Evaluating the benefits of picking and packing planning integration in e-commerce warehouses

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Abstract

Motivated by recent claims on the potential value of integration in warehouse management, this study evaluates the benefits arising from integrating the planning of order picking and packing processes in e-commerce warehouses. A set of research questions are proposed for exploring various benefits under different operational conditions and an experimental study is designed to answer them. In order to have a concrete model to represent the integrated planning method, a mixed-integer nonlinear programming model is developed, and then compared against a non-integrated variation. The experimental study makes the comparisons by analysing the collected empirical data from a real-life warehouse. Our findings indicate that integrated picking and packing planning can yield improved performance in different aspects under different configurations of objectives, order quantities, order categories or workforce allocation.

Keywords: Logistics, Integration, Order picking and packing, Warehousing, E-commerce

1. Introduction

Order picking and packing are two key processes warehouses use to fulfil customer orders. Order picking deals with the collection of required goods from their storage locations, followed by packing where goods are packed into different types of containers (boxes, parcels, bags etc.). Improving order picking has been a popular topic for warehouse researchers and practitioners for many years. This is because order picking not only accounts for about 55% of warehouse operating costs, but it can also be a critical operation for warehouse performance overall (Bartholdi III & Hackman, 2019). In an e-commerce setting in particular, the responsiveness of order picking can have a direct impact on customer satisfaction as it affects the lead time between order placement and order receipt (Giannikas et al., 2017). In order to cope with the challenges of e-commerce, order-fulfilment warehouses have emerged in the past few years (Boysen et al., 2018) to meet the speed and flexibility requirements of

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online shopping (Yang et al., 2021). Other than picking items associated with a customer order, these warehouses offer packing and delivery services which are necessary for the successful fulfilment of an order. As a result, both order picking and packing play a critical role in defining the flow time an order spends in a warehouse, from the point it is placed by a customer to the point it is ready for dispatch (Klapp et al., 2018).

Synchronising the sequences and times associated with picking and packing has the potential to achieve efficiency gains for warehouses. In this paper, we study the integration of order picking and packing planning aiming at the improvement of warehouse performance and the reduction of idle time. The contribution of this study is twofold:

1. The evaluation of the benefits of integrated order picking and packing planning in warehousing under different conditions. We achieve this by designing an empirically-driven study based on the data collected from a real-life e-commerce warehouse. In doing so, we contribute to recent arguments in literature (Bottani et al., 2019; Boysen et al., 2020; McFarlane et al., 2016; Sprock et al., 2019; Van Gils et al., 2018a,b) calling for further investigation of process integration in warehousing by virtue of strong interdependence between different stages.
2. The development of a novel mathematical model for the integration of order picking and packing planning. The model simultaneously determines three planning problems in picking and packing: order batching, batch assignment and sequencing. In the scope of this study, the model is established to perform fair comparisons between integrated and non-integrated methods. Moreover, it can also be used to develop integrated order picking and packing planning functionalities in warehouse management systems (Lee et al., 2018; Leung et al., 2018).

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and proposes four research questions on how an integrated method may benefit warehouse performance. Section 3 develops a novel integrated picking and packing mathematical model required for exploring the study's research questions. Section 4 designs an experimental study, the results of which are presented in Section 5. Section 6 presents research and managerial implications of this study and future research directions.

2. Literature review and research questions formulation

In this section, we review integrated planning problems of processes in order fulfilment broadly, and more specifically of picking and packing processes in warehouses. We then propose four research questions on the benefits of integration that guide the remaining of our study.

2.1. Integrated planning of processes in order fulfilment

Order fulfilment consists of consecutive processes of receiving, picking, packing and delivering orders to customers (Croxton, 2003). In e-commerce settings, order fulfilment plays a critical role as it can directly affect the overall customer experience (Hübner et al., 2016). Order picking and packing are normally implemented physically inside warehouses, while order receiving takes place primarily via the internet and delivery concerns the transportation of items to customers. Among the four processes, picking planning has received a lot of attention as it concerns the most labour-intensive process in most warehouses and it affects successive packing and delivery operations largely (Bartholdi III & Hackman, 2019; Croxton, 2003; De Koster et al., 2007). There have been several studies on picking planning examining the impact interdependent activities such as storage, zoning, picking and sorting have on warehouse performance (De Koster et al., 2007). Nevertheless, the integration of these activities has received less attention and it is only recently that researchers have started examining this issue in more detail (Van Gils et al., 2018a,b, 2019b).

More specifically, the main outcome of the picking planning is the creation of *picklists*. Typically, a picklist includes information about the relevant customer orders, stock keeping units (SKUs) requiring picking, the storage locations to be visited and the allocated picker. Taking as an example packing, a process that follows picking in e-commerce warehouses, the picklists used to plan the picking process often have a direct impact on the packing process, too. That is to say, more generally, that the way orders are grouped together to plan the picking process in an effective way is going to also affect the performance of other associated process process and —as a result— the overall warehouse performance.

Planning for different warehouse processes in an integrated, rather than in an isolated way appears to be a logical approach to improve warehouse performance and academics have recently started investigating ways to integrate different processes. We summarise existing relevant literature in Table 1. It is worth noting here that we are not reviewing approaches for the integration of sub-processes often used to plan for picking (i.e. batching, routing, sequencing), but approaches used to integrate different warehouse processes. The most interesting observation from the synthesis of this table is that, even though there are studies where processes are planned jointly, the objectives of several of them are inclined towards one of the processes. In other words, many existing approaches are dedicated to improving or optimising the performance of a certain process instead of aiming to improve the overall performance across multiple processes. Moreover, a lot of attention has been given to the integration of storage and picking, which stimulates us to focus on the integrated planning of other processes in order fulfilment.

2.2. Integrated planning of order picking and packing

In many warehouses, and certainly in those offering services for online retailing and other aspects of e-commerce, order preparation considers not only picking the required items but also packing them in parcels/boxes that will be delivered to the customer. As a result, measuring the performance of the warehouse in terms of order handling and processing requires considering both picking and packing processes and the time an order spends in them (Leung et al., 2018; Liu et al., 2017). Improving any single process in an isolated manner is not necessary to lead to better overall performance, as one process is likely to affect the other significantly. In this direction, there has been some literature considering picking and packing planning problems in an integrated way, albeit available studies are limited and most of them remain conceptual.

An integrated scheduling of order picking and delivery was developed in Zhang et al. (2016) for connected processes of picking, packing and delivery, but assumed the same picker who undertook

Table 1: Integrated planning of order picking, packing and delivery processes in order fulfilment

References	Integrated processes	Results from integration
Gallien & Weber (2010)	picking, sorting & packing	Waveless picking policy yields larger throughput, sorter utilisation, and packer utilisation comparing with wave picking.
Battini et al. (2015)	storage & picking	Best storage assignment can be found with the aim of ensuring minimum picking travel distance.
Claeys et al. (2016)	storage & picking	Order flow time in picking helps set targets for storage retrieval rate.
Zhang et al. (2016)	picking, packing & delivery	Maximal number of orders can be delivered within a minimal service time.
Onal et al. (2017)	storage & picking	Explosive storage policy reduces picking time by 16%.
Boysen et al. (2018)	sorting & packing	Minimum spread of orders (number of conveyor segments from an order's first occurrence to last) in release sequence of bins.
Van Gils et al. (2018a)	any two among storage, zoning & picking	Warehouse achieves significant benefit in overall picking performance (reduced picking time).
Zhang et al. (2018)	picking & delivery	The sum of makespan and total delivery cost is minimised.
Bahrami et al. (2019)	storage & picking	Total picking travel distance and order lead time are shorten.
Bottani et al. (2019)	any two among storage, zoning & picking	Consideration of interdependencies between key design factors ensures perfect design of whole picking system.
Calzavara et al. (2019)	storage & picking	It enables warehouse to assess cost and ergonomic (energy expenditure and worker posture) objectives in picking.
Tappia et al. (2019)	storage & picking	Total order throughput time and order waiting time can be estimated for single-line (non-splittable) orders.
Van Gils et al. (2019b)	any two among storage, zoning & picking	Joint effect of these policy decisions significantly influences picker travel time and waiting time due to picker blocking.
Zhang et al. (2019)	picking & delivery	Global optimal order fulfilment performance is achieved with minimum makespan and delivery cost as objective.
Jiang et al. (2020)	storage & picking	Scattered storage assignment strategy minimises walking distance in picking.
Kübler et al. (2020)	storage & picking	Total travel distance of item relocation and order picking is significantly reduced.
Wang et al. (2020)	storage & picking	Orders are picked with minimum total travel distance.

picking jobs for a batch also continued to pack it. The packing time was also simplified as a constant added to the picking time and handled as a component of the picking time. Often, however, the implementations of order picking and packing in warehouses are successive but separate processes performed by two employee teams, respectively. Although packing was inclusive in the planning, it was not profiled effectively in essence. The influential and actually occurred interaction and waiting between picking and packing processes were omitted in this study, as well as in Liu et al. (2017) and

Moons et al. (2018) which took account of vehicle routing in delivery along with picking and packing. This makes the benefits of using the integrated philosophy to manage multiple processes, especially picking and packing in warehouses for order fulfilment not well verified.

In addition, several studies conceived that the idle time during packing under the pick-and-sort policy could be reduced particularly by improvement in sorting, which is a step between picking and packing. Gallien & Weber (2010) developed a queueing model to maximise throughput and predict warehouse flow dynamics (sorter and packer utilisation) under waveless and wave picking policies. The packing performance data were simply collected after the optimisation of picking for the purpose of reporting and analysis. The packing process has not actually been improved. In order to consolidate orders quickly at packing stations, from the sorting perspective, Boysen et al. (2018) minimised the spread of orders in bin (containing partial orders picked) release sequence from automated storage and retrieval system (ASRS) in automated conveyor-based sorting system, while Boysen et al. (2019b) minimised the completion times of orders assembled in put wall. However, both studies did not calculate the performance of packing to justify the reason for improving sorting, and they were based on the prerequisite that picking has finished under some batching policy.

Even though existing studies have attempted to either plan picking and packing together, or regard the improvement in packing as a by-product of improvement in picking, the treatment of packing has been rather limited —making it difficult to quantify the benefits in combining the planning of these two operations. Hence, this gap motivates us to examine the advantages of optimising picking and packing processes collectively.

2.3. Research questions

Considering that the in-house operations of order fulfilment cover the whole period from order picking until the order is ready for dispatch, we propose that managing order picking and packing in an integrated way might lead to improved warehouse performance in comparison to managing each operation separately. This section introduces four research questions used to evaluate the benefits of the integration of picking and packing planning under different operational conditions. Specifically, we explore, under different situations, how performance criteria are affected by integration, the extent of any benefits, and the mechanism that creates the benefits.

In short, taking an integrated picking and packing approach enables us to not only focus on improving the performance of each standalone process but to also reduce the waiting time between them. As it is often the case in practice, warehouse orders can spend a significant amount of time waiting either for picking resources (i.e. pickers, picking carts etc.) or for packing resources (i.e. packers, packing stations etc.) to be available. Similarly, pickers and packers may remain idle while waiting for orders to arrive for processing. Managing picking and packing in an integrated way is expected to also take into account idle time which plays an important role in overall warehouse performance.

Several measures for warehouse picking performance have been used in academia and practice. In this study, we use two of such metrics that have been widely-used in recent studies. Firstly, the *order processing time*, which concerns the time needed for an order to be prepared and ready for dispatch (Giannikas et al., 2017; Hong & Kim, 2017; Li et al., 2017; Matusiak et al., 2017; Van Gils et al., 2018a, 2019a; Žulj et al., 2018b). Secondly, the *makespan*, that captures the time required by the warehouse to process a certain number of orders until they are ready for dispatch (Ardjmand et al., 2018; Zhang et al., 2017, 2018). Our first research question, hence, is posed to investigate the different key performance indicators under which integrating picking and packing can be beneficial and that can therefore be used to improve the performance of a warehouse in different ways. This is due to the fact that an integrated approach takes into account the whole lifecycle of an order in a warehouse rather than focusing on a specific part of it.

RQ 1. How can an integrated approach to planning picking and packing improve warehouse performance comparing with a non-integrated way, when the minimisation of order processing time, makespan or a combination of both is targeted?

Due to demand fluctuations or different sized warehouses, warehouses are likely to experience different amounts of orders that need to be processed by a warehouse. As a result, it is worth testing the performance of any method under varied amounts of orders (Li et al., 2017; Marchet et al., 2015; Van Gils et al., 2018a). Our second research question explores the performance benefits from integration when different order quantities need to be processed.

RQ 2. How can an integrated approach to planning picking and packing improve warehouse performance comparing with a non-integrated way, under varying order quantities?

A common characteristic of e-commerce warehouses is that they often receive orders of different categories (Boysen et al., 2019a). Generally, an e-commerce order can be classified into one of four categories depending on the number of SKUs it contains and the quantity requested by each SKU. These are 1-SKU-1-item, 1-SKU-multiple-items, multiple-SKUs-1-item, and multiple-SKUs-multiple-items. These categories are important for warehousing operations as they affect the number of storage locations that need to be visited (typically a factor of the number of SKUs) and the retrieval, sorting and packing time (typically a factor of the number of items). As a result, the structure of the *order pool*, which contains all orders to be processed in a planning period, is expected to have a significant impact on picking efficiency in practice. However, the literature lacks studies that incorporate different order pool structures while testing the effectiveness of order picking and packing planning methods (Boysen et al., 2020; Kembro et al., 2018). This is addressed by our third research question which explores the performance benefits from integrated planning under different order pool structures. An integrated way is expected to better manage the differences occurring between the time an order is required to be picked and the time it is required to be packed, both of which vary depending on the number of SKUs and items this order contains.

RQ 3. How can an integrated approach to planning picking and packing improve warehouse performance comparing with a non-integrated way, for different order pool structures?

The performance of a warehouse operation is often highly dependable on the workforce assigned to it. In practice, the labour resources available for picking and packing in warehouse are finite. The number of personnel allocated to each operation is often a decision that warehouse managers need to carefully make as it can influence performance (Difrancesco et al., 2021; Grosse et al., 2017; Vanheusden et al., 2020; Xie et al., 2021). Even though the maximum number that can be assigned to each operation might be limited by the number of pick carts and packing stations, warehouse managers often move personnel from one operation to the other depending on the requirements on a certain day. The number of personnel in each operation can, as a result, affect the benefits of integration. Our fourth research question investigates the performance benefits from the integration under different levels of workforce assigned to picking and packing. We expect an integrated method to adapt itself to take into account the fact that part of the process can be slower than the other part and improve them in a combined way.

RQ 4. How can an integrated approach to planning picking and packing improve warehouse performance comparing with a non-integrated way, when available workforce is allocated to each process in different loads?

In order to examine these research questions, we designed an experimental study based on empirical data of a warehouse company. We first developed a mathematical model that enables us to fairly compare picking and packing integration with non-integration of these planning.

3. A mathematical model for integrated picking and packing

In the absence of integrated picking and packing methods that we can directly employ to explore our research questions, a novel integrated picking and packing mathematical model, is developed in this section.

3.1. Problem description

The order picking and packing planning problem concerned here aims to optimise the performance of picking and packing processes taking an integrated perspective. As discussed previously, this problem aims to optimise not just the pick and pack processes per se but also to reduce the time an order is waiting to be processed. The problem combines the following three questions (Henn, 2015; Scholz et al., 2017; Zhang et al., 2017):

1. How should orders be grouped into picklists (i.e. the order batching problem)?
2. How and in what sequence should the picklists be assigned to pickers (i.e. batch assignment and sequencing problem for picking)?
3. How and in what sequence should the picklists be assigned to packers after picking completed (i.e. batch assignment and sequencing problem for packing)?

For the needs of this study, the problem considers the following warehousing characteristics, inspired by relevant literature and by the operations of our case company. The warehouse runs a low-level picker-to-part, sort-while-pick order picking system. The picking area includes a multiple block layout of wide pick aisles and cross aisles and a depot, with each SKU assumed to be stored in a single location (Kulak et al., 2012; Mirzaei et al., 2021; Wang et al., 2020). The contents of an order cannot be split in multiple picklists and all orders are known at the beginning of the picking process. To enable sort-while-pick, a picker uses a picking trolley of a certain capacity with totes representing different orders. Empty trolleys and totes are always available. Pickers and packers are assumed to have similar skills. Finally, pickers follow an S-shape routing policy and packers are fixed at a packing station. The S-shape routing policy has been widely used in practice for years due to its simplicity and performance (Elbert et al., 2017; Scholz et al., 2017) and it is prevalent today (Hong & Kim, 2017; Žulj et al., 2018a).

3.2. Model formulation

We propose a mixed-integer nonlinear programming (MINLP) model to formulate the integrated picking and packing problem.

3.2.1. Notations

The indices, parameters, decision variables and variables in the MINLP model are introduced in Tables 2-4, respectively.

Table 2: Indices

Indices	
A	set of picking locations for storing SKUs
I	set of customer orders
J	set of picklists
K	set of queuing positions of a picker to which picklists can be assigned
L	set of queuing positions of a packer to which picklists can be assigned
P	set of pickers
R	set of packers
U	set of SKUs in the warehouse

3.2.2. Objective functions

Following RQ 1, we propose three different objective functions for the MINLP model. These are based on the processing timeline of an order in a warehouse as it is depicted in Fig. 1. Firstly, we propose an objective function for *the minimisation of both total order processing time and makespan* as defined in Eq. (1),

$$\min \left(\sum_{j \in J} td_j^{process} + \max_{r \in R} \left\{ t_{r\bar{L}}^{complete\_pack} - t^{enter\_pick} \right\} \right). \quad (1)$$

The 1st term measures the total order processing time; it sums up the processing time of all picklists including the waiting time when handing an order over from picking to packing. The 2nd term measures the overall makespan as the time horizon from picking entry time to last packing completion time of all

Table 3: Parameters

Parameters	
$lgth^{aisle}$	length of aisles in picking zones
$lgth^{vert}$	average vertical length travelled in picking zones
M	sufficiently large number
m	sufficiently small number
os_{iu}	order attribute, i.e. number of items with SKU $u \in U$ in order $i \in I$
Q^{pick}	capacity per picklist (number of orders)
Q^{SKU}	capacity per picklist (number of SKUs)
Q^{wait}	upper limit of packing waiting time duration
q_i^{item}	number of items in order $i \in I$
sl_{ua}	whether SKU $u \in U$ is stored in picking location $a \in A$ ($sl_{ua} = 1$) or not ($sl_{ua} = 0$)
t^{enter_pick}	picking entry time (i.e. picklists generated time)
td^{pack}	pack time duration per item
td^{pick}	pick time duration per item
td^{search}	search time duration per SKU
td^{setup}	setup time duration per picklist
td^{sort}	sort time duration per item
td^{travel}	travel time duration per meter

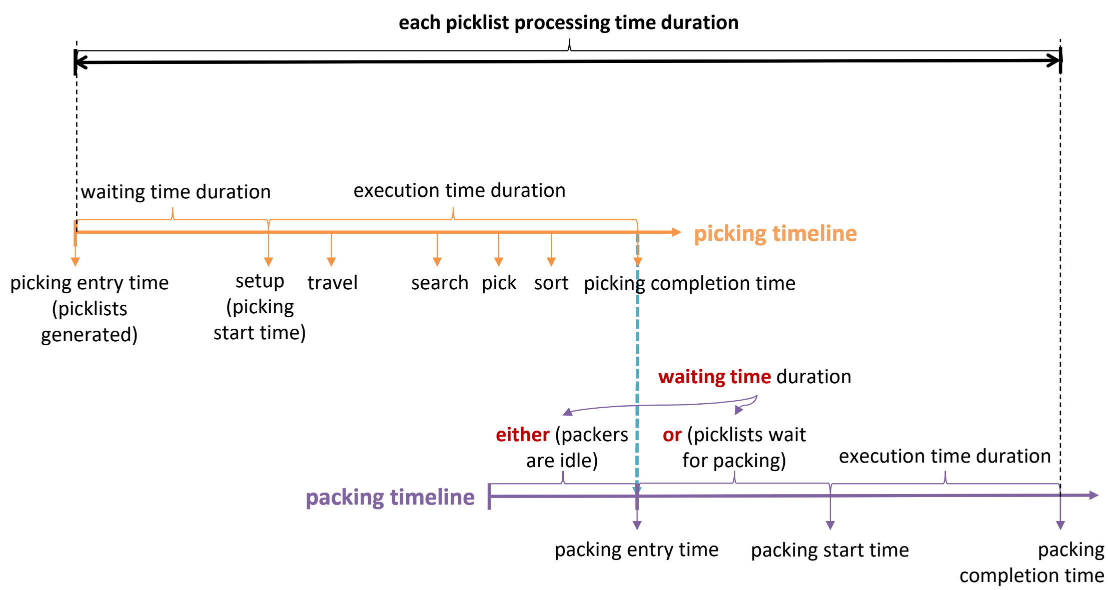

Fig. 1: The processing timeline in the objective.

Table 4: Decision variables

Decision variables	
bl_{ja}	number of SKUs (in picklist $j \in J$) stored in location $a \in A$
bs_{ju}	number of items with SKU $u \in U$ in picklist $j \in J$
d_j	travel distance covered in picklist $j \in J$
q_j^{od}	whether picklist $j \in J$ contains any orders ($q_j^{od} = 1$) or not ($q_j^{od} = 0$)
q_j^{SKU}	number of SKUs in picklist $j \in J$
q_{ja}	whether picklist $j \in J$ has any SKUs stored in location $a \in A$ ($q_{ja} = 1$) or not ($q_{ja} = 0$)
q_{ju}	whether picklist $j \in J$ contains SKU $u \in U$ ($q_{ju} = 1$) or not ($q_{ju} = 0$)
q_p^{pl}	whether picker $p \in P$ has picklists ($q_p^{pl} = 1$) or not ($q_p^{pl} = 0$)
q_{pk}^{pl}	whether queueing position $k \in K$ of picker $p \in P$ contains picklist ($q_{pk}^{pl} = 1$) or not ($q_{pk}^{pl} = 0$)
q_r^{pl}	whether packer $r \in L$ has picklists ($q_r^{pl} = 1$) or not ($q_r^{pl} = 0$)
q_{rl}^{pl}	whether queueing position $l \in L$ of packer $r \in R$ contains picklist ($q_{rl}^{pl} = 1$) or not ($q_{rl}^{pl} = 0$)
$t_j^{complete\_pack}$	packing completion time of picklist $j \in J$
$t_{pk}^{complete\_pick}$	picking completion time of the picklist that is assigned to queueing position $k \in K$ of picker $p \in P$
$t_{rl}^{complete\_pack}$	packing completion time of the picklist that is assigned to queueing position $l \in L$ of packer $r \in R$
$t_{rl}^{enter\_pack}$	packing entry time of the picklist that is assigned to queueing position $l \in L$ of packing station $r \in R$
$td^{makespan}$	makespan, i.e. horizon from picking entry time to last packing completion time of all picklists
$td_j^{execute\_pack}$	packing execution time duration of picklist $j \in J$ (consisting of pack time duration)
$td_j^{execute\_pick}$	picking execution time duration of picklist $j \in J$ (consisting of setup, travel, search, pick and sort time duration)
$td_j^{process}$	picking and packing processing time duration of picklist $j \in J$ (from picking entry to packing completion)
$td_j^{process\_pick}$	picking processing time duration of picklist $j \in J$ (from picking entry to picking completion)
$td_{pk}^{execute\_pick}$	picking execution time duration of the picklist that is assigned to queueing position $k \in K$ of picker $p \in P$
$td_{rl}^{execute\_pack}$	packing execution time duration of the picklist that is assigned to queueing position $l \in L$ of packer $r \in R$
x_{ij}	whether order $i \in I$ is assigned to picklist $j \in J$ ($x_{ij} = 1$) or not ($x_{ij} = 0$)
y_{jpk}	whether picklist $j \in J$ is assigned to queueing position $k \in K$ of picker $p \in P$ ($y_{jpk} = 1$) or not ($y_{jpk} = 0$)
z_{jrl}	whether picklist $j \in J$ is assigned to queueing position $l \in L$ of packer $r \in R$ ($z_{jrl} = 1$) or not ($z_{jrl} = 0$)

picklists. The choice to combine these terms is in order to take into account two popular performance indicators that look at the lifecycle of the warehouse orders separately (order processing time) but also collectively (time to prepare all orders).

In order to test the integrated approach under different performance indicators, we also use each of these terms separately to form different objective functions (Eq. (2) for *makespan minimisation*, and Eq. (3) for *total order processing time minimisation*),

$$\min \max_{r \in R} \left\{ t_{r\bar{L}}^{complete\_pack} - t^{enter\_pick} \right\}, \tag{2}$$

$$\min \sum_{j \in J} td_j^{process}. \tag{3}$$

3.2.3. Constraints

We propose 35 sets of constraints in the MINLP model, to restrict the following conditions mainly covering assignment, capacity and time calculation:

Eq. (4): Each order is assigned to only one picklist.
Eq. (5): Each picklist is assigned to only one queueing position of a picker.
Eq. (6): Each picklist is assigned to only one queueing position of a packer.
Eq. (7): No more than one picklist can be assigned to any queueing position of a picker.
Eq. (8): No more than one picklist can be assigned to any queueing position of a packer.
Eq. (9): Each picklist can contain a limited number of orders.
Eq. (10): Indicate the number of items with each SKU in each picklist.
Eq. (11): Check whether a picklist contains a certain SKU.
Eq. (12): Indicate the number of SKUs in each picklist.
Eq. (13): Each picklist can contain a limited number of SKUs.
Eq. (14): Check whether each picklist contains any orders.
Eq. (15): Check whether each picklist assignment to pickers associates with a non-empty picklist.
Eq. (16): Check whether each picklist assignment to packers associates with a non-empty picklist.
Eq. (17): Check whether each queueing position of pickers contains picklist.
Eq. (18): Check whether each queueing position of packers contains picklist.
Eq. (19): For any picker, no empty queueing positions are before any position with picklist.
Eq. (20): Check whether each picker has any picklists.
Eq. (21): For any packer, no empty queueing positions are before any position with picklist.
Eq. (22): Check whether each packer has any picklists.
Eq. (23): Indicate the number of SKUs (in each picklist) stored in each picking location.
Eq. (24): Check whether a picklist has any SKUs stored in a certain location.
Eq. (25): Indicate the approximated travel distance for in each picklist (as a factor of the number of aisles that need to be visited and the length of the picking zone)

Eq. (26): Indicate the picking execution time duration of each picklist which consists of setup, travel, search, pick and sort time duration.

Eq. (27): Assign the picking execution time duration of each picklist to the correspondingly assigned queueing position of pickers.

Eq. (28): Indicate the picking completion time in the 1st queueing position of each picker.

Eq. (29): Indicate the picking completion time in rest queueing positions of each picker.

Eq. (30): Assign the picking completion time in each queueing position of pickers to the packing entry time in the correspondingly assigned queueing position of packers.

Eq. (31): The packing entry time in any queueing position after should be later than that in any position before.

Eq. (32): Indicate the packing execution time duration of each picklist which consists of pack time duration.

Eq. (33): Assign the packing execution time duration of each picklist to the correspondingly assigned queueing position of packers.

Eq. (34): Indicate the packing completion time in the 1st queueing position of each packer.

Eq. (35): Indicate the packing completion time in rest queueing positions of each packer.

Eq. (36): Each picklist has an upper limit of packing waiting time at each queueing position of packers.

Eq. (37): Assign the packing completion time in each queueing positions of packers to the correspondingly assigned picklist.

Eq. (38): Indicate the picking and packing processing time duration of each picklist (from picking entry to packing completion).

3.2.4. A mixed-integer nonlinear programming model

Combining any one of the objective functions Eqs. (1)-(3) with the 35 constraints as introduced, an MINLP Model$^{\mathrm{I}}$ for our integrated order picking and packing method is constructed as follows:

$$\min \left(\sum_{j\in J} td_j^{process} + \max_{r\in R} \left\{ t_{r\bar{L}}^{complete\_pack} - t^{enter\_pick} \right\} \right) \quad \text{or} \tag{1}$$

$$\min \max_{r\in R} \left\{ t_{r\bar{L}}^{complete\_pack} - t^{enter\_pick} \right\} \quad \text{or} \tag{2}$$

$$\min \sum_{j\in J} td_j^{process} \tag{3}$$

s.t.

$$\sum\nolimits_{j\in J} x_{ij} = 1, \quad \forall i \in I \tag{4}$$

$$\sum\nolimits_{p\in P} \sum\nolimits_{k\in K} y_{jpk} \leq 1, \quad \forall j \in J \tag{5}$$

$$\sum\nolimits_{r\in R} \sum\nolimits_{l\in L} z_{jrl} \leq 1, \quad \forall j \in J \tag{6}$$

$$\sum\nolimits_{j\in J} y_{jpk} \leq 1, \quad \forall p \in P, k \in K \tag{7}$$

$$\sum\nolimits_{j\in J} z_{jrl} \leq 1, \quad \forall r \in R, l \in L \tag{8}$$

$$\sum\nolimits_{i\in I} x_{ij} \leq Q^{pick}, \quad \forall j \in J \tag{9}$$

$$\sum\nolimits_{i\in I} x_{ij} \cdot os_{iu} = bs_{ju}, \quad \forall j \in J, u \in U \tag{10}$$

$$m \cdot q_{ju} \leq bs_{ju} \leq M \cdot q_{ju}, \quad \forall j \in J, u \in U \tag{11}$$
$$\sum\nolimits_{u \in U} q_{ju} = q_j^{SKU}, \quad \forall j \in J \tag{12}$$
$$q_j^{SKU} \leq Q^{SKU}, \quad \forall j \in J \tag{13}$$
$$m \cdot q_j^{od} \leq \sum\nolimits_{i \in I} x_{ij} \leq M \cdot q_j^{od}, \quad \forall j \in J \tag{14}$$
$$m \cdot \sum\nolimits_{p \in P} \sum\nolimits_{k \in K} y_{jpk} \leq q_j^{od} \leq M \cdot \sum\nolimits_{p \in P} \sum\nolimits_{k \in K} y_{jpk}, \quad \forall j \in J \tag{15}$$
$$m \cdot \sum\nolimits_{r \in R} \sum\nolimits_{l \in L} z_{jrl} \leq q_j^{od} \leq M \cdot \sum\nolimits_{r \in R} \sum\nolimits_{l \in L} z_{jrl}, \quad \forall j \in J \tag{16}$$
$$m \cdot q_{pk}^{pl} \leq \sum\nolimits_{j \in J} y_{jpk} \leq M \cdot q_{pk}^{pl}, \quad \forall p \in P, k \in K \tag{17}$$
$$m \cdot q_{rl}^{pl} \leq \sum\nolimits_{j \in J} z_{jrl} \leq M \cdot q_{rl}^{pl}, \quad \forall r \in R, l \in L \tag{18}$$
$$q_{p,k-1}^{pl} \geq q_{pk}^{pl}, \quad \forall p \in P, k \in K \backslash \{1\} \tag{19}$$
$$m \cdot q_p^{pl} \leq \sum\nolimits_{k \in K} q_{pk}^{pl} \leq M \cdot q_p^{pl}, \quad \forall p \in P \tag{20}$$
$$q_{r,l-1}^{pl} \geq q_{rl}^{pl}, \quad \forall r \in R, l \in L \backslash \{1\} \tag{21}$$
$$m \cdot q_r^{pl} \leq \sum\nolimits_{l \in L} q_{rl}^{pl} \leq M \cdot q_r^{pl}, \quad \forall r \in R \tag{22}$$
$$\sum\nolimits_{u \in U} q_{ju} \cdot sl_{ua} = bl_{ja}, \quad \forall j \in J, a \in A \tag{23}$$
$$m \cdot q_{ja} \leq bl_{ja} \leq M \cdot q_{ja}, \quad \forall j \in J, a \in A \tag{24}$$
$$2 \cdot lgth^{vert} \cdot q_j^{od} + 2 \cdot lgth^{aisle} \cdot \sum\nolimits_{a \in A} q_{ja} = d_j, \quad \forall j \in J \tag{25}$$
$$td^{setup} \cdot q_j^{od} + td^{travel} \cdot d_j + td^{search} \cdot q_j^{SKU} + (td^{pick} + td^{sort}) \sum\nolimits_{i \in I} q_i^{item} \cdot x_{ij} = td_j^{execute\_pick}, \quad \forall j \in J \tag{26}$$
$$td_j^{execute\_pick} - M(1 - y_{jpk}) \leq td_{pk}^{execute\_pick} \quad \forall j \in J, p \in P, k \in K \tag{27}$$
$$t^{enter\_pick} + td_{p1}^{execute\_pick} = t_{p1}^{complete\_pick}, \quad \forall p \in P \tag{28}$$
$$t_{p,k-1}^{complete\_pick} + td_{pk}^{execute\_pick} = t_{pk}^{complete\_pick}, \quad \forall p \in P, k \in K \backslash \{1\} \tag{29}$$
$$t_{pk}^{complete\_pick} - M(2 - y_{jpk} - z_{jrl}) \leq t_{rl}^{enter\_pack}, \quad \forall j \in J, p \in P, k \in K, r \in R, l \in L \tag{30}$$
$$t_{r,l-1}^{enter\_pack} \leq t_{rl}^{enter\_pack}, \quad \forall r \in R, l \in L \backslash \{1\} \tag{31}$$
$$td^{pack} \cdot \sum\nolimits_{i \in I} q_i^{item} \cdot x_{ij} = td_j^{execute\_pack}, \quad \forall j \in J \tag{32}$$
$$td_j^{execute\_pack} - M(1 - z_{jrl}) \leq td_{rl}^{execute\_pack} \quad \forall j \in J, r \in R, l \in L \tag{33}$$
$$t_{r1}^{enter\_pack} + td_{r1}^{execute\_pack} = t_{r1}^{complete\_pack}, \quad \forall r \in R \tag{34}$$
$$\max \left\{ t_{r,l-1}^{complete\_pack}, t_{rl}^{enter\_pack} \right\} + td_{rl}^{execute\_pack} = t_{rl}^{complete\_pack}, \quad \forall r \in R, l \in L \backslash \{1\} \tag{35}$$
$$\left| t_{r,l-1}^{complete\_pack} - t_{rl}^{enter\_pack} \right| \leq Q^{wait} \quad \forall r \in R, l \in L \backslash \{1\} \tag{36}$$
$$t_{rl}^{complete\_pack} - M(1 - z_{jrl}) \leq t_j^{complete\_pack}, \quad \forall j \in J, r \in R, l \in L \tag{37}$$
$$t_j^{complete\_pack} - t^{enter\_pick} = td_j^{process}, \quad \forall j \in J \tag{38}$$
$$x_{ij}, y_{jpk}, z_{jrl} \in \{0,1\}, \quad \forall i \in I, j \in J, p \in P, k \in K, r \in R, l \in L \tag{39}$$
$$td_j^{process}, d_j, td_j^{execute\_pick}, td_{pk}^{execute\_pick}, td_j^{execute\_pack}, td_{rl}^{execute\_pack}, t_{pk}^{complete\_pick}, t_{rl}^{enter\_pack}, t_{rl}^{complete\_pack},$$
$$t_j^{complete\_pack} \geq 0,\ bs_{ju}, q_j^{SKU}, bl_{ja} \in \mathbb{N}_0,\ q_{ju}, q_j^{od}, q_{pk}^{pl}, q_{rl}^{pl}, q_p^{pl}, q_r^{pl}, q_{ja} \in \{0,1\}, \quad \forall i \in I, j \in J, p \in P, k \in K, r \in R, l \in L. \tag{40}$$

In order to solve the model more easily, it is converted to an equivalent mixed-integer linear programming (MILP). The details of the linearised MILP Model^{L} can be found in Appendix A.

4. Methodology

The methodology for exploring the research questions based on utilising mathematical programming to solve order picking and packing planning problems is introduced in this section, in terms of the case context, operations performance criteria we evaluate, and experimental design for each research question.

4.1. Case company

We study an e-commerce B2C manual warehouse in China as the case company, whose operations align closely with the problem presented in Section 3.1. The warehouse acts as an order fulfilment centre for an online retailer. The layout of the order picking area under consideration is 49×38.8m-size, consisting of four picking zones with 9 main aisles and 2 cross aisles, storing 1010 SKUs in total, and a depot located in the north. Picking always starts from the depot and follows S-shape routes before picked items are brought back to the depot. Once picking is completed, picked orders are passed to the earliest available packer for packing. In particular, the company operates a manual, sort-while-pick operation using picking trolleys and small baskets/totes to pick customer orders. There are normally 8 workers assigned to picking and 4 to packing. Empirical data were collected by the company that cover both orders received and operational characteristics for picking and packing, such as setup, travel, search, pick, sort and pack time. Table 5 summarises this operational information and the parameters they are assigned to in our experiments. With regards to orders received by the warehouse, actual orders received on a randomly selected day were collected. These were then used as an input in our experiments, with each set of experiments using a different order set (as described in Section 4.3). Each order contains information about the ordered SKUs and the number of items for each SKU. On day under consideration, the warehouse received in total 8276 orders covering 1010 SKUs, among which 25.7% orders were 1-SKU-1-item category, 51.8% were 1-SKU-multiple-items, 11.2% were multiple-SKUs-1-item, and 11.3% were multiple-SKUs-multiple-items. These orders follow a typical ABC inventory classification with 5% of the SKUs responsible for 65% of the total volume, 15% of SKUs for 20% of volume, and 80% of SKUs for 15% of volume.

4.2. Performance comparison

In this section, we describe how we evaluate the performance of integration. First, we describe the performance metrics used to measure performance. Then, we describe the non-integration method that we use to compare the performance of integration with.

Among its key performance indicators, the company uses two categories of metrics to measure for the performance of its warehousing operations: time-related metrics and labour-related metrics. In the former category, the company is measuring the total and average order processing time[1] along with the makespan for the preparation of a certain number of orders. In the latter category, the

[1] Average order processing time is comparable regardless of order quantity. For consistency, mainly average order processing time instead of total order processing time in objective is evaluated in experiments to analyse results.

Table 5: Operational parameter values provided by the case company

Operational parameters	Values
$lgth^{aisle}$	17.32m
$lgth^{vert}$	19.73m
Q^{pick}	16 orders per picklist
Q^{SKU}	24 SKUs per picklist
Q^{wait}	900s
td^{pack}	15.90s per item
td^{pick}	3.97s per item
td^{search}	11.47s per SKU
td^{setup}	90s per picklist
td^{sort}	1.04s per item
td^{travel}	0.67s per meter

company is interested in the total labour efficiency[2] which can be further broken down into picker and packer efficiency. The total order processing time and makespan are formulated in Eqs. (2)–(3) as objectives. The metrics of average order processing time, total labour efficiency, picker efficiency and packer efficiency are derived in Eqs. (41)–(44).

Average order processing time, $\overline{td}^{process}$:

$$\overline{td}^{process} = \sum_{j \in J} td_j^{process} / card(I). \tag{41}$$

Total labour efficiency, EFF:

$$EFF = \frac{card(I)}{\max_{r \in R} \left\{ t_{r\bar{L}}^{complete\_pack} - t^{enter\_pick} \right\} \cdot (card(P) + card(R))}. \tag{42}$$

Picker efficiency, eff^{pick}:

$$eff^{pick} = \frac{card(I)}{\max_{p \in P} \left\{ t_{p\bar{K}}^{complete\_pick} - t^{enter\_pick} \right\} \cdot card(P)}. \tag{43}$$

Packer efficiency, eff^{pack}:

$$eff^{pack} = \frac{card(I)}{\max_{r \in R} \left\{ t_{r\bar{L}}^{complete\_pack} - t_{r1}^{enter\_pack} \right\} \cdot card(R)}. \tag{44}$$

In setting up the experiments required to answer RQs 1-4, we use linearised Model$^{\mathrm{L}}$ as the integrated

[2]The total labour efficiency is defined as the number of orders processed per hour per person.

method for picking and packing. For the sake of a fair and valid evaluation of the benefits of the integrated method, we introduce a non-integrated picking and packing method. In this non-integrated method, picking is managed using the same principles used for picking in Model$^{\mathrm{I}}$. A picking-only Model$^{\mathrm{NI}}$ is proposed in this regard as follows. For packing, a simple first-in, first-out (FIFO) policy assigns the picked picklists to the earliest available packer.

$$\min \left(\sum_{j \in J} td_j^{process\_pick} + \max_{p \in P} \left\{ t_{p\bar{K}}^{complete\_pick} - t^{enter\_pick} \right\} \right) \quad \text{or} \tag{45}$$

$$\min \max_{p \in P} \left\{ t_{p\bar{K}}^{complete\_pick} - t^{enter\_pick} \right\} \quad \text{or} \tag{46}$$

$$\min \sum_{j \in J} td_j^{process\_pick} \tag{47}$$

s.t.

$$(4), (5), (7), (9) - (15), (17), (19), (20), (23) - (29)$$

$$t_{pk}^{complete\_pick} - M(1 - y_{jpk}) \leq t_j^{complete\_pick}, \quad \forall j \in J, p \in P, k \in K \tag{48}$$

$$t_j^{complete\_pick} - t^{enter\_pick} = td_j^{process\_pick}, \quad \forall j \in J \tag{49}$$

$$x_{ij}, y_{jpk} \in \{0, 1\}, \quad \forall i \in I, j \in J, p \in P, k \in K \tag{50}$$

$$td_j^{process\_pick}, d_j, td_j^{execute\_pick}, td_{pk}^{execute\_pick}, t_{pk}^{complete\_pick}, t_j^{complete\_pick} \geq 0, \; bs_{ju}, q_j^{SKU}, bl_{ja} \in \mathbb{N}_0,$$
$$q_{ju}, q_j^{od}, q_{pk}^{pl}, q_p^{pl}, q_{ja} \in \{0, 1\}, \quad \forall i \in I, j \in J, p \in P, k \in K. \tag{51}$$

4.3. Experimental design

In this section, a set of experiments are designed to answer the research questions of this study. In all experiments the integrated picking and packing method (as it is described in Model$^{\mathrm{L}}$) is compared against the non-integrated method (as it is described in Model$^{\mathrm{NI}}$ and FIFO packing). The objective function is always the one described in Eq. (1) apart from when exploring RQ 1 where other objective functions are also tested.

In particular, for RQ 1 experiments, we use 300 customer orders which are used to generate a maximum of 24 picklists. Among the selected 300 consecutive orders (covering 135 SKUs), 24% orders were 1-SKU-1-item category, 49.3% were 1-SKU-multiple-items, 11.7% were multiple-SKUs-1-item, and 15% were multiple-SKUs-multiple-items. We conducted experiments with different objectives functions as they appear in Table 6, with each row representing a different experiment.

Table 6: RQ 1: Objective functions used in mathematical models

Objective functions	Formulations
total order processing time + makespan	Eq. (1)
makespan	Eq. (2)
total order processing time	Eq. (3)

For RQ 2, we compare the two methods under different order quantities ranging from 100 to 600 in

100-steps as described in Table 7). Among the selected 600 consecutive orders (covering 333 SKUs), 25.5% orders were 1-SKU-1-item category, 50.7% were 1-SKU-multiple-items, 10.8% were multiple-SKUs-1-item, and 13% were multiple-SKUs-multiple-items. As the amount of input orders varies, the corresponding number of picklists (and their associated queuing positions) need to also change to different configurations.

Table 7: RQ 2: Order quantities and picklists

Order quantities	#Picklists
100	8
200	16
300	24
400	32
500	40
600	48

RQ 3 deals with different order pool structures. Once again, 300 orders are used as an input but the contents of each order vary so that they can create different structure types for the whole order pool. Table 8 presents the seven different types we run experiments on. In order to have enough numbers of original orders to create the seven types from, 2900 orders were used as the source. In Types 1 to 7, each 300-order set covered 184, 165, 101, 277, 288, 334, and 274 SKUs, respectively.

Table 8: RQ 3: Order pool structure types and their ingredients

Order pool structure types	Order catergories			
	1-SKU-1-item	1-SKU-multiple-items	multiple-SKUs-1-item	multiple-SKUs-multiple-items
1	100%	0%	0%	0%
2	50%	50%	0%	0%
3	0%	100%	0%	0%
4	25%	25%	25%	25%
5	0%	0%	100%	0%
6	0%	0%	50%	50%
7	0%	0%	0%	100%

Finally, for RQ 4, we experiment with different allocations of the available personnel in the picking and packing processes as it is described in Table 9. We keep the total number of available workers the same (i.e. 12 workers) and we investigate how differences in the capacity of each process might affect the benefits of an integrated method. The same 300 consecutive orders were used here as in RQ 1.

Table 9: RQ 4: Personnel allocation to picking and packing

#Pickers	#Packers
10	2
8	4
6	6
4	8

The experimental environment developed for these experiments is developed using MATLAB R2019b on a computer running 64-bit Windows 10 system on a Intel Core i5-7300U processor. The Gurobi Optimizer 9.1 is used to solve the mathematical models in each method. The termination criterion for both methods was set to 24 hours of computational time which deemed to be sufficiently long for the complex mathematical models compared in this paper. In other words, this appropriately long duration was set in order to make sure that the technical characteristics of the Gurobi Optimizer would not affect the measurement of the benefits of integration, which is the focus of this paper. This methodological choice is also in line with recent research on warehousing (Mirzaei et al., 2021).

5. Results

In this section, the results of the experiments described in the previous section are presented. Each subsection presents results relative to RQs 1–4, respectively.

5.1. Performance comparison under different objectives (RQ 1)

The benefits of the integrated picking and packing under different objectives stated in RQ 1 are demonstrated by the experimental results. We begin with Fig. 2 which provides a snapshot of all experiments conducted for this research question. Regardless of the objective function that is optimised (shown with different colours), the integrated method (asterisk marker) performs better than the non-integrated method (circle marker) both in terms of makespan (x-axis) and average order processing time (y-axis). The figure also indicates that, depending on the priorities of a company, different objective functions can be chosen to minimise those key performance indicators that are considered as more important.

Numerical results of more performance criteria are presented in Table 10 both in absolute numbers and in percentage difference to better illustrate the benefits of the integrated method. It can be seen that the integrated method outperforms the non-integrated one in most cases for a number of criteria, except for the picker efficiency criterion. The reason of this exception will be explained later.

In order to further investigate the reasons why the integrated method performs better, we can take a closer look at the total order processing time and makespan. In Fig. 3, the time required for each component of the total order processing time is presented. The two blue components represent time spent in picking while the two brown components represent time spent in packing. The first

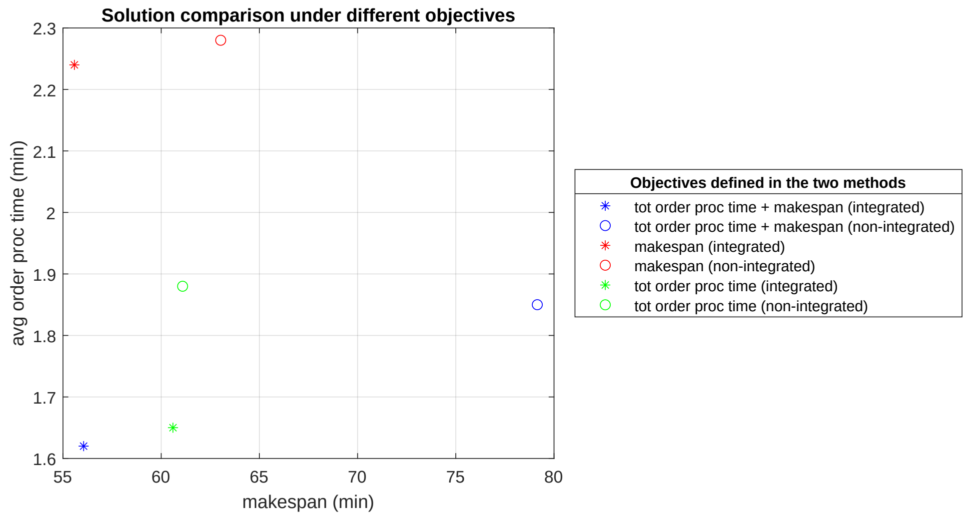

Fig. 2: Performance of integrated and non-integrated methods under different objectives (RQ 1).

Table 10: Performance comparison of integrated and non-integrated methods for different objectives and criteria (RQ 1).

Objective function	Method	Makespan (min)	Avg order proc time (min)	Total labour efficiency (#orders/hr/pax)	Picker efficiency (#orders/hr/pax)	Packer efficiency (#orders/hr/pax)
total order processing time + makespan	integrated	56.05	1.62	26.76	84.54	84.47
	non-integrated	79.15	1.85	18.95	121.27	59.20
	improved %	*29.19*	*12.66*	*41.21*	*-30.28*	*42.69*
makespan	integrated	55.58	2.24	26.99	75.82	85.23
	non-integrated	63.03	2.28	23.80	120.88	78.31
	improved %	*11.81*	*1.90*	*13.40*	*-37.27*	*8.83*
total order processing time	integrated	60.60	1.65	24.75	71.15	79.27
	non-integrated	61.09	1.88	24.55	98.10	78.32
	improved %	*0.81*	*12.28*	*0.82*	*-27.48*	*1.21*

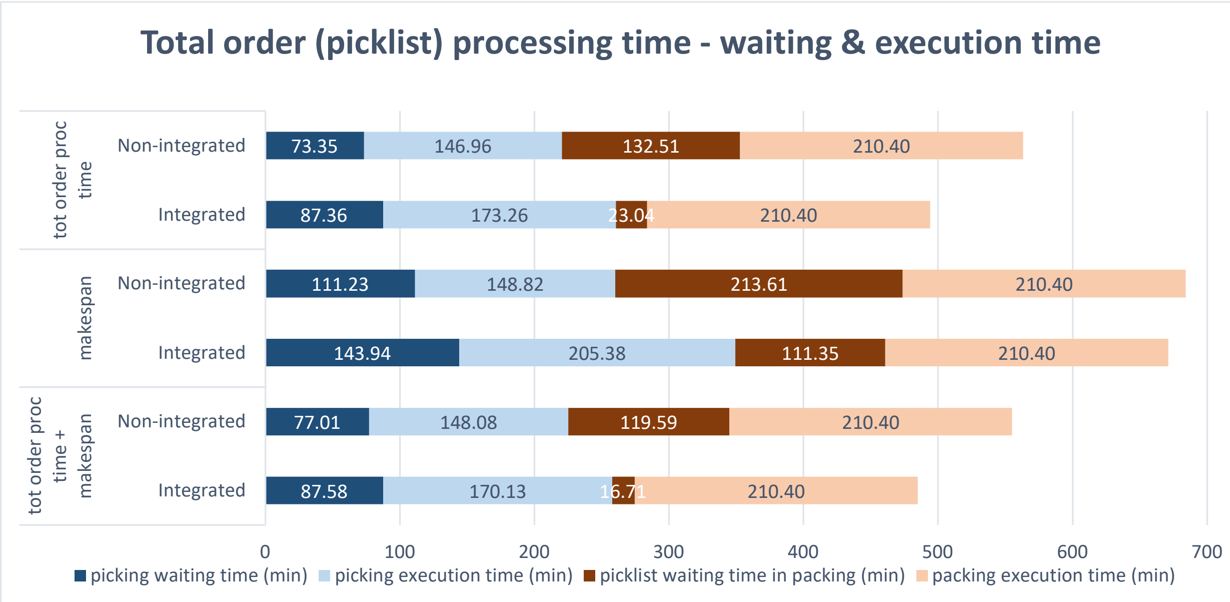

Fig. 3: Picking and packing waiting and execution time of integrated and non-integrated methods (RQ 1).

observation one can make from Fig. 3 is that the integrated method "sacrifices" some time while picking (thus making it longer by $14.49 - 34.33\%$ compared to the non-integrated method), in order to gain significant savings from packing time ($24.12 - 31.92\%$ shorter packing processing time). A second observation is that the main reason for these savings comes from the reduction in waiting time before a picklist can be packed (dark brown colour). Even though the picking process itself is always longer in an integrated method (light blue colour), the savings gained from reducing the waiting time in packing are enough to improve the performance overall. This highlights the fact that focusing on the optimisation of the picking process only will not necessarily lead to improved performance in more inclusive operations, like packing process in our paper, or even beyond.

A closer look at the makespan criterion in Fig. 4 reveals a similar finding. Even though picking is executed in a way that allows all orders to be picked (and thus be ready for packing) faster in the non-integrated method, the method does not take into account the packing process that follows, and results in a longer time required for all orders to get packed. Moreover, as the labour-related metrics are defined based on the inverse of the makespan criterion, the fact that picker efficiency is higher in the non-integrated method can be explained — it reflects faster picking but does not result in an improvement in the overall labour efficiency.

5.2. Performance comparison under under different order quantities (RQ 2)

The benefits of the integrated picking and packing under different order quantities stated in RQ 2 are demonstrated by the experimental results. Numerical results and improvement percentages of two performance criteria (i.e. average order processing time and makespan) are presented in Table 11, showing the benefits of the integrated method under different order quantities. Besides demonstrating

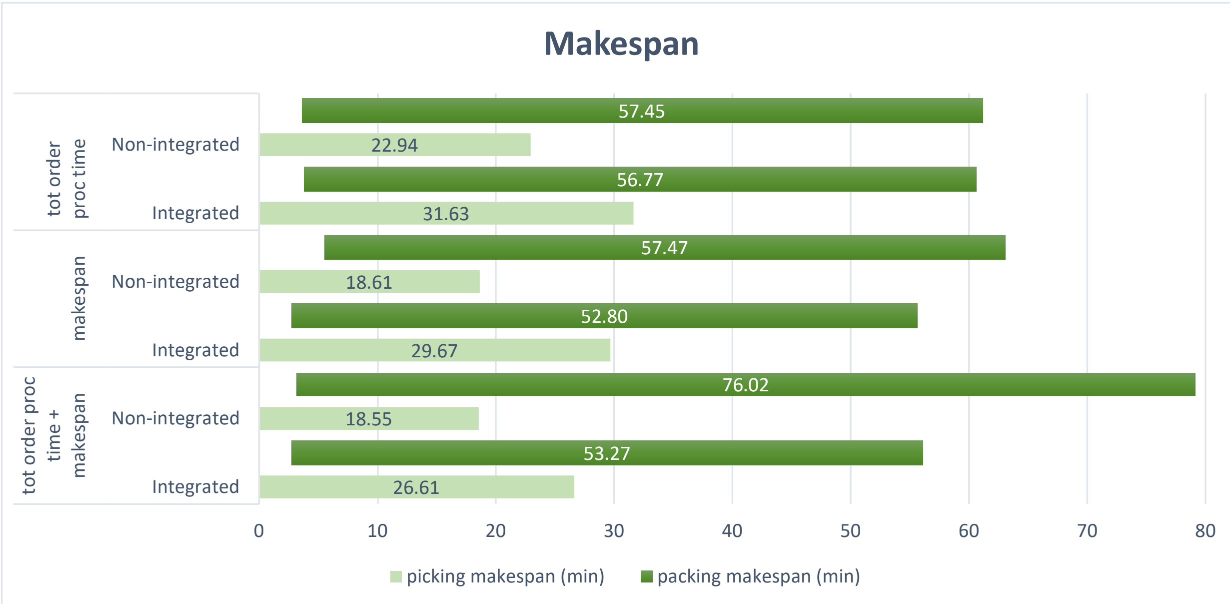

Fig. 4: Picking and packing makespan of integrated and non-integrated methods (RQ 1).

the performance improvement achieved by using the integrated method, the table also indicates that there is a trend that shows that as the order quantity increases, the size of the improvement generally decreases. This demonstrates the importance of selecting an appropriate wave size in designing an integrated method.

There is only one case where we do not observe an improvement in one of the two performance indicators. This concerns the makespan criterion for the case of 600 orders, where the integrated method is 0.69% worse than the non-integrated one. This is due to the small role the makespan criterion plays in our objective function for such large number of orders. More specifically, the value of makespan counts only for 5.37% of the overall objective function and, as a result, most of the method's attention is automatically given towards minimising the total processing time part of the objective function. This results not only in a 0.37% improvement for the order processing time but also in an overall improvement of 0.31%.

Finally, although not reported here for simplicity, a similar analysis to that of RQ 1's results was conducted here to further investigate the reasons that lead to performance improvement. Our findings are very similar to the ones presented earlier: the main reason for the observed improvement is in the reduction of the waiting time before packing can take place.

5.3. Performance comparison for different order pool structures (RQ 3)

The benefits of the integrated method for different order pool structures stated in RQ 3 are demonstrated by the experimental results. More specifically, it can be seen in Table 12 that the results of the main criteria under different types of order pool structures from the integrated method transcend those from the non-integrated one. The results indicate that an integrated method can take into account the

Table 11: Performance comparison of integrated and non-integrated methods under different order quantities (RQ 2).

Order quantities	Method	Makespan (min)	Avg order proc time (min)	Total order processing time + makespan (min)
100	integrated	24.08	1.45	169.04
	non-integrated	35.60	1.68	203.73
	improved %	*32.37*	*13.78*	*17.02*
200	integrated	40.18	1.61	361.35
	non-integrated	46.93	1.87	420.03
	improved %	*14.38*	*13.91*	*13.97*
300	integrated	59.49	1.98	653.47
	non-integrated	67.09	2.39	785.13
	improved %	*11.33*	*17.28*	*16.77*
400	integrated	79.14	2.39	1034.10
	non-integrated	91.29	2.73	1184.24
	improved %	*13.31*	*12.63*	*12.68*
500	integrated	98.29	2.87	1531.00
	non-integrated	109.82	3.17	1693.26
	improved %	*10.49*	*9.52*	*9.58*
600	integrated	123.34	3.60	2284.30
	non-integrated	122.49	3.61	2291.37
	improved %	*-0.69*	*0.37*	*0.31*

special characteristics of different orders and plan their picking and packing in a way that improves system performance. We observe the largest benefits from the cases where order pools have medium complexity (i.e. Types 2–3), but there are also benefits for more complex combinations of orders (i.e. Types 4–7). A deeper analysis on this research question similar to the one presented in RQ 1 indicated that the main benefit of integration arises from the fact that waiting time before packing can be reduced considerably.

5.4. Performance comparison under different workforce allocation (RQ 4)

The previous three sections indicated the importance of this final research question. One could logically argue that one of the ways to reduce the waiting time before packing would be to shuffle the available workforce and move some workers from picking to packing. In this section, we will investigate the benefits of the integrated method when available workforce is allocated to each process in different loads. Details on the performance of the integrated and non-integrated methods in RQ 4 can be found in Table 13. As Table 13 demonstrates, the integrated method outperforms the non-integrated one in terms of makespan and average order processing time when there are more pickers than packers. The integrated method also achieves big reduction in makespan for the remaining two cases for a small increase in average order processing time. Moreover, since this research question considers labour-specific issues, we also report the respective picker and packer labour efficiency. The performance of these two criteria from the integrated method is higher except for the picker efficiency criterion. The

Table 12: Performance comparison of integrated and non-integrated methods under different order pool structures (RQ 3).

Order pool structure types	Method	Makespan (min)	Avg order proc time (min)	Total order processing time + makespan (min)
1	integrated	25.23	1.00	324.30
	non-integrated	25.96	1.04	339.45
	improved %	*2.83*	*4.60*	*4.46*
2	integrated	46.87	1.52	501.83
	non-integrated	59.35	1.78	592.53
	improved %	*21.02*	*14.67*	*15.31*
3	integrated	72.41	2.51	825.15
	non-integrated	86.79	2.99	982.91
	improved %	*16.57*	*16.00*	*16.05*
4	integrated	61.63	2.12	697.34
	non-integrated	64.08	2.28	749.36
	improved %	*3.83*	*7.23*	*6.94*
5	integrated	53.46	2.08	678.28
	non-integrated	61.16	2.26	739.08
	improved %	*12.60*	*7.83*	*8.23*
6	integrated	75.18	2.81	919.48
	non-integrated	83.71	3.04	996.67
	improved %	*10.18*	*7.52*	*7.75*
7	integrated	101.81	3.61	1183.90
	non-integrated	114.93	4.01	1317.00
	improved %	*11.42*	*9.98*	*10.11*

reason for this exception has been explained in RQ 1 as lower picking efficiency levers higher packing efficiency to improve the total labour efficiency.

Table 13: Performance comparison of integrated and non-integrated methods under different workforce allocations (RQ 4).

#Pickers, #packers	Method	Makespan (min)	Avg order proc time (min)	Total labour efficiency (#orders/hr/pax)	Picker efficiency (#orders/hr/pax)	Packer efficiency (#orders/hr/pax)
10 pickers, 2 packers	integrated	107.65	2.45	13.93	55.76	85.48
	non-integrated	116.93	3.02	12.83	118.22	79.95
	improved %	*7.93*	*18.81*	*8.61*	*-52.84*	*6.91*
8 pickers, 4 packers	integrated	56.05	1.62	26.76	84.54	84.47
	non-integrated	79.15	1.85	18.95	121.27	59.20
	improved %	*29.19*	*12.66*	*41.21*	*-30.28*	*42.69*
6 pickers, 6 packers	integrated	44.94	1.64	33.38	106.66	71.02
	non-integrated	56.25	1.59	26.67	121.31	56.10
	improved %	*20.11*	*-2.84*	*25.17*	*-12.07*	*26.58*
4 pickers, 8 packers	integrated	53.40	1.95	28.09	116.13	44.08
	non-integrated	68.93	1.91	21.76	120.27	34.20
	improved %	*22.53*	*-2.12*	*29.08*	*-3.44*	*28.91*

Fig. 5 provides a closer look into how the two methods compare. When there are more pickers than packers, the main benefit of the integration is reflected on largely reduced waiting time before packing (similar to what was found in RQ 1). When there are fewer pickers than packers, the biggest contribution is made by the saving on waiting time before picking. No waiting time before packing is observed here as queues disappear due to the fact that the picking process becomes so slow that a packer is always available when needed. This indicates that, for certain scenarios, the integrated method would not provide any benefits as there are no opportunities to optimise the packing process. A final observation is that another type of waiting in packing process, i.e. the packer's waiting time, is reduced by 27.10% using the integrated method in the case of fewer pickers. This implies that the packers' time can be used much more efficiently.

6. Conclusions and implications

6.1. Implications for research

In this paper, we examined the benefits of integrating picking and packing planning in warehouse operations, motivated by the characteristics of e-commerce order fulfilment. Our results indicate that integrated planning can result in improved performance under various conditions and for several performance indicators. Via the exploration of four research questions, it was shown that focusing solely on the improvement of the picking process does not guarantee gains in overall system performance as the packing process that follows can act as a bottleneck. In particular, it was found that using an integrated method, small sacrifices in the performance of the picking process can lead to greater gains

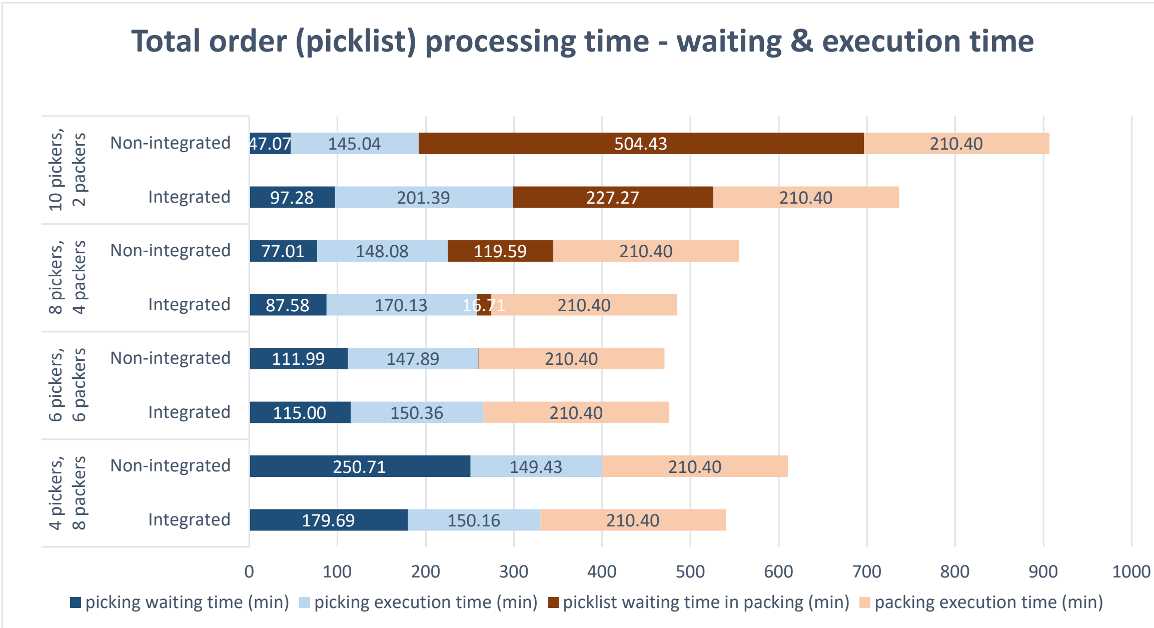

Fig. 5: Picking and packing waiting and execution time of integrated and non-integrated methods under different workforce allocations (RQ 4).

during the packing process, thus resulting in improved overall performance. It was also shown that the usage of performance indicators that consider multiple processes jointly can lead to a more accurate picture of a warehouse's actual performance. This finding resonates with several claims found in the literature on the potential benefits of a more holistic approach in warehouse operations planning and performance measurement (Boysen et al., 2020).

An integrated method can be beneficial for warehouses that receive different numbers of orders, even though there appears to be an inverse relationship between the number of orders one has to plan for and the benefits integration can offer. Benefits were also observed in cases where different categories of orders were received by a warehouse, an important characteristic of e-commerce operations. Finally, we found benefits from integrating picking and packing planning, which are likely to depend on the workforce allocation in each process. This is logical as, in many cases in operations management, the efficiency of a process heavily depends on the (manual or automated) resources assigned to it.

Overall, this study provides the first evidence on the potential benefits of integrating picking and packing processes, thus directly contributing to the academic literature on warehouse integration (Bottani et al., 2019; Boysen et al., 2020; Sprock et al., 2019; Van Gils et al., 2018a,b). At the same time, it presents a new mathematical model for enabling such integrated planning that can form the basis for future mathematical modelling developments in the area.

6.2. Managerial implications

This study has been motivated not only by recent academic literature but also by a real-life operations observed in a warehousing company which was also used to collect empirical data for an experimental study. As a result, both the findings of the study and the proposed mathematical model that formed the basis for the integrated method can be of interest and applicability to practice. Result-wise, this paper provides evidence that practitioners (both warehouse managers and developers of warehouse management systems) can use while considering the integration of different processes. It shows that integration can improve performance in different operational scenarios and that such improvement is possible using the mathematical model developed in the paper coupled with a commercial solver.

The fact that the benefits of integration seem to decrease as the number of orders increases highlights the importance of deciding how many orders should be grouped together before a planning process begins, known as wave release (Çeven & Gue, 2017; Gallien & Weber, 2010). As the results of this study indicate, in practice, it might be preferable to opt for multiple, smaller waves to benefit the most from integrated planning. Moreover, demonstrating benefits for different order categories can be key for practice and an important functionality for warehouse management systems intended to be used by e-commerce warehouses, especially ones that act as third-party providers and they experience various types of demand. In general, the speed at which good solutions can be provided by any method can often be a differentiating factor for many practical applications and should be carefully considered before any real-life implementations.

On the topic of resourcing, practitioners could seek to examine different workforce allocations in an attempt to minimise or even remove bottlenecks. We showed, however, that integration can still be beneficial regardless of how available workers are allocated to each process. In a real system, an integrated method can automatically adapt to actual demand taking into account the available workforce and outperform a non-integrated approach. Finally, even though this study is motivated by and designed based on characteristics commonly found in e-commerce warehousing, our results indicate that one would expect benefits of integration in non e-commerce warehouses wherever consecutive processes can be planned together. Examining such cases would extend the impact of this work to other warehousing types.

6.3. Limitations and future research

This study, being among the very first ones investigating this integrated picking and packing planning model, opens various potential streams of future research. Firstly, even though the warehousing system under consideration here has been a primarily manual one, this work can be easily extended for warehouses with different levels of automation in the picking or in the packing process. Similarly, further extending the scope of our models to include processes such as sorting (for transportation providers) and delivery (or other consecutive processes) will allow a more holistic consideration of the integration problem. Other ways this line of work can be extended is by including aspects of packing (policy) optimisation which was not considered in this study. Moreover, more complex ways for multi-objective optimisation could be considered to better reflect the co-existence of many key performance indicators for practitioners.

There are various ways this study can be extended to examine warehouses with different operational characteristics. Firstly, different routing policies can be explored, to cater for different warehouses and to offer a better approximation of a picker's travel distance, something that can be easily implemented by adapting accordingly constraints Eqs. (23)–(25). Since both integrated and non-integrated methods use the same routing policy we expect its replacement by other policies not to have a great impact on the benefits observed; this is because any routing policy will still apply to both methods and will only affect part of the overall performance (i.e. the one that has to do with travel time) in a similar way. Secondly, storage policies that use multiple locations per SKU are worth considering given their usage by some e-commerce warehouse following recent trends in academic literature (Yang et al., 2020). Thirdly, it would be interesting to compare the performance of a common operational choice where workers pick and then pack the orders they are responsible for. This was not considered here as a) it can lead to queues in warehouses where the infrastructure does not allow for many packing stations and b) it does not look into the picking and packing process holistically but rather aims to eliminate the waiting time before packing without considering the impact this has on picking waiting time.

Methodologically, this study is somewhat limited by its case example and the use of a commercial solver. On the first issue, studying the operations of another case company and/or conducting a simulation study where empirical data are used to form input distributions (rather than specific instances) would offer an opportunity for further statistical validation of the benefits demonstrated. On the latter issue, due to the complexity of the mathematical models, reaching optimal solutions require significant computational resources. The development of faster methods for solving the mathematical models introduced here (e.g. specialised heuristics) could therefore make a useful academic contribution while helping drive industrial adoption as computation time can play an important role in industrial warehouse management systems.

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Appendix A. MINLP Model$^{\mathbf{I}}$ linearisation

In order to solve the MINLP Model$^{\mathrm{I}}$ more easily, this section presents how the model is converted to an equivalent mixed-integer linear programming (MILP). The nonlinear objective function Eq. (1) in Model$^{\mathrm{I}}$ can be rewritten to the equivalent linear expression as,

$$\begin{aligned}
&\min \left(\sum\nolimits_{j \in J} td_j^{process} + td^{makespan}\right) \\
&\text{s.t.} \\
&td^{makespan} \geq t_{r\bar{L}}^{complete_pack} - t^{enter_pick}, \quad \forall r \in R \\
&td^{makespan} \geq 0,
\end{aligned} \tag{A.1}$$

and the nonlinear constraints Eq. (35) in Model$^{\text{I}}$ can be rewritten as,

$$\frac{1}{2}t_{r,l-1}^{complete\_pack} + \frac{1}{2}t_{rl}^{enter\_pack} + \frac{1}{2}\left|t_{r,l-1}^{complete\_pack} - t_{rl}^{enter\_pack}\right| + td_{rl}^{execute\_pack} = t_{rl}^{complete\_pack}, \quad \forall r \in R, l \in L\backslash\{1\}, \tag{A.2}$$

and Eq. (A.2) can be further rewritten to the equivalent linear expression as,

$$\begin{aligned}
& t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} \leq 2t_{rl}^{complete_pack} - t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} - 2td_{rl}^{execute_pack}, \quad \forall r \in R, l \in L\backslash\{1\} \\
& -t_{r,l-1}^{complete_pack} + t_{rl}^{enter_pack} \leq 2t_{rl}^{complete_pack} - t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} - 2td_{rl}^{execute_pack}, \quad \forall r \in R, l \in L\backslash\{1\} \\
& t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} + M \cdot a_{rl} \geq 2t_{rl}^{complete_pack} - t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} - 2td_{rl}^{execute_pack}, \quad \forall r \in R, l \in L\backslash\{1\} \\
& -t_{r,l-1}^{complete_pack} + t_{rl}^{enter_pack} + M(1-a_{rl}) \geq 2t_{rl}^{complete_pack} - t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} - 2td_{rl}^{execute_pack}, \quad \forall r \in R, l \in L\backslash\{1\} \\
& a_{rl} \in \{0,1\}, \quad \forall r \in R, l \in L,
\end{aligned} \tag{A.3}$$

and the nonlinear constraints Eq. (36) in Model$^{\text{I}}$ can be rewritten to the equivalent linear expression as,

$$\begin{aligned}
& t_{r,l-1}^{complete_pack} - t_{rl}^{enter_pack} \leq Q^{wait}, \quad \forall r \in R, l \in L\backslash\{1\} \\
& -t_{r,l-1}^{complete_pack} + t_{rl}^{enter_pack} \leq Q^{wait}, \quad \forall r \in R, l \in L\backslash\{1\}.
\end{aligned} \tag{A.4}$$

Thus, a linearised MILP Model$^{\text{L}}$ is formed.

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