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Invited Review

Warehousing in the e-commerce era: A survey

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A B S T R A C T

E-commerce retailers face the challenge to assemble large numbers of time-critical picking orders each consisting of just a few order lines with low order quantities. Traditional picker-to-parts warehouses are often ill-suited for these prerequisites, so that automated warehousing systems (e.g., automated picking workstations, robots, and AGV-assisted order picking systems) are applied and organizational adaptions (e.g., mixed-shelves storage, dynamic order processing, and batching, zoning and sorting systems) are made in this branch of industry. This paper is dedicated to these warehousing systems especially suited for e-commerce retailers. We discuss suited systems, survey the relevant literature, and define future research needs.

1. Introduction

Warehousing, i.e., the intermediate storage of goods in between two successive stages of a supply chain (Bartholdi & Hackman, 2016), and its basic functions, i.e., receiving, storage, order picking, and shipping (Gu, Goetschalckx, & Ginnis, 2007), are essential components in any supply chain. Therefore, it is not surprising that a vast body of literature on this topic has accumulated over the past decades (see the most recent surveys of Gu et al. (2007), Gu, Goetschalckx, and McGinnis (2010), de Koster, Le-Duc, and Roodbergen (2007), and Azadeh, de Koster, and Roy (2018)). According to de Koster et al. (2007), in 2007, more than 80% of all warehouses in Western Europe still followed the traditional picker-to-parts setup. Here, human pickers pick order after order while successively visiting shelves on which the demanded stock keeping units (SKUs) are stored. The major drawback of these traditional warehouses is the unproductive picker walking when moving from shelf to shelf and back to the central depot.

The ever increasing sales volumes of e-commerce in the past decade (e.g., see Statista, 2017), however, gave rise to a new generation of warehouses, which are specifically tailored to the special needs of online retailers directly serving final customer demands in the business-to-consumer (B2C) segment. They, typically, face the following requirements:

- *Small orders:* Most private consumers order rather few order lines each demanding only very few items. At German Amazon warehouses, for instance, the average order demand amounts to merely 1.6 items (Boysen, Stephan, & Weidinger, 2018c).
- *Large assortment:* Items offered on websites consume no costly storage space in stores and are, nonetheless, accessible to a broad public. That is why online retailers can afford a much larger assortment, and niche products, typically, account for a much larger proportion of sales in e-commerce than they do in brick-and-mortar stores. This phenomenon is also known under the term “the long tail” (Brynjolfsson, Hu, & Smith, 2003).
- *Tight delivery schedules:* Next-day or even same-day deliveries are an elementary promise of many online retailers especially in the B2C segment (e.g. Yaman, Karasan, & Kara, 2012). This puts increasing stress on warehouse operations and leads to highly time critical order fulfillment processes.
- *Varying workloads:* Many online retailers have dynamically expanded their warehouse capacities over the past years (Laudon & Traver, 2007) and face highly volatile demands, depending on the offered products, e.g., due to seasonal sales. Thus, scalable warehouse capacities are required that can flexibly be adjusted to varying workloads.

Conventional warehouses have difficulties meeting these requirements. In a traditional pick-by-order, picker-to-parts system a picker starts and ends each tour collecting a pick list in a central depot. If orders are small, the fraction of unproductive work while walking to and from the depot and between shelves is overproportionally large. If not counterbalanced by a large (and costly) workforce or by batching multiple orders, the resulting loss of

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level of automation		(i) small orders	(ii) large assortment	(iii) tight schedules	(iv) varying workload	
	traditional order-by-order picker-to-parts warehouses		✓		✓	
	mixed-shelves storage	✓	✓	✓	✓	scope of survey
	batching, zoning & sorting	✓	✓	✓		scope of survey
	dynamic order picking	✓		✓	✓	scope of survey
	AGV-assisted Picking	✓	✓	✓	✓	scope of survey
	shelf-moving robots	✓	✓	✓	✓	scope of survey
	advanced picking workstation	✓	✓	✓		scope of survey
	compact storage systems		✓		✓	
	A-Frame system	✓		✓		

Fig. 1. Overview of warehousing systems suited for e-commerce.

throughput makes it hard meeting the tight delivery schedules of online retailing.

To avoid these problems of traditional warehouses, novel warehousing systems have been developed that either apply automation or implement organizational adaptions. They have a much better fit for online retailers in the B2C segment. This paper is dedicated to surveying these warehousing systems from an operational research perspective. We introduce these systems, discuss their suitability for e-commerce, describe the basic decision problems to be solved when setting up and operating each system, and review the relevant literature. Furthermore, we define future research needs in this area.

For this purpose, the remainder of the paper is structured as follows. Section 2 defines the scope of our survey by identifying the investigated warehousing systems relevant for e-commerce and by specifying the structure of our survey. Then, Sections 3–8 are each dedicated to a specific warehousing system and, finally, Section 9 concludes the paper by discussing some general research directions in warehousing.

2. Scope and structure

This survey is dedicated to warehousing systems that are well suited for the special requirements of online retailers in the B2C segment. A warehousing system consists of *hardware*, which can be further subdivided into storage devices (e.g., a rack), material handling systems (e.g., a conveyor belt) and picking tools (e.g., a pick-by-voice solution or a picking workstation), and *processes* defining the work flow along the applied hardware elements. The critical element which makes a warehouse system suited for online retailing can be either related to hardware or processes. Typically, however, a combination of multiple hardware innovations and process elements is applied, so that we do not further differentiate hardware and processes, but refer to most important entities in both areas. We, thus, define a warehousing system as a hardware or process element (or a combination of both) that enables the intermediate storage of goods in between two successive stages of a supply chain (Bartholdi & Hackman, 2016).

Online retailing, typically, has to assemble (i) small orders from (ii) a large assortment under (iii) great time pressure and has to flexibly adjust order fulfillment processes to (iv) varying workloads (see Section 1). Clearly, the importance of these four requirements varies, e.g., with the offered products and the business strategy, and there are special cases where other requirements may be even more important, e.g., the flexibility to also handle large orders of brick-and-mortar stores in an omni-channel sales strategy (Hübner, Holzapfel, & Kuhn, 2016). For special products some of these requirements may even not hold at all. In online grocery retailing, for instance, orders containing dozens of order lines are rather the norm (Valle, Beasley, & da Cunha, 2017). We, however, exclude these special cases and presuppose that requirements (i) to (iv) are of outstanding importance in online retailing. It is part of our survey to discuss the suitability of each introduced warehousing system for these requirements.

This leads us directly to the question, which specific warehousing systems fit these requirements and should, thus, be considered in this survey. Unfortunately, deriving objective selection criteria seems barely possible, so that we decide for the following approach. First, we preselected the list of warehousing systems depicted in Fig. 1 (ordered according to their level of automation), which is based on numerous warehouses visits, interviews with warehouse managers and experts, and the websites of manufacturers of warehousing solutions. Then, the authors rated whether or not the respective warehousing system fulfills requirements (i) to (iv) on a binary scale and discussed the plausibility of the outcome with warehousing experts (scientists and consultants). The result is depicted in Fig. 1 where a system fitting the respective requirement is indicated by the check icon. Based on these results we review all warehousing systems fulfilling at least three out of four requirements. Consequently, we exclude the following warehousing systems from our survey:

- For traditional reasons, quite a few online retailers still use their conventional picker-to-parts warehouses from pre-internet times where unit loads are stored in racks and order after order is picked and brought to a central depot. Due to the large fraction of unproductive walking (or driving) time, however, these traditional systems can reach the tight deadlines of online retailing only at the cost of an excessively large (and expensive) workforce. Although these warehouses are still applied for online retailing, we rather focus on systems specifically designed for the aforementioned requirements. Note that extensions of this basic setup, e.g., batching of orders, have a better fit and are, thus, considered in our survey.
- In the recent years, quite a few automated compact storage systems have been developed. Examples are movable rack systems (Boysen, Briskorn, & Emde, 2018b), shuttle-based deep lane storage systems (Boysen, Boywitz, & Weidinger, 2018a; Zaerpour, Yu, & de Koster, 2015), the live-cube system (Zaerpour, Yu, & de Koster, 2017), and puzzle-based storage systems (Gue & Kim, 2007). A detailed overview on compact storage is provided by the survey paper of Azadeh et al. (2018). These systems use space efficiently by storing products closer together without providing a direct access to each single item (at any time). With automation and intelligent planning approaches, these systems aim to, nonetheless, ensure acceptably fast retrieval times. In spite of these efforts, compact storage is, typically, not suited for the tight delivery schedules and vast assortments of today's online retailing. Seeing the recent trends, however, where online retailers offer premium delivery services within the next few hours, the stored products have to move closer to the customers where storage space is rare and costly. Thus, for these express services compact storage directly in the city centers may be an adequate choice in the future. We rather aim at the status quo and exclude compact storage systems from this survey.
- Fully automated A-Frame systems process up to 750,000 units per day at an order accuracy of more than 99.95% (Caputo & Pelagagge, 2006). An A-Frame consists of a set of successive vertical channels filled with stockpiles of SKUs. The channels are arranged along two opposite frames, which have their top ends tilted toward each other like a pitched roof. In between the two frames runs a conveyer belt, so that from the side view the system looks like an "A". At the bottom of each channel there is an automated dispenser, which pushes one or more bottommost items toward the conveyor whenever the respective items are required by an order passing by on the conveyor. Due to their efficiency A-Frames are certainly well suited to fulfill the tight deadlines of online retailing and also small order sizes seem unproblematic. However, large assortments require an excessive number of A-Frame modules, which leads to high investment costs and excessive space requirements on the shop floor. A-Frames also require a lot of fixed installed machinery, so that a flexible adjustment to varying workloads seems problematic. In addition, they have strict requirements on product shape, size, and packaging. Therefore, A-Frames are rather suited for niche online retailers with a reduced assortment of relatively small and infrangible products, e.g., pharmaceutics and cosmetics (Bartholdi & Hackman, 2016; Pazour & Meller, 2011) and, thus, excluded from our survey.
- Some systems are rather dedicated to processing larger customer orders consisting of multiple order lines and/or multiple requested items per line, e.g., placed by brick-and-mortar stores. Examples are, for instance, inverse order picking systems (also denoted as put-to-light systems), see (Füßler & Boysen, 2017a). These systems are not treated in this survey.
- We also exclude systems dedicated to specific product types that require specific handling, e.g., due to their weight or dimension. Examples are, for instance, hanging trolley solutions for foodstuffs (Swisslog, 2016) and clothes or crane-based systems for tires (Cimcorp, 2011).
- Finally, prototype systems that have not outgrown the evaluation phase and are yet not applied by large online retailers are also excluded. Examples are the Toru robot of Magazino (2017) or the Robo-Pick system of Schäfer (2017), which promise fully automated order picking from shelves and bins, respectively.

Excluding these warehousing systems leaves behind the six systems that are discussed in the following sections ordered by an increasing level of automation, e.g., in the same order depicted in Fig. 1. For each system we elaborate the following aspects:

(a) System description: We give a brief introduction of the main system elements and their involvement in the order fulfillment process.
(b) Suitability for e-commerce: Given our four basic requirements of e-commerce warehouses (see Section 1), we briefly summarize the fit of each system.
(c) Decision problems: For each system, basically the following three main decision areas exist (ordered according to planning horizon): (i) layout design planning, (ii) storage assignment, and (iii) order picking. We discuss what peculiarities have to be considered when addressing these planning tasks for the respective warehousing system.
(d) Literature survey and future research: Finally, we also serve the main intention of a survey paper, that is we review the relevant literature and outline future research needs.

The fundamental functionality of warehousing makes it anything but astounding that quite a few survey papers on warehousing already exist. First, there are the general surveys of van den Berg (1999), Rouwenhorst et al. (2000), Gu et al. (2007, 2010), and de Koster et al. (2007). These papers address the complete field of warehousing, but mostly focus on traditional picker-to-parts systems. Since their publication, some time has passed and online retailing is still a comparatively novel phenomenon that has dynamically evolved in the last decade, so that there is not much overlap with these general surveys. Moreover, other surveys on special warehousing aspects, e.g., automated storage and retrieval system (Gagliardi, Renaud, & Ruiz, 2012; Roodbergen & Vis, 2009) and crane scheduling in these systems (Boysen & Stephan, 2016) exist. Furthermore, Azadeh et al. (2018) focus on robotized warehousing systems. From those systems reviewed in our paper only AGV-assisted order picking (see Section 6) and shelf-moving robots (see Section 7) fall into this category. Mostly, Azadeh et al. (2018) address compact storage systems, so that there is not much overlap with their paper. The recent survey of van Gils, Ramaekers, Caris, and de Koster (2018) is dedicated to holistic warehousing research that combines two or more planning tasks. Holistic models are without doubt an important matter especially from the practitioner's perspective (see Section 9), but lead to a completely different focus. Gong and de Koster (2011) address methodological aspects and focus stochastic models. Finally, there is the survey of Agatz, Fleischmann, and van Nunen (2008), which addresses e-fulfillment in a multi-channel environment. The warehousing aspect is only briefly covered in this survey. Thus, we think that due to the great relevance of online retailing and the deviating topics of all these previous papers, yet another survey on warehousing seems well justified.

Finally, we briefly specify our database search for retrieving the papers to be reviewed (see, e.g., Hochrein and Glock (2012) for

Fig. 2. Mixed-shelves in a scattered storage warehouse.

a general description of how to set up a systematic literature retrieval). As keywords specifying the business function we apply “warehousing”, “distribution center”, “order fulfilment”, and “order processing”. Furthermore, a second group of keywords, i.e., “e-commerce”, “online retailer”, “online retailing”, and “e-fulfillment” is applied to specify the branch of industry. Any combination of keywords from the first and second group has been applied as a query in two scholarly databases, namely Business Source Premier and Scopus. Additional queries were executed with the names of the six reviewed warehousing systems. All English-language papers published in peer-reviewed journals that have been retrieved and those cited in their reference lists (snowball approach) were checked for relevance by analyzing their abstracts. Additionally, some selected working papers and conference proceedings have been integrated, if (according to the authors’ subjective assessment) they considerably contribute to the surveyed field. Note that we try to build up on the work of existing survey papers as far as possible to avoid repetition. Batching and zoning, for instance, is surveyed in detail by Gu et al. (2007) and de Koster et al. (2007), so that we limit our literature review on both topics to work published after these surveys have appeared. The same holds for the routing of automated guided vehicles, which has been summarized by Qiu, Hsu, Huang, and Wang (2002) and Vis (2006), such that we only discuss literature published after 2006 here.

3. Mixed-shelves storage

Mixed-shelves storage is a special storage assignment strategy applied by many large-sized facilities in the B2C segment, such as the distribution centers of Amazon Europe and fashion retailer Zalando (Weidinger, Boysen, & Schneider, 2017). Incoming unit loads of SKUs are purposefully broken down into single units that are spread all over the shelves throughout the warehouse. This is why this storage assignment strategy is also denoted as scattered storage (Weidinger & Boysen, 2017). An example warehouse is depicted in Fig. 2.[3]

The basic intention of mixed-shelves storage is that with units scattered all around the warehouse the average distances from anywhere in the warehouse toward the closest unit of each SKU are considerably reduced. This increases the probability that a demanded SKU is close by. Furthermore, mixed-shelves warehouses often have multiple access points (depots) where completed orders are handed over to the central conveyor system. In this way, the unproductive walking of pickers considerably decreases and tight delivery schedules can better be met. Scattered storage comes without excessive automation, so that by adding or removing pickers an adaption to varying workloads is easily possible. The large assortments of the B2C segment seem also unproblematic as long as there is enough space in the warehouse for placing racks.

On the negative side, scattered storage causes additional effort during the put-away of units. Logistics workers have to visit multiple storage positions instead of just a single one when putting a complete unit load into storage. Moreover, orders demanding larger order quantities of some SKU cause problems. In this case, a picker has to visit multiple storage positions of the requested SKU until enough units are collected. However, in the B2C segment SKUs are seldom ordered in large quantities, so that mixed-shelves storage seems well suited to this field of application.

During the *layout design phase* of a mixed-shelves warehouse especially the placement of shelves, aisles, and depots have to be considered and the support equipment of pickers has to be selected. To use space efficiently, most warehouses place the man-high racks in multi-story mezzanine systems. While layout design is a widely elaborated field of research for traditional picker-to-parts warehouses (e.g., see Baker & Canessa, 2009; Roodbergen & Vis, 2006), scientific decision support for mixed-shelves warehouses, e.g., on how to position mixed-shelves or where to place middle aisles and depots, is yet not existent. In mixed racks specific units cannot be found without IT support, so that pickers need to be equipped with a handheld scanner or some other device (e.g., a pick-by-voice solution) directing the way toward the picking positions. Furthermore, in most mixed-shelves warehouses, pickers are equipped with picking carts, which have a capacity for multiple bins, so that multiple orders can be picked in parallel. Properly dimensioning these carts according to the basic trade-off between additional capacity and reduced maneuverability and vice versa seems an interesting task for future research.

Like in any other warehouse, the *storage assignment* decides on the exact storage position of each unit to be stored. All mixed-shelves warehouses known by the authors just apply random storage and leave the selection of storage positions to the logistics workers replenishing the shelves. Equipped with a cart full of units to be stored as well as a handheld scanner or a comparable device, these workers walk into the warehouse, place units just where they find suited storage space, and register the new storage position of the respective SKU in the IT system making use of their device. In the long run, random storage leads to an equal distribution of units all over the warehouse. Note that one could argue that the human selection makes the choice not actually random, but leads to most convenient racks within easy reach being filled first. Nonetheless, we follow the existing literature and call this a random storage assignment policy. Weidinger and Boysen (2017) show that planning the storage positions such that the scatteredness of units is optimized, may lead to a much higher picking performance. They operationalize the scatteredness by minimizing the weighted sum of maximum distances toward the closest unit of each SKU seen from the access points to the central conveyor system. They develop a heuristic binary search based solution procedure and compare the results with random storage. By simulating picker tours through both alternative storage plans they show that optimization leads to much better results. Their solution procedure is able to handle a few hundred SKUs. Seeing the huge facilities and thousands of SKUs in the B2C segment, however, future research could try to develop even better solution procedures that can handle data instances of real-world size.

The main decision problems to be solved during *order picking* are the prioritization of orders, their assignment to pickers and picker routing. The prioritization mainly depends on the urgency of orders, which, e.g., is influenced by the value of the customer, promised delivery dates, and the departure times of the targeted delivery trucks. To the best of the authors’ knowledge research on

[3] The picture is published under the Creative Commons License (BY 2.0). The author of the picture is Álvaro Ibáñez.

this topic in the mixed-shelves context is not yet existent. The assignment of orders to pickers has to consider fairness aspects (i.e., the workload should be evenly shared among pickers) and the fit of orders assigned to the same picker, such that short picking routes are enabled. The assignment decision is, thus, heavily influenced by the picker routing, which decides on the sequence of visited storage positions where units are retrieved. Scattered storage warehouses cause some peculiarities, which are not considered by the traditional routing methods tailored to unit-load warehouses (see de Koster et al. (2007)). First, the routing of pickers also requires a selection of alternative storage positions each requested SKU is stored at. Once a predecessor order has depleted a storage position these units are no longer available for successor orders. Moreover, many mixed-shelves warehouses have multiple depots and apply carts with bins for multiple orders, so that further peculiarities need to be considered. Existing research in this context limits itself to single picker routing. Daniels, Rummel, and Schantz (1998) were the first to integrate the selection of units from alternative storage positions into picker routing. They prove NP-hardness for facultative distance matrices and develop multiple heuristics. Among them a tabu search approach is shown to have the best solution performance. Weidinger (2018) extends their findings to rectangular warehouses with parallel aisles by proving NP-hardness for this special layout setting, which is rather standard in business practice. He also provides a new decomposition approach for solving the picker routing problem in rectangular warehouses by combining multiple selection rules and the efficient dynamic programming approach of Ratliff and Rosenthal (1983). Finally, this study provides insight into the disadvantage of mixed-shelves storage when processing orders demanding many units of the same SKU and gives managerial insights into an appropriate level of unit scatteredness for multi-channel strategies. While all previously mentioned papers deal with the isolated picker routing problem, Weidinger et al. (2017) combine picker routing and sort-while-pick batching. The latter means that the picker directly sorts orders into bins, such that no subsequent consolidation process is required. Given multiple customer orders, a given capacity of the picking cart pushed by the picker, and a multi-depot configuration of the mixed-shelves warehouse, they search for the shortest picking tour satisfying all orders, while picking multiple orders in parallel. Future research could extend the current findings to routing multiple pickers in parallel, integrating a parallel replenishment of the shelves (see Wruck, Vis, & Boter, 2013), congestion in narrow aisles, and order batching. The latter should integrate time-critical orders with individual due dates into picker routing, which seems highly relevant regarding the trend to ever tighter delivery schedules.

4. Batching, zoning, and sorting

Two warehousing policies that also have the basic intention of reducing the unproductive walking of pickers are batching and zoning. These policies have a much longer tradition and are applied in traditional picker-to-parts warehouses (where unit loads are kept together) for decades. In the recent years, large online retailers like Amazon Europe and fashion retailer Zalando, however, couple batching and zoning with mixed-shelves storage (Weidinger et al., 2017), so that further reductions on non-value adding walking are achieved. Batching and zoning can be defined as follows (also see de Koster et al., 2007):

- *Batching:* Instead of returning to the central depot each time a single picking order is completed, multiple orders are unified to a batch of orders jointly assembled in a picker tour. Only if the complete batch of orders is assembled the picker returns to the depot and starts the next tour with the successive batch. In this way, the pick density per tour is increased and a more efficient picking process is enabled.
- *Zoning:* A further reduction of the picking effort is enabled, if the warehouse is partitioned into disjoint zones. Order pickers only pick the part of an order that is stored in their assigned zone. Parallel zoning enables a parallel processing of orders and, thus, a faster order processing. Furthermore, each picker only traverses smaller areas of the warehouse. Note that a progressive zoning where orders visit zones subsequently seems problematic when facing the tight deadlines of online retailers (see below).

Either only one of these policies is individually applied or both of them are combined. In either case, a major drawback of these policies is that they require a subsequent consolidation process where picking orders are isolated. Batched orders need to be separated and a parallel zoning requires the merging of multiple partial orders picked in different zones. Note that the latter can be avoided if zoning (in isolation) is applied in a sequential manner (also denoted as *progressive zoning*, see Yu & de Koster, 2009). In this case, bins in which orders are collected visit zones subsequently, so that an additional consolidation process is not required. Seeing the great time pressure of online retailing, however, subsequent visits of multiple zones, typically, require too much time, so that we restrict our view on parallel zoning (see also Petersen, 2000). Here, partial orders are simultaneously collected in multiple zones and, thus, need to be consolidated afterwards. The need for consolidation separates the complete order fulfillment process of warehouses applying batching and/or zoning into the following three steps:

(a) *Order picking* is executed by human order pickers that collect batches of partial orders in their respective zones. Many online retailers equip their pickers with small picking carts carrying multiple bins to collect multiple (partial) batches per picker tour in parallel. Once a picker tour is completed, the filled bins are handed over to the central conveyor system at an access point (depot) of the respective zone and the next tour starts.

(b) *Intermediate storage:* Completed bins could directly be conveyed into the consolidation area. Especially in large warehouses, however, the time span between completion of the first and last bin of a batch arriving from different zones may become large. For instance, inventory differences or misplaced units can occur, so that some parts of a batch arrive considerably delayed. If the bins of such a batch would directly be released into the consolidation area, then, at least some positions where orders are collected, i.e., some dead-end lane of a conveyor-based sorting system or the shelves of a put wall (see below), would be blocked for a prolonged time span until the delayed bins arrive. To avoid the excessive consolidation capacity required by such a direct bin release (or the threat that all positions are blocked and a deadlock occurs), bins are typically collected in the central conveyor system and only released into the consolidation area once the batch is complete and all bins have arrived from their zones. Automated (i.e., conveyor-based) consolidation systems often apply a closed-loop conveyor where units circulate until the complete batch has arrived in the loop (Johnson, 1998; Meller, 1997). A loop conveyor for a huge number of orders, however, requires excessive space on the shop floor. Therefore, especially large-sized facilities rather apply automated storage and retrieval systems (ASRS), e.g., crane-operated high-bay racks (Boysen & Stephan, 2016) or carousel systems (Litvak & Vlasiou, 2010), to temporarily store bins in a more space-efficient manner. Additionally, these storage systems allow to release bins in a specific

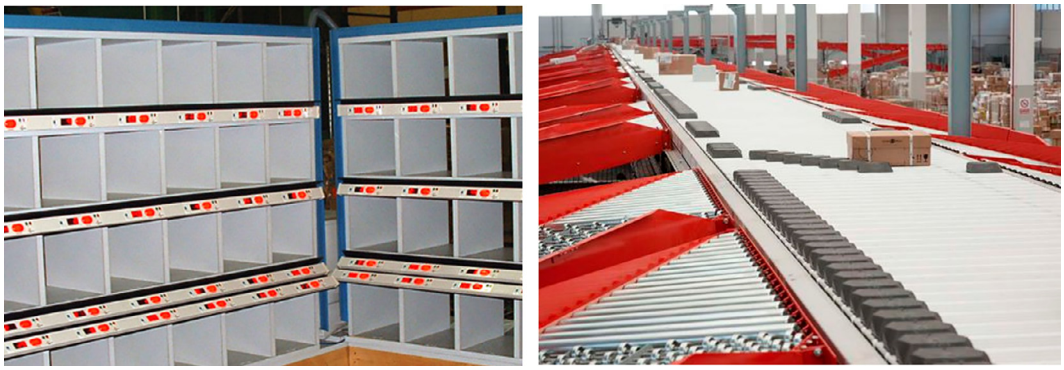

Fig. 3. Put-to-light rack (Source: Lightning Pick Technologies, left) sliding shoe sorter (Source: Vanderlande, right).

order toward the consolidation area, so that orders are not spread over an excessive number of conveyor segments. Orders kept closer together on the belt reduce the time span consolidation capacity is blocked by the collection of orders.

(c) Finally, the bins of a batch reach the *consolidation area*. Here, individual picking orders are to be assembled, packed into their shipping cartons and forwarded to the truck trailers serving the respective destinations. There exist two alternative solutions of how the consolidation process is organized. A *manual* consolidation applies so-called put walls (see Fig. 3 (left)). A put wall is a simple reach-through rack separated into multiple shelves, which are accessible from both sides. Each shelf is temporarily assigned to a separate order. On one side of the wall, a logistics worker (for a better distinction called the *putter*) scans a unit taken from the current bin and a put-to-light mechanism indicates into which shelf it is to be put. In this way, bin after bin is sorted into the wall. On the other side of the wall reside other logistic workers (called the *packers*). Here, another put-to-light mechanism indicates completed orders, so that a packer can empty an indicated shelf and pack the respective units into a cardboard box. Packed orders are, finally, handed over to another conveyor system bringing them toward the shipping area. Put walls are, for instance, applied in the Poznan (Poland) facility of Amazon (Boysen et al., 2018c). The big advantage of a manual consolidation process is its scalability. By extending the put wall and/or adding additional putters and packers consolidation capacity can quickly be adapted to an increasing workload. On the negative side, there are high labor costs, so that other warehouses apply *automated* solutions where human putters are substituted by a sortation conveyor. The central conveyor system, first, delivers the bins toward an induction station where either a human worker or fully automated induction technology (see Gallien & Weber, 2010) depletes the bins and isolates the units on separate segments, e.g., of a sliding shoe sorter depicted in Fig. 3 (right). Depending on the SKUs to be handled and the sorting throughput to be reached, other sorter technology, e.g., crossbelt, bomb-bay, and tilt tray sorters (see Briskorn, Emde, & Boysen, 2017; Johnson & Meller, 2002), can be applied. After passing a recognition station, where the bar code is scanned to identify each unit, the belt moves along a sequence of successive exit lanes. Once the lane currently assigned to the customer order of the present unit is reached, the sorter is initiated and moves the unit – often via a gravity chute – to the respective packing station assigned to the exit lane. As soon as all units of a customer order are collected, a beacon indicates the new status, a packer moves to the station and fills the collected units into a cardboard box. This releases the lane, so that it can be assigned to a subsequent customer order. Automated sortation conveyors revert the assessment of put walls. They reduce wage costs, but require a higher investment and the fixed hardware is less scalable.

In the *layout design phase* a decision on the number (and size) of zones as well as a suited intermediate storage system and the right consolidation technique has to be made. Due to the long tradition of batching and zoning, a large body of literature has accumulated with regard to the first decision. The survey papers of Gu et al. (2007) and de Koster et al. (2007) summarize the research efforts on how to partition the total warehouse into an appropriate number of zones. After the publication of these survey papers, quite a few new articles on the topic of sizing zones in an e-commerce environment has been published (i.e., de Koster, Le-Duc, & Zaerpour, 2012; Melacini, Perotti, & Tumino, 2011; Parikh & Meller, 2008; Yu & de Koster, 2009), which are summarized in the following. Yu and de Koster (2009) and Melacini et al. (2011) study progressive zoning, which due to the delays of the successive zone visits seems not well suited for the tight deadlines of e-commerce (see above). Parikh and Meller (2008) introduce a cost model supporting the choice between a batch and a zone picking strategy. In modern e-commerce warehouses, however, both strategies are usually applied in parallel. de Koster et al. (2012) investigate the problem of determining the optimal number of zones. They introduce a mixed-integer program to assign order lines to picking tours minimizing the throughput time of complete orders. Having multiple zones and a picking capacity necessitating multiple picking tours per zone and batch, the assignment of units to picking tours impacts the performance of the consolidation process. The authors aim to assign units to tours, such that both processes are synchronized and the total throughput time, including picking, consolidation, and packing, is reduced. Based on this, the optimal number of zones is determined for the example of a Dutch online retailer. To the best of the authors' knowledge, no research on sizing zones in mixed-shelves warehouse is available yet. A similar conclusion can be drawn for the choice of the consolidation technique. Only Russell and Meller (2003) provide decision support for this decision task. They address the choice between manual and fully automated order consolidation in a warehouse with a picking area directly connected to the consolidation area via a conveyor. Finally, no publication on the choice of a suited intermediate storage device, i.e., loop conveyor vs. high-bay rack vs. carousel, is available, so that further research on all decisions of the layout design phase seems necessary.

The problems occurring during *storage assignment* in a single zone are basically the same as for mixed-shelves warehouses, because batching and zoning are typically coupled with mixed-shelves storage in e-commerce warehouses. For the sake of conciseness, we, therefore, refer to Section 3. On a higher planning level, however, warehouse managers additionally have to distribute incoming goods among picking zones. Decision criteria are, for instance, an equal fill level of inventory in all zones and the availability of each SKU in multiple zones to increase flexibility. This decision is tackled by Yuan, Cezik, and Graves (2018) based on a flexibility perspective inspired by Jordan and Graves (1995). The authors assume an initially empty warehouse and benchmark eight policies for distributing units among zones. Aiming at a high service level when having limited picking capacity in each zone, they identify two policies being superior. The first one tracks expected workload in each zone and assigns incoming SKUs to zones with lower utilization. The second policy assigns half of the total stock to two randomly selected zones each. In this way, SKUs can be picked from alternative zones, which increases the flexibility when having to react to varying workloads or picker workforces in different zones.

The outstanding *operational problem* in a batching, zoning, and sorting context is the batch formation problem. Batch formation, i.e., the decision which picking orders should be jointly processed per picker tour, is a very active field of research and plenty relevant papers have accumulated over the past decades. An overview is, again, provided by the in-depth survey papers of Gu et al. (2007) and de Koster et al. (2007). We only review the papers published after these surveys, which is still a considerable amount. The basic trade-off to be resolved during batch formation is the one between urgency and efficiency. On the one hand, urgent orders, e.g., of customers taking part in premium delivery programs and with nearing promised delivery time, should be preferred and added to the next batches. On the other hand, orders consisting of units with close-by storage positions should be unified to batches, such that the resulting picker tours are shortened.

The most basic approach to consider this trade-off is implicitly contained in offline order batching. Here, it is assumed that the set of most urgent orders has already been selected (according to some urgency criterion outlined above). The result is a deterministic set of (equally urgent) picking orders, which can be partitioned into batches merely according to the maxim of finding efficient picker tours. This branch of batching research has a comparatively long tradition and current research mainly addresses the development of high-performance solution procedures. Ho and Tseng (2006) as well as Ho, Su, and Shi (2008) investigate seed algorithms for classical offline batching. They combine several seed-order selection rules with other selection rules for extending picker tours. These combinations are tested on two different pick-frequency distributions, i.e., derived from dedicated and random storage, and for two route-planning algorithms, i.e., largest gap (see Hall, 1993) and largest gap with simulated annealing improvement. Henn, Koch, Doerner, Strauss, and Wäscher (2010) introduce two novel solution procedures. The first approach is based on iterated local search and the second one on a rank-based ant algorithm. Both algorithms are compared and shown to outperform existing procedures. Due to its shorter solution time the authors, finally, recommend the iterative local search approach. Hsieh and Huang (2011) propose solution approaches on the basis of data mining techniques. Hong, Johnson, and Peters (2012b) provide a fast heuristic, based on a decomposition approach, that is suitable for large instances of the offline batching problem. The authors limit themselves to traversal routing (see Hall, 1993) and suggest a new MIP model for the batching problem making use of this routing policy. Employing a novel, tight lower bound they show that the approach results in good quality solutions even for instances with more than 2000 orders and 10 aisles within a warehouse. For this instance size, the approach consumes between 60 and 80 seconds on average. Kulak, Sahin, and Taner (2012) and Li, Huang, and Dai (2017) also propose a decomposition of the joint batching and routing problem. Bozer and Kile (2008) provide a MIP model for offline batch formation under the S-shape routing policy. Making use of newly developed bounds several state-of-the-art heuristics are evaluated. Their results are improved by Hong and Kim (2017) who also consider batch picking with S-shaped routes. Žulj, Kramer, and Schneider (2018) propose a more general setting where any routing policy can be employed. They propose a hybrid of adaptive large neighborhood search and tabu search, which is shown to outperform all existing solution procedures, e.g., the ones of Henn and Wäscher (2012), Oncan (2015), and Koch and Wäscher (2016).

A straightforward alternative to explicitly integrate the basic urgency-efficiency trade-off of batch formation into offline batching is to assign each order a due date. A due date is, typically, defined by a cut-off date, which leaves enough time after picking to pack the order into a cardboard box and to timely reach the scheduled departure of the dedicated truck trailer. In this context, Henn and Schmid (2013) aim to minimize the total tardiness of all orders and propose an iterated local search procedure as well as an attribute-based hill climber approach for solving the resulting problem. In a comprehensive computational study, the approaches are benchmarked for different warehouse settings and iterated local search shows superior. In the setting of Zhang, Wang, and Huang (2016), vehicles' departure times have to be met. In a first setting, they minimize the sum of service times of batches. In a second setting, they maximize the quantity of orders timely reaching their trucks. They, additionally, compare the results of both objectives and adapt existing solution procedures to the new requirements. The currently best solution approach to the problem setting minimizing total tardiness is provided by Menéndez, Bustillo, Pardo, and Duarte (2017a). They develop a variable large neighborhood search procedure and benchmark it against state-of-the-art solution procedures. Based on the former work of Chen, Cheng, Chen, and Chan (2015) and Scholz, Schubert, and Wäscher (2017) study a holistic planning approach for batch formation, assigning batches to pickers, sequencing of batches, and picker routing. To optimize large instances, a variable neighborhood descent algorithm is suggested. In comparison to considering all subproblems separately, the authors show that a holistic approach is able to reduce total tardiness by up to 84%. Tsai, Liou, and Huang (2008) treat an alternative problem setting where orders face earliness and tardiness costs.

A relatively new branch in this field is online (or dynamic) order batching. Instead of partitioning a previously known, deterministic set of orders into static batches, the dynamic arrival of new orders is explicitly considered here. Online batching can further be subdivided into fixed-time-window batching (see, e.g., Bukchin, Khmelnitsky, & Yakuel, 2012; Henn & Wäscher, 2012), where all new orders are considered that have arrived during a fixed time span, and variable-time-window batching (see, e.g., Le-Duc & de Koster, 2007; Xu, Liu, Li, & Dong, 2014), where batch formation is triggered whenever a predefined number of orders have arrived. By applying analytical models, van Nieuwenhuyse and de Koster (2009) investigate the impact of varying setup parameters on both online batching strategies, e.g., variable- and fixed-time-window batching, in a 2-block warehouse with multiple pickers, general setup and service time distributions, as well as a downstream packing process. While it is assumed that the online batching strategy is given, the computational study clearly shows that a pick-and-sort configuration is superior to the sort-while-pick strategy in nearly every setting. This means that the additional effort for sorting the picked units into bins while the picker is still on the move during sort-while-pick order processing is higher than the additional double handling caused by the two successive picking and sorting process steps of a pick-and-sort strategy. In addition to that, extensive experiments on other system parameters (e.g., the warehouse size or the average customer order volume) are executed to assist practitioners during the layout phase. Henn and Wäscher (2012) adapt solution procedures for offline batching to the online case. They consider several existing batching algorithms and selection rules for the batch to be processed next and compare them. In their computational study, a combination of iterated local search and selecting the batch with highest savings of processing time is identified to result in the lowest order completion times. Xu et al. (2014) provide an analytical model for a variable-time-window batching environment, implementing random storage and S-shaped routing. They measure the effect of varying order and system parameters, e.g., the number and length of picking aisles, the interarrival times of orders, and the batch sizes, on the expected throughput time.

Another stream of batching research tries to extend offline and online batching by further peculiarities of practical relevance. For instance, order batching and sequencing in narrow aisles where pickers cannot pass each other is investigated by Hong, Johnson, and Peters (2012a). They consider congestion among pickers, typically resulting in reduced pick performance (see also Gue, Meller, & Skufca, 2006; Parikh & Meller, 2010), and present an integer program as well as a heuristic based on simulated annealing for the resulting optimization problem. In their computational study, the holistic optimization approach leads to a 5–15% shorter total retrieval time compared to a successive execution of batch formation and picker routing. Matusiak, de Koster, and Saarinen (2017) investigate a special offline batching problem where different performance levels of pickers are considered. They solve the partitioning of orders into batches, the assignment of these batches to pickers, and the picker routing problem in a holistic approach, such that the total picking time is minimized. They also propose an estimation method for batch execution times and an adaptive large neighborhood search heuristic for the integrated problem. The methods are tested on data of a large retail warehouse and improvements of nearly 10% of total batch execution time are obtained. A similar problem setting for online order batching is investigated by Zhang, Wang, Chan, and Ruan (2017). They do not assume different processing times of pickers, but only coordinate the assignment of batches to the workforce. The same setting is investigated for the offline case by Henn (2015). Another special order batching problem is addressed by Matusiak, de Koster, Kroon, and Saarinen (2014) where precedence constraints among picked units have to be considered. Precedence constraints may result from weight and stability aspects on a picking cart or different shapes of products. The problem is modeled and a suited heuristic solution procedure based on a decomposition approach is presented. In a computational study, the new approach is tested on real-world data of a large Finnish warehouse. Reductions of the total travel distances about 15% compared to the currently implemented routing policy are recorded. Grosse, Glock, and Ballester-Ripoll (2014) consider weights restrictions directly in their joint order batching and picker routing approach. Wruck et al. (2013) integrate forward and return product flows, caused by customer returns, into one single approach and solve the combined batching problem of timely delivering customers and efficiently stowing returned products. Suited solution procedures, based on seed algorithms, are proposed and tested on real-world data of a library warehouse. The combined approach leads to up to 44% shorter total travel distances in comparison to handling picking and stowing separately.

Batch formation is even more complicated if, in addition to batching, the warehouse is subdivided into multiple zones. In this case, the *wave of orders* to be processed next determines the workload in all zones and leads to an interdependent batching problem in each zone. The parts of the wave of orders to be picked in the respective zone, additionally, have to be partitioned into batches in each zone. When selecting the wave of orders to be picked next from all zones in parallel, in addition to the urgency-efficiency trade-off, an equal distribution of the workload among the zones should be considered. A fair distribution of workload ensures that all partial orders are finished at about the same time and can advance jointly into the consolidation area. If some zones, however, receive a considerably higher workload their partial batches may arrive late, which bears the risk that consolidation capacity is blocked by orders waiting for late units. In the worst case, this may lead to deadlocks where all sortation lanes are blocked, newly arriving orders cannot be sorted, and costly recovery procedures for the steadily succeeding units need to be executed. Çeven and Gue (2015) give advice regarding the optimal number and timing of waves in such an environment. They develop analytical models and test their approach on real-world data from a large distribution center. It is shown that an optimized wave release strategy significantly improves the ratio of shipments on time in comparison to a simple rule of thumb. The decision on whether wave picking should be applied at all is tackled by Gallien and Weber (2010). The alternative is to directly release each incoming order without collecting them for a while and unifying them to waves that are jointly collected in all zones. The authors compare waveless and wave-based picking strategies in an e-commerce warehouse, utilizing a newly developed queueing model. Based on the results gained by applying this model to real-world data, an optimization technique based on dynamic programming for the timely release of orders in a waveless environment is introduced. In a thorough simulation study, superiority (or at least equal performance) of waveless picking in all considered scenarios is shown when applying their approach. An alternative to integrate the coordination of multiple zones into offline order batching has been introduced by Gademann, van den Berg, and van der Hoff (2001). They subdivide the total set of orders into a given number of waves by minimizing the maximum processing time over all zones summarized over all waves. This problem is reconsidered by Menéndez, Pardo, Snchez-Oro, and Duarte (2017b). They suggest a new parallel variable neighborhood search, which outperforms previous solution procedures.

Batch formation is (by far) the most well researched problem within the scope of our survey. However, there still remains room for future research. In today's e-commerce warehouses batching and zoning is typically coupled with mixed-shelves storage. In a mixed-shelves warehouse, SKUs are stored at multiple positions and, thus, also in different zones. Therefore, batch formation has additionally to decide from which zone a specific unit should be picked. To the best of the authors' knowledge, no publication on the special batching problems arising from this peculiarity is available yet. This finding is also valid for some further *operational problems* beyond batch formation that are addressed in the following.

The release sequence of bins from intermediate storage containing the order batches to be sorted is considered by Boysen, Fedtke, and Weidinger (2018a) and Boysen et al. (2018c) for automated and manual sorting systems, respectively. Boysen et al. (2018a) describe the minimum order spread sequencing problem, which aims to release the bins in such a way that the number of sorter segments between the first and the last unit of an order on a sortation conveyor is minimized. In this way, orders can quickly be assembled in their dedicated packing stations and consolidation capacity of the automated sorter can be released earlier. The problem is formalized, NP-hardness is proven, and a suited solution procedure based on dynamic programming is introduced. In a simulation study, superiority over randomized bin release sequences is shown and the impact of multiple additional problem parameters on order consolidation performance is investigated. Among them is, for instance, the impact of the number of bins a given batch is divided into. Having a manual consolidation process, the resulting problem is described by Boysen et al. (2018c). They consider the release of bins from intermediate storage toward a manual put wall. They model the problem as a special machine scheduling problem with a *m:n*-relationship among jobs (bins). The problem is proven to be NP-hard and exact and heuristic solution procedures are suggested. A significant reduction on both, idle times of packers and throughput time of batches, is shown in a simulation study for optimized bin sequences. Similar to Bozer, Quiroz, and Sharp (1988), Meller (1997) describes a planning problem and proposes solution procedures for assigning exit lanes and packing stations to orders in an automated sorting system. Both papers consider no intermediate storage system but a direct release from the picking area into the consolidation system. They propose an optimization procedure for the order-to-lane assignment given a fixed sequence of units on the sortation conveyor. In a computational study, a reduction of average sortation time by more than 40% is shown when applying the optimization procedure in comparison to a simple decision rule applied in business practice. Johnson (1998) introduces a stochastic model for the same setting and shows that, given little lane blockings, assigning the next order to a free lane outperforms more complex rules.

5. Dynamic order processing

In traditional order processing, a pick list is fixed once order picking is initiated. This policy results in distinct waves each picked, sorted, and shipped one after another. Dynamic order processing systems, however, allow pick list updates even after the respective picking tour has started. Incoming urgent orders are instantaneously added to the current picker route and there is no need to waitlist them until the next wave is processed. Whenever a new order arrives, it has to be decided whether or not this order should be dynamically added to the current tour of a picker. Such a decision is, for instance, required if the picking capacity, e.g., on a picking cart, is scarce and adding the new order necessitates a postponement of earlier orders already on the tour.

Furthermore, adding a new order may require to alter the current picker tour. No tour adaption is required if each picker always traverses his/her complete zone on any tour anyway. Then, new orders only need to be indicated by a display or a light signal at the respective shelves and the picker collects these units when passing by. As pickers operate on fixed tours in such a system, this mode of dynamic order processing is also denoted as *milk-run picking*. If pickers do not apply fixed tours through the complete warehouse, but specifically address the current pick list on individual tours, then adding a new order requires an instantaneous adaption of the current picker tour. This mode of dynamic order picking is often called *interventionist order picking*. Once additional units arrive, the current tour is discarded and a novel tour including the not yet picked and novel units is quickly generated and announced to the picker, e.g., via a handheld or pick-by-voice system. In both kinds of dynamic order processing systems, picked units have to be consolidated after picking into distinct orders, so that dynamic order processing requires sortation technology (see Section 4) (Gong & de Koster, 2008).

The biggest advantage of dynamic order processing is certainly the flexibility to quickly process urgent orders, which is especially valuable for the tight schedules of online retailers. This flexibility comes at the price of a frequent replanning of picker tours if interventionist picking is applied. Milk-run picking struggles if large assortments have to be handled. Then, the fixed tours through the complete warehouse may become fairly large compared to individual tours just addressing the current subset of units to be actually picked. The other requirements of online retailers, i.e., the ability to process small orders and varying workloads, is not affected if dynamic order processing is applied, but rather depends on sufficient sortation capacity for isolating the orders.

Dynamic order processing is an organizational adaption of picker-to-parts systems, so that, during the *layout design phase* and *storage assignment*, the same general decisions as elaborated in the previous section have to be taken (see Section 4). A further interesting long-term research task is the question under which circumstances either milk-run or interventionist order picking should be preferred. A main influencing factor is certainly the size of the assortment to be handled. Calculating the break-even point up to which assortment size the prolonged routes of milk-run picking are acceptable and still outweigh the larger turmoil of continuous tour replanning required by interventionist picking is a challenging task for future research.

Short term *operational problems* include the update mechanism during the tour. Gong and de Koster (2008) study milk-run picking by applying stochastic polling theory (Srinivasan 1991). They survey three different update mechanisms for pick lists, finding that their so-called exhaustive service policy performs best. Under this policy, all requests of a SKU are processed, even if the request is received during processing that very SKU. It is shown that dynamic order processing outperforms traditional wave-based batch picking systems in an environment without zones and a single order line per customer order. They, furthermore, provide decision support on the workforce size depending on the cost structure of workers and disappointed customers as well as depending on a maximum waiting time of orders. Based on this, van der Gaast, de Koster, and Adan (2018) benchmark a basic batch picking approach with milk-run picking with single and multi-line orders picked from a zoned warehouse. In line with the previous paper, order throughput time as well as waiting time of orders can be improved when applying dynamic order processing. Lu, McFarlane, Giannikas, and Zhang (2016) address interventionist picking. They determine a (new) shortest picker tour whenever the pick list of a picker is updated and, thus, integrate detours into the current picker route in order to access new units. They introduce a novel routing algorithm for this purpose, based on the one of Ratliff and Rosenthal (1983). In their simulation study, they benchmark their approach with static batching and show that the average completion time of orders is significantly reduced. These performance gains, however, induce longer travel distances of pickers. Giannikas, Lu, Robertson, and McFarlane (2017) propose another interventionist order picking strategy. In their paper, they compare several combined strategies for dynamic order batching and interventionist pick list updates and compare them to a purely static and a purely dynamic batching strategy. Considering the performance indicators average order completion time and average travel distance, it is shown that the new approach significantly outperforms both benchmarks.

6. AGV-assisted picking

Another alternative to reduce unproductive walking times in a picker-to-parts system is to support the pickers with automated guided vehicles (AGVs). These AGVs carry the picked units in bins (or on pallets, containers, or roll cages if large-sized SKUs are processed) and autonomously accompany pickers on their way through the warehouse. Each picker puts his/her units onto the AGV and once the current orders are complete, the AGV autonomously returns to the depot, while the picker remains in the storage area. A new AGV is requested to meet the picker at the first storage position of the successive pick list. In this way, pickers can continuously pick order after order without intermediate returns to a depot. We call this the *fixed-assignment* policy. In an alternative setting, AGVs are not fixedly assigned to a specific picker during processing the current order. They autonomously drive toward a picking position and wait there until some picker loads the

Fig. 4. AGV for small-sized items with trailer.

requested units, then they move to the next position where another picker can execute the pick (Azadeh et al., 2018). We call this mode of operation the *free-floating* policy.

AGV-assisted order picking is often applied for heavy and bulky items. Products such as white goods, large consumer electronics or carpets cannot be carried by the picker all the way back to the depot, so that vehicle support is required anyway. The additional investment for upgrading a traditional forklift to an AGV is comparatively low. However, AGV-assisted picking is not bound to heavy and bulky goods; Fig. 4 depicts an AGV for small-sized items[4]. Small-sized AGVs can also be applied to support pickers in mixed-shelves warehouses (see Section 3) and in a zoning and batching environment (see Section 4), so that they are a valid alternative for online retailers too.

Layout design phase: The most important long-term decision when setting up an AGV-assisted order processing is certainly the interdependent sizing of AGV fleet and picker workforce. A bottleneck on either side is to be avoided, because otherwise idle times of either pickers or AGVs will considerable reduce picking performance. Scientific decision support on this problem is yet not available. When closing this gap, future research should also consider the impact of the selected picking policy (fixed-assignment vs. free-floating) on this decision. The free-floating policy promises a smaller picker workforce, but is prone to short-term plan alterations due to picker delays.

Existing *storage assignment* policies for traditional picker-to-parts warehouses, such as full turnover storage and class-based storage, see de Koster et al. (2007), aim to store frequently requested SKUs closer to the depot. With AGV assistance, however, pickers do not have to return to the depot, but remain in the warehouse, so that fast-moving items should rather be stored somewhere in the center of the warehouse or in areas easily accessible via (middle) aisles. An adaptation of traditional storage assignment rules and a development of new rules for AGV-assisted picking is an interesting field for future research.

Order picking with AGV assistance has only been considered by Löffler, Boysen, Glock, and Schneider (2017) yet. They optimize the routing of a single picker under the fixed-assignment policy. For a given set of orders, they aim to minimize the makespan of picking, if AGVs are no bottleneck. They modify the efficient algorithm of Ratliff and Rosenthal (1983) for picker routing in a rectangular warehouse and integrate it into a dynamic programming approach, so that for a given order sequence the minimum makespan can efficiently be found in polynomial time. This procedure is integrated into myopic search procedures and a genetic algorithm to also evaluate alternative order sequences. Future research should address the alternative picking policy of free-floating pickers. This policy requires an interdependent scheduling of all AGVs and all pickers under synchronization constraints (i.e., for picking an AGV and a picker must be simultaneously present at the respective picking location). Also, short-term reactions to unforeseen delays, which require a quick re-routing of AGVs and/or pickers, is a challenging task for future research.

7. Shelf-moving robots

Mobile robot fulfillment systems (MRFS) are parts-to-picker systems where mobile robots are able to lift movable racks (also denoted as inventory pods) and bring them directly toward stationary pickers operating in workstations. According to Azadeh et al. (2018), Jünemann (1989) was the first to conceptualize MRFS. Afterwards, the system was brought to the market in 2003 (Guizzo, 2008) and U.S. patented in 2008 (Mountz et al., 2008) by KIVA Systems Inc., which is why MRFS are widely known under the name KIVA systems and the mobile robots as KIVA robots. In 2012, Amazon acquired the company, renamed it to Amazon Robotics, and, now, applies the system in many of its U.S. distribution centers. Since then, other providers have entered the market with comparable mobile robots (Banker, 2016; Kirks, Stenzel, Kamagaew, & ten Hompel, 2012) – one of them, CarryPick™ of Swisslog, is depicted in Fig. 5 (left) – and other online retailers such as Alibaba apply MRFS too (Techinasia, 2017).

In the KIVA system, robots have a rotation and a lifting mechanism and are electrically powered. For their orientation, the shop floor is subdivided into a grid and each square is labeled with a barcode. The robots' integrated camera system continuously reads these barcodes to locate themselves and the rotation mechanism allows them to move rectilinearly from square to square. The lifting unit is able to lift more than 1,000 kilograms so that a robot can drive directly under a man-high rack, lift it, and bring it from the storage area to a stationary picker (D'Andrea & Wurman, 2008). In a picking station (see Fig. 5 (right)), multiple customer orders are processed concurrently. Assisted by a pick-to-light system, e.g., a laser pointer (Wurman, D'Andrea, & Mountz, 2008), the picker retrieves units from the current rack and puts them into bins associated with the active customer orders. In a continuous process, racks are successively moved toward a station, units are retrieved, customer orders are completed and replaced by new bins of subsequent orders. The system is described in even more detail by D'Andrea and Wurman (2008), Wurman et al. (2008), and Enright and Wurman (2011).

Due to the elimination of non-value adding picker walking MRFS have a high picking performance, which is reported to reach 600 and more order lines per hour and picker (Wulfraat, 2012). This makes them well suited for the tight deadlines of e-commerce. Also, small order sizes and a large assortment seem unproblematic, as long as there is enough space for the inventory pods on the shop floor. In contrast to other parts-to-picker systems, MRFS have a flexible layout and come by without fixedly installed hardware. Thus, by adding pods and robots to or removing them from a facility MRFS are easily scalable to varying workloads.

During the *layout design phase* mainly the following decisions have to be made: How many picking and replenishment stations for picking orders and refilling the mobile racks, respectively, should be erected and where should these stations be located? The latter question is closely interdependent with the sizing and the layout of the storage area for the inventory pods. Existing

[4] The picture is published under the Creative Commons Attribution ShareAlike License. The author of the picture is AGVExpertJS.

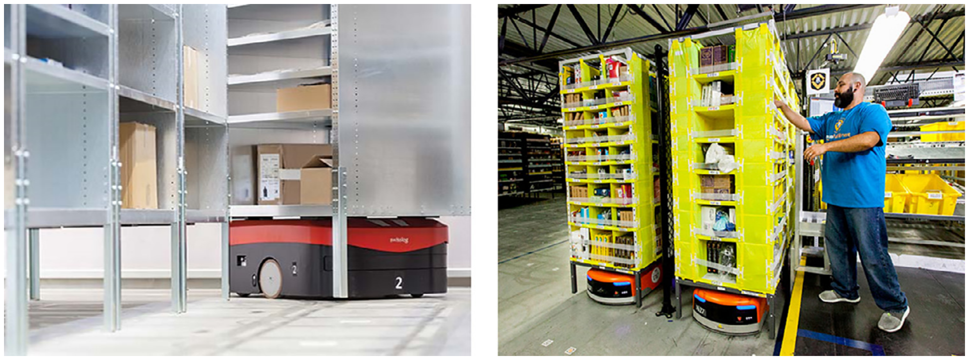

Fig. 5. CarryPick™ (Source: Swisslog, left) and picking station (Source: Amazon Robotics, right).

MRFS storage areas copy traditional warehouse layouts with parallel aisles dedicated to robot movement and accessing the racks stored in parallel lines along the aisles. Empty robots, however, can drive unobstructed below the racks, so that also pods without direct access to an aisle can easily be reached. Other robots could then be applied to dynamically free an aisle, so that compact storage layouts similar to puzzle-based storage systems (see Gue, Furmans, Seibold, & Uludağ, 2014; Gue & Kim, 2007) could easily be realized. The only paper addressing layout aspects of MRFS is provided by Lamballais, Roy, and de Koster (2017a). They provide an extensive performance analysis of different (traditional) layouts employing queuing models, which are validated by a simulation study. They focus their study on a single workstation and transfer their findings to a full warehouse. In consequence, robots are assigned exclusively to a single workstation. The study shows that the performance measures considered, i.e., robot utilization, the mean length of external order queues, the average order cycle time, and the utilization of the workstations, are robust to the length-to-width ratio of the warehouse but highly sensitive to the location of the workstations. Furthermore, they evaluate the impact of the storage assignment policy, i.e., they compare random storage with a zone-based assignment where fast-moving items are stored closer to the stations.

Storage assignment in MRFS can be subdivided into two basic decision tasks. On the one hand, incoming units referring to different SKUs have to be put away into specific inventory pods. Existing research (Boysen et al., 2018b; Lamballais, Roy, & de Koster, 2017b) has shown that applying mixed-shelves storage where units of the same SKU are spread over multiple racks greatly improves picking performance. In this case, multiple alternative pods are available for satisfying a specific customer demand, so that the probability is high that a suited rack stored close to the respective picking station is available. This reduces the probability of idle pickers waiting for pods that have not yet arrived and reduces the travel distances of the robots. Once the composition of the racks is determined, the racks themselves need to be put into storage. After picking, robots need not take pods back to their previous storage position in the storage area. Instead, any other open storage position can be selected, e.g., closer to the picking station to be visited next, so that a dynamic storage assignment, which rather resembles a short-term parking problem, becomes relevant. In this context, Lamballais et al. (2017b) study the impact of the number of pods storing the same SKU, the ratio of picking stations to replenishment stations, and the replenishment level of the pods on the mean throughput time of an order. They confirm the result of Boysen et al. (2018b) that a higher degree of scatteredness of units within pods reduces the mean processing time of orders. Additionally, a ratio of twice as much picking as replenishment stations and a replenishment level of 50% is identified as a promising configuration. The only existing paper on the short-term parking problem is the one of Weidinger, Boysen, and Briskorn (2018). They aim to find an assignment of pods to parking positions, which minimizes the travel distance of robots loaded with racks to satisfy a given set of rack visits at different picking stations. A mathematical definition of the problem, a proof of NP-hardness even for a rectangular storage layout and a suited matheuristic are provided. In a simulation study, the approach is compared to five other, simple storage assignment rules, e.g., random storage. It is shown that the size of the robot fleet as well as the total travel distance of the robots is significantly reduced when optimizing the parking positions of racks. However, one of the simple storage assignment rules (denoted shortest-path storage) is shown to deliver nearly as good solutions as the sophisticated optimization approach.

Short-term *order picking* has to select a specific pod to satisfy the demand of an order that has to be fulfilled at a specific picking station. Once these decisions are made, a specific robot is to be assigned to the resulting movement of the pod, which also involves finding a suited travel path and coordinating it with competing robots. To the best of the authors' knowledge, no literature exists regarding the assignment of orders to picking stations. Instead, existing research assumes that an assignment of orders to picking stations has already been determined. Under these circumstances, Zou, Gong, Xu, and Yuan (2017) tackle the assignment of robots to picking stations having different picking performance due to individual processing speeds of the respective pickers. For the solution of the resulting optimization problem they provide a neighborhood-based optimization approach. Solutions are evaluated via a semi-open queueing network, which itself is verified by a simulation study. It is shown that the neighborhood search is able to find near optimal solutions and optimized assignments are superior to randomized ones. In the paper of Yuan and Gong (2017), a dedicated assignment of robots to picking stations is compared with a pooled approach. The latter means that robots can deliver pods to all stations and are not reserved for single pick stations. It is shown that the throughput time can be considerably reduced when using the pooled strategy. The study is based on open queuing networks, which are also employed to determine the optimal number and velocity of robots as well as the ratio of robots to pickers. The assignment of racks to orders of a station is tackled by Boysen et al. (2018b). They consider a single picking station and aim at a schedule for a given set of orders. Given that a predefined number of orders can be picked in parallel on the workbench of the picking station, they search for a sequence of order batches and rack visits minimizing the total quantity of racks to be transported to the station in order to satisfy all orders. A suited decomposition approach is presented and tested in a simulation study. According to this study, the size of the robot fleet can be more than halved when using an optimized schedule. Additionally, it is shown that the more scattered the SKUs among the racks, the fewer rack visits are required to satisfy a given set of orders. Once the movements of inventory pods between picking stations and storage area have been derived, the routing of the robots becomes relevant. A vast body of literature is available on routing AGVs, which is summarized, e.g., in the survey papers of Qiu et al. (2002) and Vis (2006). We only review the literature published since then and suited to MRFS. Herrero-Peérez and Martínez-Barberá (2011) decompose the coordination of multiple AGVs into path planning, obstacle avoidance and traffic control which are solved in a decentralized manner. They present suited solution procedures, which are tested in a simulation study as well as a real-world scenario. Other papers are explicitly treating MRFS. Yu (2016) studies path planning of multiple robots on a planar graph. NP-hardness of four basic problem settings is proven and sharing paths among robots with opposing directions is identified to considerably complicate the problem. The idea of having an adaptive highway system has been brought up by Roozbehani and D'Andrea (2011). They try to find one-way expressways in real time to maximize the average speed of moving robots.

8. Advanced picking workstations

Advanced picking workstations (also denoted as picking bays, see Dallari, Marchet, & Melacini, 2009) promise a picking performance of up to 1000 order lines per hour (de Koster, 2008; de Koster et al., 2007). They resemble the picking stations of the KIVA system, but are ergonomically designed and automatically fed with bins from a directly connected storage system via conveyors. An order fulfillment system based on picking workstations consists of the following three elements:

- *Storage system:* The bins containing the SKUs are stored in an automated storage system. Typical systems are either one or multiple carousel racks (see Litvak & Vlasiou, 2010), a crane-operated ASRS (i.e., a miniload system, see Manzini, Gamberi, & Regattieri, 2006; Roodbergen & Vis, 2009), or a lift and shuttle system where horizontal and vertical movement is separated (see Azadeh et al., 2018).
- An intermediate *conveyor system* that delivers requested bins between storage systems and stations. This system also buffers bins until all bins required for a specific customer order have arrived.
- Finally, within each advanced *picking workstation* requested items are withdrawn by a human picker from the arriving storage bins and put into other bins (denoted as order bins) that are associated with customer orders (see Fig. 6). Typically, a workstation has enough space on the workbench for multiple order bins processed in parallel. A monitor assists the identification of how many units to put into which order bins. One after another, storage bins arrive at the station, are processed by the picker until an order bin is completed and automatically swapped with a new (empty) order bin. In this way, a parts-to-picker system is realized where the picker is relieved from any unproductive work and only has to pick units.

Due to their high performance advanced picking workstations seem well suited for the tight deadlines of e-commerce. Large assortments and small-sized orders also seem unproblematic for these parts-to-picker systems. However, adding new stations and/or larger storage systems (or removing them) requires plenty constructional effort and is, therefore, barely possible on short notice. The major disadvantage when applying picking workstations for online retailing is, thus, their lack of scalability.

Research focusing on the *layout design phase* of picking workstations is scarce. The few existing approaches all address performance estimation with simulation studies or queuing models in order to quickly evaluate different layout setups. In the study of

Fig. 6. Pick-to-tote station™ SSI Schäfer.

Andriansyah, Etman, Adan, and Rooda (2014), a picking workstation is supplied from a crane-operated ASRS. They evaluate different retrieval policies of storage bins from the rack and quantify the impact of these policies on the picking performance via simulation. Additionally, they propose a new design for the conveyor system, a carousel mechanism to avoid deadlocks between completed and new storage bins. Further simulation studies predicting the picking performance if a workstation is supplied from a crane-operated ASRS are provided by Andriansyah, Etman, and Rooda (2010) and Manzini et al. (2006). Andriansyah et al. (2010) study a picking workstation that assembles one order at a time. The station is connected to an ASRS via a multi-lane buffer. They aggregate several effects on the pick performance in a single relevant performance measure called Effective Processing Time (EPT). For the same basic setup of Andriansyah et al. (2010) the paper of Claeys, Adan, and Boxma (2016) provides queuing models for performance analysis. They also restrict their research to the assembly of one order at a time, whereas parallel processing of multiple parallel order is quite common in business practice (Füßler & Boysen, 2017b). They study the effect of an arrival process of bins, which is not Poisson distributed. The latter results from the application of specific batching and/or storage assignment strategies. Tappia, Roy, Melacini, and de Koster (2018) compare the integration of advanced picking workstations with different storage devices, i.e., crane-operated vs. lift and shuttle ASRS. By applying semi-open queuing models they conclude that shuttle-based ASRS yield investment cost savings (i.e., fewer aisles in the storage area

Table 1
Surveyed literature sorted by warehousing system and decision problem.

	Layout design	Storage assignment	Order picking
Mixed-shelves storage	0	1	3
Batching, zoning, and sorting	5	1	42
Dynamic order processing	0	0	4
AGV-assisted picking	0	0	1
Shelf-moving robots	1	2	6
Advanced picking workstations	5	0	1

and fewer picking stations), paired with a lower total throughput time at a given order arrival rate.

Storage assignment and *order picking:* Existing research in this area rather focuses on the storage systems (in isolation). Where to store items in an automated storage system and how to efficiently schedule the retrieval and storage requests are among the classic research questions of warehousing research. Instead of trying to summarize the vast body of literature on these topics we only refer to the most recent existing survey papers on carousel systems (Litvak & Vlasiou, 2010), crane-operated ASRS (Boysen & Stephan, 2016; Manzini et al., 2006; Roodbergen & Vis, 2009), and lift and shuttle systems (Azadeh et al., 2018) instead. Literature on the operational decision problems of advanced picking workstations and their interplay with the storage and conveyor system, however, is barely existent. The only paper in this direction is provided by Füßler and Boysen (2017b). They aim to synchronize the arrival sequence of storage bins with the batches of orders simultaneously processed on the workbench of a single picking workstation. If orders are unified to batches, such that multiple active orders require the current SKUs provided in a storage bin, then fewer bins need to be delivered to the station. This relieves the storage system in an indirect manner. In their paper, Füßler and Boysen (2017b) show that this indirect effect can indeed lead to a much larger relief of the storage system than optimizing its storage and retrieval sequence directly. Future research should follow this research direction and investigate holistic systems consisting of picking workstations, conveyor and storage system rather than only addressing each element in isolation.

9. Future research needs and conclusions

The surveyed literature for each of the reviewed systems is summarized in Table 1. This summary reveals that each single warehousing system still has plenty demand for future research; some systems, i.e., mixed-shelves storage, dynamic order processing, and AGV-assisted picking, are barely addressed at all. Only batch formation in a batching, zoning, and sorting environment has received plenty attention so far. However, even for this problem the peculiarities of e-commerce (i.e., a widespread coupling with mixed-shelves storage) have not exhaustively been addressed. Beyond these specific systems, we see some emerging general trends in (e-commerce) warehousing that require further scientific consideration.

Novel systems: Additional research is required whenever novel systems are presented in order to evaluate their potential picking performance and their suitability for e-commerce. One of these novel ideas for which implementations in large real-world facilities of online retailers already exist (but no scientific literature) is the so-called bag sorter system (see Fig. 7). Bag sorters adapt the basic principle of hanging goods handling and move units in bags hanging from trolley conveyors. The Zalando distribution center in Mönchengladbach (Germany), for instance, applies a large system with a capacity for 500,000 bags servicing 80 packing stations (RP Online, 2016). First, individual units are filled each in a bag, which are moved into the storage area. Upon request, bags are moved out

Fig. 7. Bag sorter system (Source: Dürkopp).

of storage, automatically sorted into the right sequence via a system of switches, and conveyed to packing stations. Here, units arrive in the proper sequence, so that one order after the other can be packed into its shipping carton. The capacity of a bag sorter is typically not large enough to store all units of a warehouse. This leads to the interesting operational research question, how many units of each SKU should be put into bags facing the highly volatile demands of customer households. During the layout design phase, the sizing of the storage area and the required number of bags for a smooth picking process are, thus, important issues.

System selection: A question of utmost importance for warehouse managers is the question for the right system best suited for their specific situation. Our discussion in this survey regarding the suitability of each system for the special needs of online retailing is certainly not sufficient to guide a real-world system selection. On the one hand, empirical research could record the systems selected for real-world operations depending, e.g., on the branches of industry, customer and product characteristics, size and throughput of the facilities. First steps in this direction are provided by Marchet, Melacini, and Perotti (2015) and Davarzani and Norrman (2015). The former record the selected warehousing systems of 40 Italian distribution centers and derive some rules with regard to the fit of different systems. The latter compare the main research issues of academia obtained by a database-driven literature search with the needs of practitioners obtained by interviews. Davarzani and Norrman (2015) find a remarkable gap. Obtained empirical data could also be applied within data-driven techniques such as data envelopment analysis (DEA) to benchmark different systems (Chen, Gong, de Koster, & van Nunen, 2010). In this way, some systematic empirical information on what warehouse systems have been chosen in what situation could be obtained. On the other hand, simulation studies evaluating the picking performance of a given set of customer orders in different warehousing systems would be a laborious, yet valuable contribution. Most online retailers we visited, however, do not apply just a single warehousing system for the complete range of products, but apply multiple systems in parallel and link them via conveyors. In this way, fast-moving items can, for instance, be picked from mixed-shelves and seldom requested C products via advanced picking workstations. Decision support under which circumstances multiple parallel warehousing systems should be applied in what combination is yet missing.

Ergonomics: Probably the most important selection criterion for warehousing systems in e-commerce is picking performance. However, if any non-value adding work content is removed and pickers have to process up to 1000 order lines per hour (see Section 8), this puts excessive physical and psychological stress on the workforce (Otto, Boysen, Scholl, & Walter, 2017). Given the aging workforce in many industrialized countries, ergonomic aspects in workplace design and a suited cooperation between automated solutions and human workers should be considered. The survey papers of Grosse, Glock, Jaber, and Neumann (2015) and Grosse, Glock, and Neumann (2017) on human factors in warehousing, however, reveal that not much research in this direction exists. Specifically, planning procedures for routing the pickers in AGV-assisted order picking (see Section 6) or for dividing a wave of orders among multiple advanced picking workstations (see Section 8) could, for instance, try to distribute the inevitable idle time where humans wait for machines fairly among the workforce.

Holistic research: To enable a rigorous analysis, most existing papers concentrate on an isolated problem of a single subsystem. Today's warehouses, however, are large facilities where plenty resources and processes cooperate. Thus, from the warehouse manager's perspective, holistic models are required that take a rather unifying look at the complete order fulfillment process. In mobile robot fulfillment systems (MRFS), for instance, the assignment of orders to picking stations, the selection and sequence of inventory pods to satisfy the demands, their parking positions in the storage area, and the assignment (along with the path choice) of robots to the specific pod movements all influence each other and can barely be investigated in an isolated manner. Satisfying the demand for practical, holistic models will remain a great challenge for future research. This aspect is also emphasized by the recent survey paper of van Gils et al. (2018) that specifically addresses the combination of multiple planning problems.

New objectives: Most of today's research tackles minimizing the average processing time per order in a direct or indirect way. However, in light of ever-shorter delivery schedules and increasing customer pretensions, robust warehousing processes are required to meet promised delivery dates as best as possible. In this context, other objectives than reducing the mean value might be the even better choice. Future research can, for instance, evaluate the impact of minimizing processing time variance or maximum values.

Omni-channel retailing is an ongoing business trend that advocates selling products to customers via multiple different (online and offline) distribution channels (Agatz et al., 2008). This considerably complicates warehouse operations, because small-sized orders for customer households have to be jointly assembled with large-sized orders for brick-and-mortar stores. Moreover, new concepts like click-and-collect, where customers order online and pick up the products in a store (Hübner et al., 2016), burden the warehousing processes for brick-and-mortar stores with the same tight deadlines as online retailing. The impact of varying order sizes on the warehousing processes has not been appropriately addressed in the literature yet. Which warehousing system is best suited to handle small and large-sized orders together? Or is a mix of systems better suited? Answering these questions is a challenging task for future research.

Return flows: Many online retailers struggle with high return rates. Rates of 20% and more seem to be rather the norm than the exception for some product categories (Statista, 2014). In personal meetings with warehouse managers, we even have heard of return rates of more than 80% for single SKUs. Some online retailers have completely outsourced the management of returns. In this case, both business processes, order fulfillment and return management, can be optimized in a decoupled way. Whenever returns are handled at the warehouses, though, interdependencies occur (de Koster, de Brito, & van de Vendel, 2002). Some retailers, for example, implement the policy that all returns of a SKU have to be shipped before factory-fresh items are picked. This leads to additional constraints for the order picking process. Additionally, returned products often have a rather high probability to be ordered once again in the near future. Therefore, they could be assigned some privileged storage positions. Systematic decision support on how to best reintegrate returns in the process steps of the forward chain of e-commerce warehouses is rare (see de Koster et al., 2002) and constitutes a challenging field for future research.

Seeing the ever growing market shares of online retailing (Statista, 2017) and the manifold unanswered questions elaborated in this paper it seems fair to predict that warehousing will remain a fruitful field of research in the years to come.

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