Decision Process (MDP), or A* for the route planning and simulated annealing for scheduling tasks. Moreover, we considered the family "simulation" to group those techniques that do not incorporate a search method that enhances the process but instead focus on evaluating a model to test its sensitivity. The remaining families have names related to well-known techniques.

IV. RESULTS

This section summarizes the main results of our research. For the sake of readability, we preserve the same structure from Section III.

A. GENERAL INFORMATION

We initially had 264 entries, and after refining our search (*cf.* Section III), we ended up with 76 articles. Figure 5 shows the growth in the number of publications related to the Kiva system or RMFS. As we can see, publications were scarce until 2016, with only one document published (in the best years). Although this innovative system was born in 2007, it was not until a decade later that scientists became interested in enhancing the associated subproblems. However, since 2017 interest in this topic has proliferated, reaching over

20 works in 2021. This significant increase implies that the topic is gaining importance and strength.

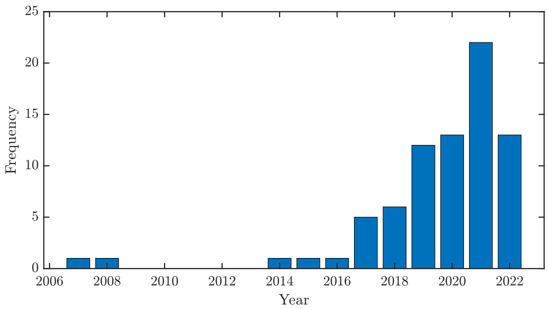


FIGURE 5. Publication growth related to Robotic Mobile Fulfillment System.

Table 1 presents the top 10 papers in terms of citation density, (1). This metric highlights relevant articles that may have been overlooked otherwise. For example, entries in positions 5 and 7 have 43 and 22 citations, respectively, despite being relatively recent (2020 and 2021, respectively). However, should we have used the raw citation data, these entries would have fallen out of the table, missing them entirely.

TABLE 1. Most relevant works according to the impact of their publications.

Rank	Authors, citation	Year	Citation density
1	Wurman *et al.*, [6]	2008	30.87
2	Lamballais *et al.*, [38]	2017	19.00
3	Boysen *et al.*, [39]	2017	14.67
4	Roy *et al.*, [40]	2019	14.50
5	Lamballais *et al.*, [41]	2020	14.34
6	Zou *et al.*, [42]	2018	12.00
7	Xie *et al.*, [43]	2021	11.00
8	Zou *et al.*, [44]	2017	10.50
9	Weidinger *et al.*, [7]	2018	9.20
10	Merschformann *et al.*, [37]	2019	8.75

Notably, citation density is significantly different between positions 1 and 2, *i.e.*, 30.87 vs. 19.00. This difference could be attributed to the fact that the article by Wurman et al. (position 1) is the one that presented the RMFS [6]. Indeed, the article is a must-read for researchers interested in this field. The authors talked about the structure of traditional distribution centers and the issues they face. Moreover, they explained the foundations of the Kiva solution and the AI techniques they included in such a system. In the second most relevant article, Lamballais et al. studied different layouts, seeking to identify the best distribution [38]. The authors found two significant results. One of them is that the length-to-width ratio of the storage area does not affect the maximum order throughput. The other one is that the location of the workstations around the storage area does affect it. The authors used queueing network models to analyze the problem and to obtain these results. Similarly, the third most relevant article is the one by Boysen et al., where the authors studied the assignment of orders to workstations. They also found that optimizing the orders can reduce the number of required robots [39].

The remaining articles of this ranking use different methods. Although authors mainly use variations of queuing theory, one can also find methods such as heuristics and metaheuristics. Additionally, the number of subproblems that these works studied is not constant. Something that stands out is that they study more than one subproblem, while some even consider up to three subproblems simultaneously. Besides, although several authors select the assignment of orders and a second subproblem, none brandishes the same combination of subproblems. Moreover, this top 10 contains applications related to all aspects of the RMFS: orders, workstations, replenishment, robots, pods, and SKUs. It is likely that the inclusion of several subproblems is what earned such works their place within the top 10.

Beyond the data from Table 1, we found other noteworthy insights. For starters, there is only one work related to studying LFR batteries. So, we could argue that such a work is the most relevant one for that specific problem. Additionally, very few authors mention or at least consider this aspect in their analyses.

Figure 6 shows that the author with the most articles related to RMFS only has five documents, representing about 6.6% of all the works. Moreover, the remaining top authors behave similarly, with half of them providing about 4% of the manuscripts each. This contribution level drops rapidly, with 20% of the authors having two manuscripts and 71.25% of them contributing with a single one. Additionally, if we delve deeper into the top 10 authors, we find that two of them, Roy, D. and Lamballais, T., have coinciding works. In fact, they have three works in common [38], [41], [44].

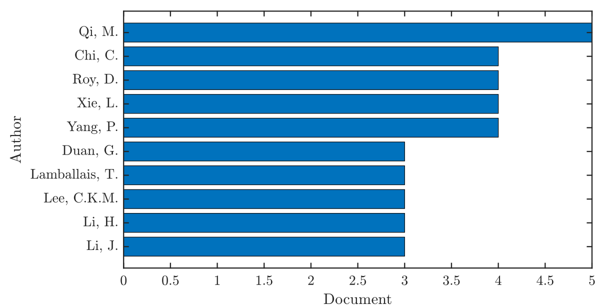


FIGURE 6. Authors with most contributions related to Robotic Mobile Fulfillment System.

Figure 7 shows the top 10 countries working with RMFSs. China seems to be the most prolific country, as it provides 50% of the manuscripts. However, this only implies that they have produced the highest number of manuscripts. Since our goal is for this work to shed light into relevant research paths, we must analyze both the number of works and their impact. Hence, after comparing the data from Figure 7 and Table 1, we found that the first five works from Table 1 miss authors from China. The sixth one, in contrast, represents a collaboration between authors from China, France, and the Netherlands. Then, some of the highest-impact papers include authors from China, but not to the extent that Figure 7 suggests.

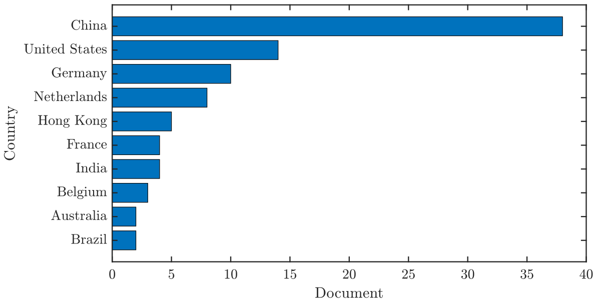


FIGURE 7. Countries that do the most research on Robotic Mobile Fulfillment System.

Let us now extend our analysis to the information related to institutions. According to Table 2, Tsinghua University (China) has published the highest number of papers related to RMFS. This agrees with the information from Figure 7, which indicates that China is the most prolific country. Currently, universities are the principal institution studying the problems revolving around RMFS: the top 10 affiliations does not contain any companies, it only includes one research center. Hence, there is a clear relationship between authors' ranking and the institutions they are affiliated with, as expected. Even so, although the university with the highest number of contributions corresponds to the country with the highest output, universities at positions two and three (Table 2) do not correspond with Figure 7. Instead, they belong to a single country, ranked fourth. Hence, two other countries produce more manuscripts, but they do so by distributing the work across more universities (eight in this case).

It is also noteworthy that China has incorporated several institutions working on the RMFS. In fact, 26% of all papers come from three institutions within China, which are located within the top 10. However, another 24% of articles from Chinese institutions are outside the top 10. Since the last institution in Table 2 has produced three articles, China has at least six more institutions working on RMFS. In contrast, institutions at positions two and three have some papers in collaboration. Thus, they may study the topic collaboratively. Actually, this is something relatively common since we also found other papers with collaborations between institutions from different countries. For example, the Netherlands has collaborated with India [38] and with Germany [37].

In terms of venues, the authors have different options for publishing their work. We use four different names separated into two categories. The first one is *Source type*, based on whether the work was published in a journal or a conference. The second category analyzes whether people have free access to the paper. So, it considers the options of open access and subscription-based. Figure 8 summarizes the results of this analysis of the data. Authors have published most of their works in journals, with only 29% of the articles belonging to conferences (Figure 8a). Additionally, access to the information is somewhat restricted, as 64% of the works appear in subscription-based sources (Figure 8c).

B. SIMULATION CONDITIONS

From the 76 articles selected, we systematically reviewed some aspects of the simulation. We considered three elements (*cf.* Section III-B): the number of workstations, assumptions, and the subproblems that the authors have analyzed. As Lamballais et al. mentioned, the number of workstations inside a warehouse affect efficiency [41]. Therefore, it is paramount to determine the optimal location of workstations, as Yang et al. suggested [45]. Nevertheless, this also implies an increase in the complexity of the overall problem. For this reason, some authors have opted for using few workstations to focus on other problem components instead [26], [39], [46]. Even so, this limits the scope of their research since such a number of workstations is petite compared to the requirements of companies such as Amazon [28], [47].

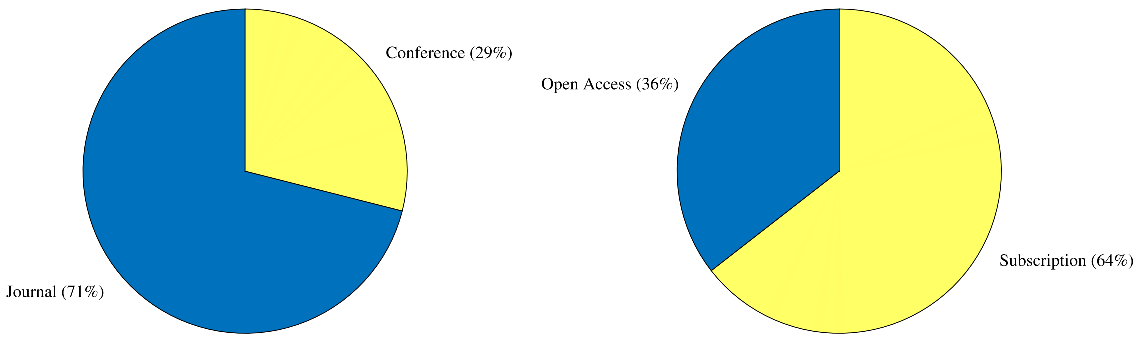
Figure 9 shows a great diversity in the number of workstations the authors have considered in their works. For example, 66% of the papers consider ten or fewer workstations. However, only 13% of the works consider between five and ten workstations. So, most authors have targeted less than five workstations. In contrast, the paper with the highest number of workstations is the one from Zhou et al. [35]. In said work, the authors considered up to 50 workstations, although this work represents an outlier. Sadly, the authors failed to provide a reason for using 50 stations. However, they ran extensive simulations with diverse experimental conditions and claimed to have achieved good results. They constructed an energy-saving strategy scheme based on a proposed MH called Multi-objective Disturbance and Repair Strategy Enhanced Cohort Intelligence (MDRCI). They recognized the importance of the impact of energy consumption and aimed to minimize it by optimizing the system. Although the authors did not mention it, we believe that their data shall provide a better overview when approaching a real-life scale for the problem. So, even though this paper represents an outlier, it does not mean that it should be discarded or that its data is insignificant. On the contrary, it means that few efforts have been made toward pushing this boundary closer to reality.

Figure 10 depicts the number of parameters the authors reported in their analyses. This is a very relevant aspect because such parameters define, for example, which of the variables that authors assume are ideal, and which ones are disregarded. As expected, we found that the selection criteria varies across authors. Moreover, they can be so different that we cannot standardize them and provide a generalized perspective.

Another meaningful insight that we detected refers to the number of parameters themselves. When one assumes

TABLE 2. Institutions with the highest output related to Robotic Mobile Fulfillment System.

Rank	Institution	Country	Documents
1	Tsinghua University	China	11
2	Erasmus University Rotterdam	Netherlands	6
3	Rotterdam School of Management, Erasmus University	Netherlands	6
4	Shandong University	China	5
5	Hong Kong Polytechnic University	Hong Kong	4
6	Indian Institute of Management Ahmedabad	India	4
7	Leuphana Universität Lüneburg	Germany	4
8	Beijing Wuzi University	China	4
9	EMLYON Business School	France	4
10	Flanders Make	Belgium	3



(a) Source type (b) Access approach

FIGURE 8. Distribution of articles related to Robotic Mobile Fulfillment System.

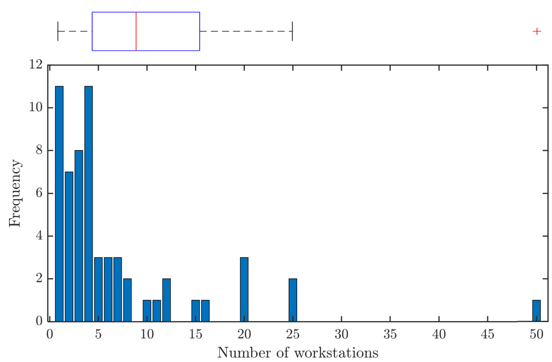


FIGURE 9. Distribution of the number of workstations considered in the existing literature.

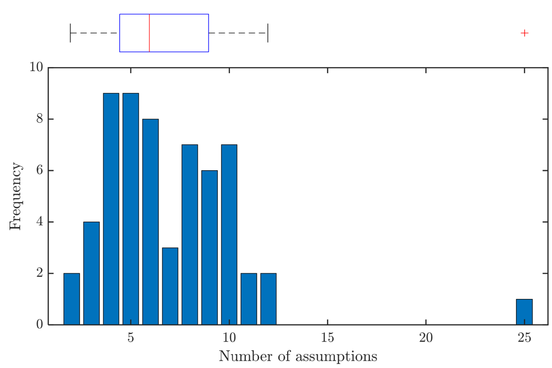


FIGURE 10. Distribution of the number of assumptions considered in the existing literature.

a parameter, it is usually to simplify one element related to the mathematical model. Hence, as the number of assumptions increases, the model falls further from reality. This is adequate if we agree that each assumption idealizes something, *e.g.*, when we assume that robots can teleport to simplify the planning of their routes. However, this is only partially true. We noticed that some authors define assumptions to clarify that some elements agree with reality. For example, the paper from Zhuang et al. has the highest number of assumptions (twenty-five). Some of them are for simplifying, such as that "racks arrive immediately when they are scheduled to be processed." Still, others are not, such as that "each order can only be processed in one workstation" [11]. This phenomenon also occurs with other works [9], [48]. So, it is not possible to conclude how close to reality a paper is exclusively based on the number of assumptions.

The RMFS has many and varied components, as we will discuss in Section V-D. However, we are interested in delving deeper into three subproblems:

- **LFR displacement**. Authors have mainly considered two approaches in this subproblem. One is that the robot travels at a constant speed, and so it requires time to move from one point to the next. This is what we call

"optimized" since usually authors strive to optimize the path of LFRs to minimize traveling costs. The second way is to assume that the robot does not travel and instead it appears instantly where it is required. This is what we call "simplified", since no route planning is required.
- **Replenishment**. Here, again we found that data fall into two approaches. The "optimized" way is when authors include in their study the trip of the pod to a resupply station. Conversely, the "simplified" way is to assume that there is an infinite number of products within each rack.
- **Pod allocation**. The "optimized" approach refers to pods that change their standby location to improve the performance of the warehouse. This process can take into account the demand for the products in that pod, for example. In contrast, the "simplified" approach assumes that pods always return to the same location. Hence, pods are initially distributed throughout the warehouse, and such an assignment remains constant.

Bear in mind that in all subproblems, we also have a N/A category. The reason is that, unexpectedly, oftentimes, authors fail to provide information about the assumptions they considered for these subproblems. This makes it hard to identify the experimental conditions of such works, which limits their repeatability and reliability. Figure 11 shows the data distribution across the subproblems. It is interesting to see that each subproblem has a particular behavior. For example, "LFR displacement" is the one that exhibits the most works with an optimized approach. In contrast, the "Replenishment" subproblem is the one that authors have paid the least attention to, failing to provide information in the highest percentage of cases (almost 50%). Finally, whenever "Pod allocation" is taken into account by the authors, it tends to be considered in a simplified fashion (about 40% of the times). However, it also exhibits a high number of works that omit the information (also about 40%).

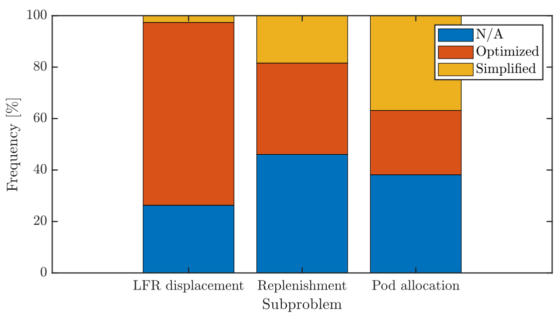


FIGURE 11. Three subproblems of interest and the kind of assumptions that authors make. Blue: authors disregard the problem or fail to mention the related assumption. Orange: Authors optimize the related subproblem. Yellow: Authors consider a simplified version of the subproblem.

Since pod allocation has been the least studied subproblem, we undertook the task of reviewing which works had the greatest impact. In terms of the citation density, the work presented by Weidinger et al. has been the one of highest impact [7]. There, the authors interpreted the assignment of pods as a particular interval scheduling problem. They proposed a new MH dubbed adaptive programming that is compared with simple rule-based assignment policies and obtained good results. The second most relevant work is the one from Yuan et al., in which the authors tested a two-stage hybrid algorithm [49]. Their initial solution was generated with a greedy methodology. Afterward, they used a Simulated Annealing algorithm for optimizing such a solution, which resulted in the pod layout. The third most relevant work befalls to that from Ji et al., where the authors tested two allocation approaches: to locate one pod at a time and to do so with multiple pods at a time. They found out that the latter was better, and they solved this problem by using a three-class-based strategy and the Kuhn-Munkras (KM) algorithm [50].

Throughout our review we also found that there are two articles in which the authors propose a simulation environment. These frameworks were created for facilitating future research on optimization strategies. One of them is Alphabet Soup, which was coded in Java [51]. Although we did not find an entry in Scopus for this framework, we did find it when reading the paper by Wurman et al. [6]. There, the authors claimed that they released the framework during 2006, which was freely available for any researcher interested in warehouse simulation. Nonetheless, it seems to have been discontinued nowadays. The second framework is RAWSim-O, which was coded in C# and published in 2018 [52]. This proposal has been cited eleven times, and seven of those mentions relate to manuscripts within our database. Moreover, the authors successfully tested their framework with real-life robots.

C. TECHNIQUES

Figure 12 summarizes the type of methods that authors have used to address the different problem components associated with the Robotic Mobile Fulfillment System (RMFS). It is interesting to see that the highest importance relates to the use of "hybrid" methods. The reason is that no matter how simple the proposed model is, it is still necessary to plan routes while assigning orders and pods, among other tasks. Hence, it becomes necessary to combine different approaches. Some examples of such methods include: a heuristic method based on Greedy and Simulated Annealing algorithms [53]; a multi-component technique merging Variable Neighborhood Search, semi-open queuing networks, and a two-phase approximate approach [43]; an A* algorithm based on a cyber-physical system [54]; and an A* approach for routing combined with a Simulated Annealing algorithm for scheduling [55].

As we have mentioned, the development of the RMFS is currently at an early stage. For this reason, it is common to find works related to the definition of the most appropriate structure within warehouses, making "simulation" the approach with the second highest relevance up to date.

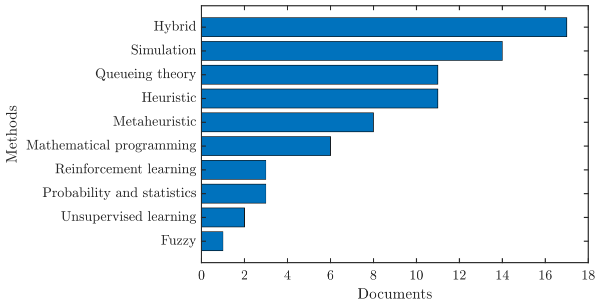


FIGURE 12. Distribution of method usage for solving each case study.

One of the two most relevant examples in this category is that of Lienert et al., who simulated changes in the storage layout [36]. After testing several options, Lienert et al. found one alternative that increased the warehouse throughput. The other work is the one from Wu et al., who also studied the effect of the layout [56]. However, Wu et al. also analyzed the warehouse structural parameter configuration.

"Queueing theory" is the approach that follows in importance, sharing the same number of papers with the "heuristic" approach. Each one of these categories has eleven papers. In the former, there is not much variety in terms of the technique, as most entries incorporate Semi-Open Queuing Networks [9], [57] or Multi-Class Closed Queuing Networks [40]. But for the latter, options are more diverse. The "heuristic" category include M-class velocity-based stowage policies [12], a heuristic method based on auctions [13], and a heuristic beam search [39], just to name a few. Notably, these top four categories stand for almost 70% of all papers. For the remaining categories, we only mention one example for brevity. In the case of "metaheuristics", Genetic Algorithms appear in two manuscripts [26], [34]. In contrast, for "mathematical programming", one finds works that incorporate Mixed-Integer Programming (MIP) [58]. Additionally, "reinforcement learning" integrates techniques such as Multi-Agent Reinforcement Learning (MARL) [19]. Similarly, "probability and statistics" relates to the use of Monte Carlo sampling [59], while "unsupervised learning" does so to clustering models [18]. Finally, it is noteworthy that we only found one paper in the case of "Fuzzy" techniques. In this case, the authors implemented a fuzzy reasoning system and a fuzzy clustering algorithm [46].

V. DISCUSSION

Let us now delve deeper into the results and their relationship, as well as comment on some recommendations that we deem noteworthy.

A. ABOUT THE GENERAL INFORMATION

In Section IV-A we mentioned the papers with the greatest impact, as well as the most relevant authors, countries and institutions. Curiously, we found that no institute from the USA appears among the top institutions (Table 2) despite the fact that it ranks second in Figure 7. After a more detailed inspection of the data, we noticed that most manuscripts belong to different institutions and authors. In fact, the most recurring feature for institutions within the USA is that they have only one paper. This leads us to think that, at least for this country, there is no continued research on the subject. Instead, work related to the RMFS seems to have been carried out sporadically and with spread out efforts. We also found that several of the papers from Figure 7 have collaborations with Chinese authors, which explains why China has such a high share of the scientific production related to the RMFS.

When we compared data about the number of published papers (Figure 5) against the citation density (Table 1), we noticed that there is a gap in the impact of the publications. As expected, the seminal work had a great impact. However, several years passed until the next work of high impact appeared, which was published in 2017. After this date, the number of articles began to grow. Hence, it seems as if it was this work the one that awoke interest towards this topic. Such an article analyzed the sensitivity of the system to several important factors, as we mentioned in Section II-C. Another noteworthy entry is that from position seven in Table 1. Such a manuscript was published in 2021 [10]. Despite being new, it achieves the same level of impact as older articles. Another relatively new paper is that from position five, which was published in 2020 [41]. That article was written by the same authors as the article in second place, showing that this team continues to work on the subject. So not only has the interest of authors in the subject grown, it has also been continuously nurtured within some teams.

Another noteworthy element is the inconsistency between the number of papers published per institution or country, and the most relevant papers. Plus, increasing the number of publications does not necessarily lead to works with a greater impact, as we mentioned. One possible explanation for this pattern is that there is no real continuity in the research, but spread out efforts across some institutions and countries. In fact, the papers with the greatest impact have been published by a reduced group of researchers. Hence, they are the ones who have weaved a research thread that allows them to achieve a greater visibility and impact. Thus, we believe that it is important to focus on a particular problem and plan out a proper research methodology across different projects and milestones.

In terms of the research output, it is interesting to see that the most productive institutions (Table 2) prefer to publish in journals. In fact, only one of the papers that we showed in Table 1 was published in a conference (National Conference on Artificial Intelligence). Moreover, 7 out of 10 articles follow a subscription-based model. So, research on the RMFS has been affected by not having made itself known at conferences and by a poor accessibility, as Figure 8 showed. A combination of both factors may explain the slow increase in research interest that the field experienced throughout its first decade.

B. ABOUT THE SIMULATION CONDITIONS

Throughout our data, we found 16 manuscripts that failed to disclose information about the number of workstations that they considered. We also found the same number of documents that omit information about their assumptions. Hence, 21% of the works have incomplete information for each one of these perspectives. Moreover, we saw a lack of information for all three subproblems of interest (*cf.* Figure 11), though it was more critical for replenishment and pod allocation. Such a lack of information limits the repeatability of the results for other authors, as well as the continuation of research. It is customary for new research to be built upon previous works. But if these articles omit critical information it will be more difficult for them to be used as a baseline, especially when more complete articles are available. This may be another reason for the low impact of some papers. Hence, we recommend to at least dedicate a few lines about the simplifications that were incorporated in each work, or whether the simulation does not really depend on such variables.

We suggest the following list of assumptions as the baseline that should be incorporated into articles, be it to disclose the specifics about each assumption or to mention that it is disregarded since it does not influence the simulation and analysis:

1) Policy for pod relocation after its usage: *static* (same place it was before) or *dynamic* (new place each time it is used).
2) Nature of robot displacement: *ideal* (robots teleport), *constant* (robots move at the same speed all the time), or *variable* (speed changes based on specific conditions).
3) Policy for product replenishment: *ideal* (infinite stock), *static* (products are refilled at fixed time intervals or item levels), or *dynamic* (the system continuously decides when it is best to refill a given product).
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* (every 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).

C. ABOUT THE TECHNIQUES

We already mentioned that it is common to find multiple techniques within the solution of the different problems that the RMFS incorporates. But within this great variety, few authors have pitted different techniques against each other. There were only seven papers in which authors compared different techniques [20], [21], [26], [35], [53], [60], [61]. In our opinion, this number should be higher and efforts should be allocated into comparing different types of techniques that have exhibited good results. It would certainly be interesting to see which kind of technique dominates on each subproblem. Nonetheless, we understand that few authors pursue this approach due to the increased computational cost, time, and complexity. This is exacerbated by how young the subject still is. We think that a global research about RMFS requires collaboration between several authors from different backgrounds to be able to cover the complete problem. We understand that a long-term investigation requires resources and time that are hard to gather, but we are confident that the RMFS is an application worth the effort.

D. ABOUT OUR PROPOSED ORGANIZATION FOR RMFSS

Managing a warehouse involves many variables. In particular, a warehouse that incorporates LFRs has more complexity, which is associated with new variables. However, it also allows for increased efficiency, should the problem be tackled properly. Following we summarize the information that we revised and propose an organization of the process in Figure 13. We divide it into three main components or subproblems: path planning, zoning, and assignment.

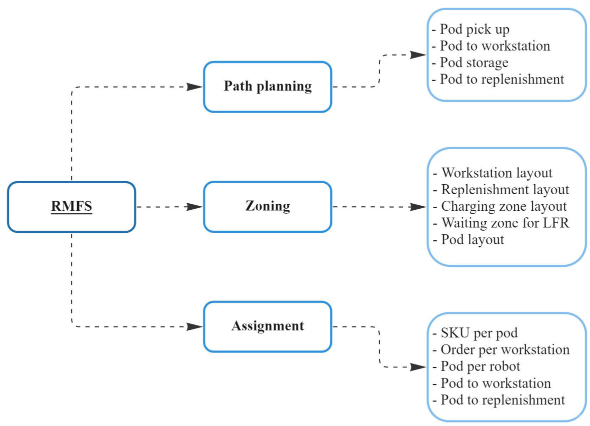


FIGURE 13. A proposed classification of subproblems associated with Robotic Mobile Fulfillment Systems (RMFS).

1) PATH PLANNING

The path planning component condenses all the routes that robots must traverse to fulfill all tasks related with the correct operation of the warehouse. All the trips that robots and pods perform fall into this category, since they are the moving parts within the system. Hence, they all require the planning of a route.

In our scheme, we distribute the path planning subproblem as follows: Whenever an order is to be fulfilled, the robot must begin by retrieving a pod from storage. Hence, the system must calculate a route for "pod pick up". Then, a new route must be planned, which is the one that the robot must traverse with the pod and until arriving to the workstation, named "pod to workstation". Afterward, the robot must return the pod and store it somewhere, hence the "pod storage" entry. At some point in time the pod will run out of product, and so a route to the replenishment zone must be planned, *i.e.*, the "pod to replenishment" entry. This whole process must be repeated for each pod that is required for fulfilling an order, and for all orders.

The paper by Liu et al. is an example of research related to path planning [8]. In their work, the authors integrated a multi-agent-based approach into an algorithm that they named Improved Cooperative A*. Their aim was to add an additional search cost to reduce the number of turns and overlapping paths, obtaining a reduction of movements. Another paper of interest is the one by Shen et al. [60]. There, authors focused on optimizing the collaboration between LFRs, and they proposed an algorithm with which they managed to obtain an average reward 25% higher than with other algorithms.

2) ZONING

The *zoning* category refers to the distribution of zones within a warehouse, which is usually defined during the design stage. Some examples of tasks related to this category include the distribution of workstations, replenishment stations, pods, charging zones, and waiting areas for LFRs. Although they may sound like trivial once-in-a-time tasks, the layout selected could affect the performance of the whole process. Moreover, one could go even further and consider dynamic zoning problems, where the warehouse is constantly shifting to better respond to the current demand.

Research about zoning is scarce, with only a few papers. Even so, the main objective of the authors has been on studying the optimal layout for the pods, where we can find four papers. By citation density, the most relevant paper is the one from Linert et al. [36] with a density of 1.60, followed by the one from Wurman et al. [56] with 1.00. The work from Luo et al. [20] and the one from Yang et al. [45] have no citations, yet.

Although there is virtually no research about the other tasks of this subproblem, we provide them into our proposed organization for shedding some light into possible research paths for moving the RMFS forward. The layout of workstations has only been tackled in the article by Feng et al. [15]. There, the authors compared a traditional and a flying-V layout, and they confirmed that the second one can reduce the total distance that LFRs must traverse to fulfill orders. In contrast, there are no works about the zoning of charging and waiting zones, as well as about the zoning of replenishment stations.

3) ASSIGNMENT

This category brings together the tasks that require some kind of assignment. Many elements require an assignment process. One of them is the assignment of "SKUs per pod". For example, some papers have the goal of optimizing SKU dispersion throughout the warehouse [17], [26], [62]. Another task is "order per workstation'. Many works tackle this topic by assigning whole orders to a given workstation. However, there is one work that is worth detailing. The paper from Xie et al. split each order across multiple workstations, seeking to implement a parallel approach for improving efficiency [10].

About the assignment of "pod per robot", we want to mention some examples of papers that investigated the topic. One is the paper of Bolu et al. that studies the planning of tasks for robots. They used adaptive heuristics to assign the tasks to the robots [63]. To validate their approach they used a task generator. Another example is the paper of Yuan et al., where they studied the correlation between tasks and picking stations [25]. Their proposal significantly shortened the overall picking time, using a four-stage balanced heuristic auction algorithm.

The assignment of the "pod to workstation" is essential for all papers related to simulation. The reason is that pods must travel to workstations so that human workers may take the SKUs and fulfill the orders. In contrast, the "pod to replenishment" task can be disregarded for the sake of simplicity. As we have mentioned previously, most studies assume an infinite amount of SKUs within the pods [17], [58], [64].

VI. CONCLUSION

In this work, we made a systematic review of the papers related to the Robotic Mobile Fulfillment System (RMFS) that have been published so far. Our purpose was to find out the state of the art in this type of warehouse and the subproblems in which efforts have been concentrated and those for which more research is still needed. We analyzed general information such as the most prolific authors and institutions, as well as the most relevant papers. We also analyzed simulation aspects that authors have considered, such as the number of workstations and assumptions, along with information about three subproblems of our interest and the techniques used for tackling the RMFS.

Throughout the manuscript, we highlighted the great complexity of the system and the need to split it. Every author has differing abilities, knowledge, and interests, which define the approaches they follow. Based on our knowledge and the data, we proposed a scheme to organize and identify how an RMFS is constituted (Fig. 13). We separated the subproblems into three large categories: path planning, zoning, and assignment. These subproblems are, by themselves, complex. So authors commonly tackle just one of them, although some authors have tackled up to three simultaneously. Nonetheless, all three categories are paramount for the efficient operation of an RMFS and Table 1 is a proper example of it. There, we can identify diverse topics from each category. In other words, the most relevant works of each category are contained within Table 1. So, it can serve as a quick-reference for anyone interested in analyzing the most relevant works from each category. This also means that each category offers research opportunities that may lead to quite an impact, which makes them all relevant.

Developing a simulation environment from scratch requires time and effort, especially those that involve a graphical user interface. Throughout our revision, we found that the literature already offers two simulation environments for the RMFS. Thus, we believe that further work should take advantage of these resources and build upon them. In this way, researchers may direct their efforts towards the application of the techniques themselves. Moreover, using the same environment should facilitate the repeatability of experiments, which may improve collaboration.

In any case, research on the RMFS is gaining momentum. This problem is quite relevant because it is directly related to e-commerce, which keeps on growing. Optimizing processes within the RMFS could lower its environmental impact. For example, by reducing the number of robot movements that an order requires, energy could be saved. This could further push e-commerce forward. However, the topic requires more visibility and an easier access to the broader research community. This can be achieved, *e.g.*, by presenting more works at conferences and by publishing them in open access journals.

VII. FUTURE RESEARCH DIRECTION

It is paramount to reflect upon the works that may come next. We detected that research on the pod allocation and replenishment subproblems is scarce. Although it is more common for researchers to work on the latter, both subproblems are prime research topics. Nonetheless, among them, we believe that more efforts should be allocated to the former, since there is already evidence that improving on this subproblem can enhance the warehouse efficiency (*cf.* Sect. IV-B).

Currently, there is only one article devoted to the study of energy-saving strategies [65]. Additionally, literature lacks research about the definition of charging zones and all issues related to the energy consumption by the robots. So, these represent other paths worthy of research. Improving upon these issues should also enhance the general efficiency of the warehouse, since they can reflect on a lower energy and resource consumption. This can be achieved by testing the sensibility of the charging zone allocation, as well as the effect of the charging and waiting policies.

Since hybrid techniques are quite common (Figure 12), we believe that techniques such as algorithm portfolios and hyper-heuristics, stand as a feasible alternative. Nonetheless, the second most used technique is queuing theory. We are confident that techniques such as decision trees, support vector machines, and neural networks, may also benefit the field of RMFS. So, the next step in optimization should be towards testing recent techniques on the different subproblems within RMFS.

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MARIA TORCOROMA BENAVIDES-ROBLES (Student Member, IEEE) was born in Ocaña, Norte de Santander, Colombia, in 1992. She received the B.Sc. degree in electronics engineering from Universidad Industrial de Santander (UIS), Bucaramanga, Santander, Colombia, in 2016, and the M.Sc. degree in mechatronics engineering from Tecnológico Nacional de México, Mexico, in 2021. She is currently pursuing the Ph.D. degree in computer science with Tecnológico de Monterrey, Mexico. Her research interests include robotic mobile fulfillment systems, heuristics, hyper-heuristics, and artificial intelligence.

GERARDO HUMBERTO VALENCIA-RIVERA was born in Barrancabermeja, Santander, Colombia, in 1991. He received the B.Sc. degree in mechatronics engineering from Universidad Santo Tomás, Bucaramanga, Santander, in 2017, and the M.Sc. degree in electrical engineering from Universidad de Guanajuato, Mexico, in 2019. He is currently pursuing the Ph.D. degree in computer science with Tecnológico de Monterrey, Mexico. His research interests include optimal control, microgrids, energetic transition, power quality, metaheuristics, and hyper-heuristics.

JORGE M. CRUZ-DUARTE (Senior Member, IEEE) was born in Ocaña, Norte de Santander, Colombia, in 1990. He received the B.Sc. and M.Sc. degrees in electronics engineering from Universidad Industrial de Santander (UIS), Bucaramanga, Santander, in 2012 and 2015, respectively, and the Ph.D. degree in electrical engineering from Universidad de Guanajuato (UGTO), Guanajuato, Mexico, in 2018.

From 2019 to 2021, he was on a postdoctoral stay with the Research Group with Strategic Focus on Intelligent Systems, Tecnológico de Monterrey (TEC), in collaboration with the Chinese Academy of Sciences (CAS). For the Integration of Data Science and Optimization. Since 2021, he has been a Researcher Professor with the Research Group on Advanced Artificial Intelligence, TEC, and a member of the Mexican National System of Researchers (SNI-CONACyT) and AMEXCOMP. His research interests include automatic design, heuristics, fractional calculus, applied thermodynamics, data science, and artificial intelligence.

IVAN AMAYA (Senior Member, IEEE) was born in Bucaramanga, Santander, Colombia, in 1986. He received the B.Sc. degree in mechatronics engineering from Universidad Autónoma de Bucaramanga, in 2008, and the Ph.D. degree in engineering from Universidad Industrial de Santander, in 2015.

From 2016 to 2018, he was a Postdoctoral Fellow with the Research Group with Strategic Focus in Intelligent Systems, Tecnológico de Monterrey (TEC). Since then, he has been a Research Professor with the School of Engineering and Sciences, TEC. His research interests include numerical optimization of both, continuous and discrete problems, through the application of heuristics, metaheuristics, hyper-heuristics, and finding new ways of using feature transformations for improving hyper-heuristic performance. He is a member of the Mexican National System of Researchers, the Mexican Academy of Computing, and the Association for Computing Machinery.

JOSÉ CARLOS ORTIZ-BAYLISS (Member, IEEE) was born in Culiacán, Sinaloa, Mexico, in 1981. He received the B.Sc. degree in computer engineering from Universidad Tecnológico de la Mixteca, in 2005, the M.Sc. and Ph.D. degrees in computer science from Tecnológico de Monterrey (TEC), in 2008 and 2011, respectively, the M.Ed. degree from Universidad del Valle de Mexico, in 2017, the B.Sc. degree in project management from Universidad Virtual del Estado de Guanajuato, in 2019, and the M.Ed.A. degree from the Instituto de Estudios Universitarios, in 2019.

He is currently an Assistant Research Professor with the School of Engineering and Sciences, TEC. His research interests include computational intelligence, machine learning, heuristics, metaheuristics, and hyper-heuristics for solving combinatorial optimization problems. He is a member of the Mexican National System of Researchers, the Institute of Electrical and Electronics Engineers, the Mexican Academy of Computing, and the Association for Computing Machinery.