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Quantifying the impact of sharing resources in a collaborative warehouse

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ABSTRACT

Collaboration in warehousing has the potential to decrease warehousing costs and increase supply chain efficiency and is therefore popular in practice. However, there is little literature quantifying the benefits of warehouse collaboration. In this paper, we study the impact of collaboration on two main internal resources of the warehouse; order pickers and dock doors. The setting we consider is relevant to multi-user warehouses, where the owner provides facilities and services to multiple clients depending on their needs. We investigate the impact of sharing the resources among the clients of such a warehouse. We present an Integer Linear Programming (ILP) formulation, which aims at planning the order picking and shipping process while minimizing the total tardiness of shipping trucks. We use this ILP to solve the non-collaborative and collaborative case and evaluate the performance improvement resulting from the collaboration, based on operational data from a retailer. We perform computational experiments under varying warehouse configurations to investigate under what circumstances collaboration leads to the highest benefit. We find that collaboration has a significant impact on decreasing the tardiness of trucks, and the benefits mostly come from sharing the pickers rather than sharing the dock doors. We further find that the maximum benefit of collaboration is obtained at the medium-level of resource utilization. Even at low levels of utilization of a particular resource, benefits can be obtained by collaborating on complementary resources.

1. Introduction

In many supply chains, multiple parties collaborate in their operations. These parties can be active at the same level or different levels of a supply chain, and collaboration can improve their performance. In warehouses, also, companies can collaborate by sharing resources such as storage space, order pickers, or dock doors. In general, warehouse collaboration can potentially decrease warehousing costs (labor and storage costs) and increase warehouse service level (Ding & Kaminsky, 2020), and enhance supply chain efficiency as a result.

1.1. Motivations for collaborative warehousing

Collaboration in warehousing helps companies in several ways. First, it can help to efficiently utilize the resources if the collaborating companies have complementary storage needs and demands. Second, it may also help small companies who individually would not have sufficient scale to run a facility independently. Finally, it can help companies that cannot afford to start their own warehouse with the required technologies. As a result of collaboration, warehouses can share resources such as storage space, order pickers, or dock doors.

1.2. Forms of collaborative warehousing

In practice, collaboration in warehousing can be achieved in different ways. First, actors at the same level of a supply chain, like retailers, can take the initiative to establish a horizontal collaboration by finding a logistic service provider (LSP) to operate a shared warehouse. As an example, in continental Europe, Kimberly-Clark and Unilever started cooperation with the logistics service provider Kuehne+Nagel, who set up a joint manufacturing consolidation center (MCC) that stores and distributes finished products of these manufacturers. This cooperation became possible because 60–70% of the customers of these two companies overlap. They combined their transport and warehousing activities, and as a result, they achieved savings in cost and energy consumption in both storage and distribution stages (Dinalog, 2018).

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Second, companies can use Urban Consolidation Centers (UCCs) that many municipalities have established. A UCC is a warehouse where goods destined for an urban area are delivered to, and then consolidated deliveries are carried out from it. UCCs are established in response to the increase in the volumes of urban freight transport and to mitigate the negative consequences, such as congestion, air pollution, and noise hindrance (Van Heeswijk, Mes, & Schutten, 2019b). The main difference between this category with the MCC-like collaboration is that municipality rules and regulations drive the initiative to use a UCC. The objective of these regulations is typically to reduce the number of movements within a city. This goal can be achieved by consolidating deliveries into an appropriately sized vehicle and decreasing the total distance traveled in urban areas (Allen, Browne, Woodburn, & Leonardi, 2012). Examples of UCCs include Binnenstadservice in the Netherlands, Gnewt Cargo in the UK, and CityDepot in Belgium (Van Heeswijk, Larsen, & Larsen, 2019a).

Third, companies can use multi-user warehouses that are owned by LSPs. In this approach, the LSP is the initiator and establishes collaboration on space and labor. The difference between this approach and the first one is that the companies do not directly collaborate but can benefit from the owner's equipment and services by outsourcing their warehousing operations. LSPs with multi-user warehouses offer a variety of services, like inventory management, conditioned storage (e.g., cold storage or humidity control), flexibility in storage space, and order picking services. LSPs with public warehouses can offer advanced automation and information management technologies that may not be financially obtainable by small businesses owning a dedicated warehouse. From the client's perspective, one of the benefits of this warehouse is that it requires no capital expenditure. However, it usually requires a higher cost per unit of storage or product movement compared to private warehouses. CEVA Logistics is an example of a company offering multi-user warehouse services. This company offers multi-user facilities around the world (CEVA, 2018). The setting we consider in this paper is similar to this group of collaborative warehouses. We consider a multi-user warehouse and investigate the impact of sharing the resources among the clients of such a warehouse rather than dedicating a specific amount of resources to each client.

1.3. Summary of contributions

Although collaboration in warehouses is popular in practice, there is not extensive body of literature quantifying the benefits of warehouse collaboration. The available literature on this topic focuses on inventory pooling in warehouses. To the best of our knowledge, collaboration on the internal resources of the warehouse (order pickers and dock doors) and its impact on system performance has not been studied yet. To fill this gap, we study collaborative warehousing with the focus on the internal resources (order pickers and dock doors) within a warehouse to study how collaboration on these resources and their utilization affect the overall performance. We consider a multi-user warehouse in which two users have their dedicated resources and are operating independently. The owner of this warehouse is able to share the internal resources of these users. We take the total tardiness of the shipping trucks as the key performance measure of each user and evaluate the impact of collaboration with internal resources. The main objective of this study is to investigate: (1) whether collaboration improves the overall performance of involved warehouses, and (2) under what circumstances (in terms of resource levels) collaboration is most beneficial.

The remainder of this paper is structured as follows: Section 2 reviews available literature related to our research. Section 3 describes the research settings and problem definition and provides an Integer Linear Programming (ILP) model that will be used to quantify the impact of collaboration. In Section 4, we generate test instances and perform some computational experiment to investigate the impact of collaboration in different settings of a warehouse. Finally, in Section 5, we discuss conclusions and possible extensions of this research.

2. Literature review

Collaboration in supply chains has been studied extensively in the literature. Collaboration can occur among different parties, such as suppliers, distributors, and retailers. Among the different activities within a supply chain, one of the activities that is suitable for collaboration is logistics, which acts as a physical link connecting customers and suppliers and thus enables the flow of materials (Naim, Potter, Mason, & Bateman, 2006). Collaboration in logistics has received attention in both theory and practice. Logistics activities include some principal operations such as freight transportation and warehousing. Collaboration on transportation and warehousing has been recognized as a practical approach to improve operational efficiency and sustainability (Pan, 2017). Collaborative transportation has received increasing attention in recent years, motivated mainly by cost and environmental concerns (Guajardo, Rönnqvist, Flisberg, & Frisk, 2018). In contrast, research on collaboration in warehouses is limited.

In the field of collaborative transportation, some studies have been done on collaborative vehicle routing. The vehicle routing problem (VRP) aims to find optimal routes for vehicles to visit a given set of customers. Gansterer & Hartl (2018) give an overview of major streams of the collaborative version of this problem, which are categorized as centralized and decentralized collaborative planning. As they report, in centralized settings, a central authority, with full information, is in charge and makes the collaborative decisions. In decentralized settings, players might cooperate individually or be supported by a central authority, which does not have full information. Besides VRP, urban transportation is also studied in collaboration settings. The main focus of collaborative urban transportation is to reduce the negative impacts of freight transport in urban areas, such as congestion, emissions, and space consumption. Cleophas, Cottrill, Ehmke, & Tierney (2019) focus on recent publications in this area and study recent advances in the theory and practice of collaborative urban transportation.

In contrast to collaborative transportation, collaborative warehousing has not received much attention. Most work on collaboration in warehouses investigates inventory pooling. Inventory pooling is a strategic tool in which several companies share their inventories at a central location, instead of multiple locations, to reduce the variability of orders and inventory costs. In this area, the main problem is how to manage the inventory to fulfill demand. An example of an inventory pooling system is given by Kim & Benjaafar (2002), where the benefits of such a system are examined. They analyze the cost advantage derived from the consolidation of multiple inventory locations into a single one, within a production-inventory system. They report that the value gained from pooling depends on several system parameters, such as demand variability, service levels, and holding costs. They also identify conditions in which pooling leads to little or no advantage to the system and warn managers to evaluate the impact of pooling in some specific systems. In another study, Wang & Yue (2015) investigate a pooled inventory model for spare units in systems that serve multi companies. The goal is to optimize the number of companies that share the inventory while taking into account a cost function consisting of storage cost, replacement costs, and downtime cost. Silbermayr, Jammernegg, & Kischka (2017) include environmental sustainability into the inventory pooling models to investigate if pooling could harm the environment. The environmental constraints are designed based on carbon emissions. The results show that if the environmental constraint is binding, expected emissions are increased in the case of pooling compared to the no pooling case.

Even though inventory pooling can be seen as collaboration in a warehouse, we consider another type of collaborative warehousing. We focus on sharing the internal resources of warehouses, such as order pickers and dock doors. Internal resources and warehouse operations are considered important in warehouse management and have been extensively studied in the literature. However, to the best of our knowledge, no academic work has investigated collaboration on these resources in warehouses. Therefore, we focus our review on researches studying warehouse operations in a non-collaborative environment. The main aspects of our problem are planning the order picking process, assigning the trucks to the docks, and scheduling the trucks departures. Thus, we focus on studies in which these topics are addressed.

In a non-collaborative setting, optimizing order picking planning problems in the warehousing is widely studied. Van Gils, Ramaekers, Caris, & De Koster (2018) present a review and classification on different order picking planning problems. Related studies consider different performance indicators as their objective functions. Many of those focus on minimizing the order tardiness. As an example, Scholz, Schubert, & Wäscher (2017) develop the joint order batching, assignment, sequencing, and routing problem. In this problem, the first step is to determine how the customer orders should be batched (grouped) and how the corresponding tours should be constructed. Then, batches are assigned to the pickers, and their sequence is arranged to minimize the total tardiness of orders. Van Gils, Caris, Ramaekers, & Braekers (2019) present a similar problem where batching, routing, and picker scheduling are taken into account simultaneously to reduce order pick time. However, in this study, orders' due times are considered as hard constraints so that all orders must be picked before their due time.

In order picking, it is also important to reduce the number of idle pickers and increase the pickers' utilization to reduce the labor cost. In this area, a new stream of research has been conducted, which aims at balancing the workload of pickers. Vanheusden, van Gils, Caris, Ramaekers, & Braekers (2020) introduce the operational workload balancing problem within the domain of order picking. The focus of their study is to evenly divide the orders over a day so that workload peaks are avoided, and then to obtain the require number of pickers for the balanced schedule. The authors worked on a case study and concluded that using a balanced schedule can increase order picking efficiency. In our paper, we aim at sharing the pickers so that the workload is balanced for the companies, especially with complementary demand patterns.

Dock doors, and the space in front of them, are also included in warehouse resources. The research developed in dock door scheduling and truck-to-dock assignment is largely related to cross-dock problems. In a cross-dock process, the incoming shipments from a supplier are distributed more or less directly to the customer. The goal is to minimize inventory costs and storage activities. Thus shipments typically spend less than 24 h, or sometimes less than an hour, at the facility (Bartholdi & Gue, 2004). Scheduling the trucks and assigning them to the docks is an important issue in cross-docking, which is less addressed in research on warehousing. Bodnar, De Koster, & Azadeh (2017) address a truck scheduling problem in a cross-dock where the tardiness of trucks is included in the objective as a cost function. This model involves many details such as truck-dependent load processing times, and mixed service mode dock doors (dock doors are capable of handling both inbound and outbound truck). Rijal, Bijvank, & De Koster (2019b) extend the work of Bodnar et al. (2017) by including dock door assignments to the truck scheduling problem.

In warehouses, the truck-to-dock assignment problem has been rarely integrated into the order picking decisions. However, there are several related studies that focus on integrating order picking and distribution decisions. For example, Moons, Braekers, Ramaekers, Caris, & Arda (2019); Moons, Ramaekers, Caris, & Arda (2018) study the integration of the order picking and vehicle routing problems. The authors propose an integrated model in a B2C e-commerce context, with the objective of minimizing the picking and routing costs. Kuhn, Schubert, & Holzapfel (2020) study the planning of order picking and vehicle routing for the supply of micro-stores while minimizing the total tardiness of all store orders. To the best of our knowledge, Rijal, Bijvank, & De Koster (2019a) are the first to include dock door considerations in their study. They study the routing decisions of vehicles to customers incorporated with order picking, staging and loading processes. Ostermeier, Holzapfel, Kuhn, & Schubert (2020) address an integrated zone picking and vehicle routing problem with restricted dock space and study the importance of simultaneous planning of picking and routing operations in the distribution processes. Although this stream of literature is similar to ours in terms of resources and operations, we do not include transportation decisions, as this phase is often outsourced and planned according to a fixed schedule. Especially in our settings in which both warehousing and transportation are outsourced to different 3PL service providers, we believe that transportation should not be affected by the internal planning.

Our study is different from this stream of literature as we do not aim to optimize the internal operations of a warehouse. Instead, we investigate how collaboration on internal resources affects warehouse performance. Therefore, we consider those primary operations that make a difference in collaboration or non-collaboration scenarios and thereby leave out some detailed decisions that would not (or only limited) be affected by such a collaboration. To this end, we develop an optimization problem for a simplified version of the operational process to quantify the performance under both collaborative and non-collaborative operations. Although the idea of sharing a warehouse is not new, there is no research investigating the impact of collaboration on warehouse operational resources. To fill this gap, we focus on two main internal resources of warehouses; order pickers and dock doors, and extend the literature on warehouse collaboration by studying how collaboration on internal resources can impact warehouse operations.

3. Problem description and model formulation

Warehouse cost is largely driven by costs of labor and space. Both are very much constrained in many areas of the world. In our study, we focus on these two resources and consider order pickers and space at dock doors as the main internal resources. Order picking is the process of retrieving products from a warehouse to fulfill customer orders. This process is carried out by order pickers who collect the products in an order. Generally, order picking is identified as the most labor-intensive and costly activity for almost every warehouse (De Koster, Le-Duc, & Roodbergen, 2007). Shipping trucks are loaded at the dock doors to deliver the orders. The collected orders for a specific truck are buffered in a temporary storage space at the dock door until all the truck's required orders have been picked. In many, particularly Asian and Western European warehouses, this space is restricted compared to the daily order picking volume of the warehouse (Rijal et al., 2019a). In such warehouses, the number of trucks departing per day can be much higher than the number of dock doors. Thus, the dock door may not yet be available for a departure and could form a bottleneck in the warehouse operations. Therefore, it is necessary to schedule these docks in order to increase the utilization and achieve bet-

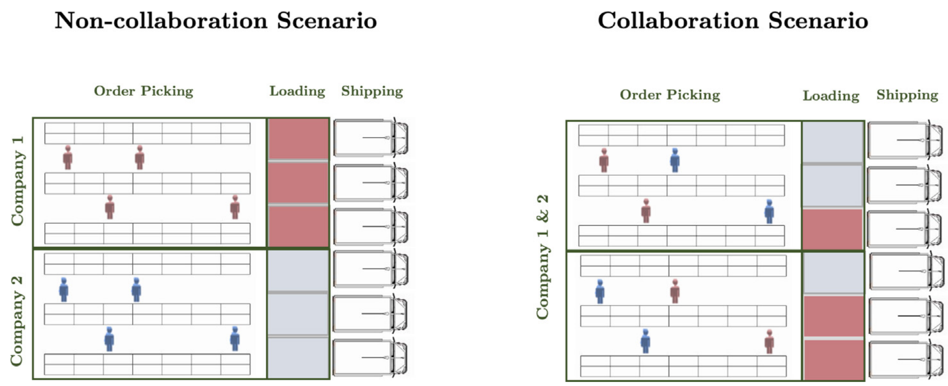


Fig. 1. Schematic graphic representing collaboration and non-collaboration scenarios.

ter performance of the transshipment network (Miao, Lim, & Ma, 2009).

Given the importance of the two mentioned resources, we investigate how the benefits of sharing these resources are affected by their utilization. For this purpose, we consider a multi-user warehousing problem in which multiple users (companies) are jointly using the internal resources (order pickers and dock doors) in a collaboration scenario. We also consider a non-collaboration scenario, where the same companies operate entirely independently and use their own resources. The difference between these two scenarios is depicted in Fig. 1.

We consider activities related to the outgoing flow of products, from picking the orders to loading them into the shipping trucks. We take the total tardiness of the shipping trucks as the key performance measure and calculate it, under different utilization levels of resources, in both the collaborative and non-collaborative scenarios to evaluate the impact of collaboration. Tardiness is a due-time oriented criterion which aims at improving the customer service level. In general, late deliveries might impose stockouts and unsaleable goods for the customers. The cost of late deliveries can be significant. In retail stores, stockout of an important product can lead to lost sales. Thus, many retailers demand their suppliers to deliver on time and within a specified delivery window. For instance, Walmart and Kroger charge their suppliers for late deliveries. Walmart also charges for deliveries received too early (Gasparro, Haddon, & Nassauer, 2017). In general, late and early deliveries can be handled as soft constraints, in which any deviation is penalized in the objective function, or hard constraints, in which deviation is not allowed, and requirements must be satisfied. In this study, we consider hard constraints for truck departures and assume that they are not allowed to depart before their due time. This assumption is relevant to the case of the retailer that provided us with the dataset we used. We aim to minimize the shipping trucks' total tardiness while constraining their early departures to capture customer satisfaction indirectly.

As a solution approach, we present an ILP model to determine the optimal use of resources and the corresponding performance for warehouse operations in collaborative and non-collaborative settings. In the non-collaborative setting, only a single warehouse operator is involved, while in the collaboration case, we consider the operator of the warehouse by two involved companies. We are then able to compare the collaborative warehouse with the non-collaborative one. In the following, the model and its assumptions are described.

We consider a warehouse where a specific number of *customer orders* must be picked and then shipped over a planning horizon. We assume that all customer orders are divided into several *pick orders*, and each pick order requires one time slot to be picked by one picker. Thus, we are given a set O of pick orders that must be picked by order pickers and then be shipped by the shipping trucks over the planning horizon which is defined by the set $T = \{1, 2, \ldots, |T|\}$ of $|T|$ time slots (with a length of e.g. 1 h). The number of available order pickers in each time slot is denoted by p. The set S represents shipping trucks that deliver customer orders. Each truck might carry the orders of more than one customer. However, all pick orders corresponding to a specific customer order will be shipped in the same truck. Set O_s indicates the pick orders that must be shipped by truck s. We assume that the assignment of customer orders to trucks has been done at a higher decision level. Each customer order should be delivered at a specific time, which is defined by the customers. From this, we deduce a departure due time for each truck (denoted by u_s) based on the minimum delivery lead time of customer orders assigned to that truck. We assume that the trucks are not allowed to depart before their due time. The set of dock doors in the warehouse is represented by D. We assume that besides the shipping lanes, there is no additional buffer space for picked items. Thus, the pick orders are kept in the dock lane after being picked and put in the truck as soon as all pick orders of this truck are picked. Therefore, the dock door is occupied from the moment the first pick order of the related truck is picked until the departure time of the truck. The problem is to schedule the picking time of the pick orders, scheduling the trucks' departures at dock doors and specify the sequence of the shipping trucks that share a dock door, while regarding the capacity of resources. The objective is to minimize the total tardiness of the trucks within a working day.

The decision variables in this model can be categorized into three groups:

1. In the *picking phase*, we use the binary variable x_{ot}, which is 1 if and only if pick order o is picked at time slot t.
2. In the *truck scheduling phase*, we use binary variable $q_{ss'}$ to track the sequence of trucks at any dock door. $q_{ss'}$ is 1 if and only if truck s' is scheduled to depart immediately after truck s at any dock.
3. In the *shipping phase*, we use y'_s and y_s that are the start time and departure time of truck s, respectively. The start time is the time period in which the first pick order for this truck is picked, which corresponds with the moment the dock lane is occupied for this truck. We also have l_s, which denotes the tardiness of truck s.

Table 1 summarizes the mentioned parameters and decision variables of the ILP model.

The model can be formulated as follows:

$$\min \quad \sum_{s \in S} l_s \tag{1}$$

$$\sum_{o \in O} x_{ot} \le p \qquad \forall t \in T \tag{2}$$

Table 1
Description of parameters and variables of the ILP model.

Sets and Parameters	
O	Set of pick orders
S	Set of shipping trucks, with 0 and $\|S\|+1$ as the dummy first and last truck, respectively
T	Set of time slots in the planning horizon
O_s	Set of pick orders assigned to truck s
u_s	Due time of truck s
p	Number of available order pickers at each time slot
d	Number of available dock doors
Decision variables	
x_{ot}	Binary decision variable which equals 1 if and only if pick order o is picked at time t
$y_s^{'}$	The picking time of the first pick order which is assigned to truck s
y_s	Departure time of truck s
l_s	Tardiness of truck s
$q_{ss'}$	Binary decision variable which equals 1 if and only if truck s' is scheduled to depart immediately after truck s at one of the docks
q_{0s} ($q_{s,\|S\|+1}$)	Binary variable which equals 1 when truck s is the first (last) truck assigned to a dock, respectively

$$l_s \geq y_s - u_s \qquad \forall s \in S \qquad (3)$$

$$y_s^{'} \leq \sum_{t\in T} t \times x_{ot} \qquad \forall s \in S, o \in O_s \qquad (4)$$

$$y_{s'}^{'} \geq y_s - M(1 - q_{ss'}) + 1 \qquad \forall s, s' \in S \qquad (5)$$

$$y_s \geq u_s \qquad \forall s \in S \qquad (6)$$

$$y_s \geq \sum_{t\in T} t \times x_{ot} \qquad \forall s \in S, o \in O_s \qquad (7)$$

$$\sum_{t\in T} x_{ot} = 1 \qquad \forall o \in O \qquad (8)$$

$$\sum_{s\in S} q_{0s} \leq d \qquad (9)$$

$$\sum_{\substack{s'\in S\cup\{0\}\\ s'\neq s}} q_{s's} = 1 \qquad \forall s \in S \qquad (10)$$

$$\sum_{\substack{s'\in S\cup\{|S|+1\}\\ s'\neq s}} q_{ss'} = 1 \qquad \forall s \in S \qquad (11)$$

$$x_{ot}, q_{ss'} \in \{0, 1\} \qquad \forall o \in O, s, s' \in S, t \in T \quad (12)$$

$$y_s, y_s', l_s \in \mathbb{Z}^+ \qquad \forall s \in S \qquad (13)$$

The objective function (1) represents the minimization of the total tardiness of the shipping trucks. Constraints (2) ensure that the total number of pick orders picked at each time slot does not exceed the number of available pickers. Constraints (3) determine the tardiness of trucks, which takes a positive value if the departure time of a truck is greater than its due time. Constraints (4) define the start time of picking the orders assigned to each truck. Constraints (5) guarantee that when two trucks are assigned to the same dock door, the successor can only start loading once the predecessor has departed. The reason is that the pick orders of a truck are put in the corresponding dock lane after being picked, therefore, there must be a free dock lane for each truck, when its corresponding orders are being picked. In this constraint, M denotes a sufficiently large number. In the case where $q_{ss'} = 1$, we have $y_s \leq y_{s'}^{'} + M - 1$. Since y_s always takes a value between 1 and $|T|$, M must be at least equal to $|T|$. Therefore, we set this parameter equal to $|T|$. Constraints (6) and (7) define the departure time of each truck. The departure of the truck must be after its due time and also after all its orders are picked and loaded. Constraints (8) guarantees that all the orders are picked in the planning horizon. Constraints (9) ensures that at most d docks may be used in total. Constraints (10) and (11) define the sequence of trucks at each dock door, so that each truck has one immediate successor and one immediate predecessor. Finally, constraints (12) and (13) specify the domain of the variables.

When we remove the dock door constraints, the problem becomes equivalent to the parallel machine scheduling problem, where the jobs and machines are equivalent to the pick orders and pickers, respectively. Thus, our problem is a stricter version of the parallel machine scheduling problem. In the parallel machine scheduling problem, several independent jobs are to be processed on some machines, and the goal is to find the schedule that optimizes the objective function, which can be makespan or total tardiness. Although different assumptions and settings can be considered for this problem, the classical parallel machine scheduling problem with the objective function of minimizing total tardiness is similar to the relaxed version of our problem where we have no dock door constraints. Exact methods such as branch and bound and linear programming algorithms are developed for this problem (Sarıçiçek & Çelik, 2011; Yalaoui & Chu, 2002). Since our problem is a stricter version of the parallel machine scheduling problem, and this class of scheduling problems is NP-hard (Koulamas, 1994), our problem is also NP-hard. Thus, our focus is to efficiently formulate it in the first step.

4. Computational experiments

In this section, we first compare collaborative and non-collaborative warehouses via a computational experiment. We describe how random instances are generated in Section 4.1, and then in Section 4.2, we perform multiple experiments to analyze the benefits of collaboration in warehouses. The experiments investigate the improvement of the performance of warehouses as a result of collaboration and how this depends on different characteristics of the warehouse. We then look into the individual benefits of involved parties and investigate whether each individual company benefits from collaboration.

4.1. Instance generation

In this section, we first generate a base case of instances derived from a real-life dataset. We used a dataset from practice (a retailer with multiple operations in Western Europe) to obtain realistic values for our parameters so that the results and the managerial insights may be translated into real-world operations. We

Table 2
Parameters of the base case instances.

Parameter	Notation	Value
Total number of pick orders	$\|O\|$	160
Total number of trucks	$\|S\|$	30
Number of time slots	$\|T\|$	24
Total number of docks	d	5
Number of pickers at each time slot	p	8

also generate additional instances to investigate the value of collaboration in various warehouse circumstances. These instances are categorized into three groups, where each group evaluates a principal characteristic of the warehouse. We aim to study how collaboration benefits depend on various warehouse characteristics, which are represented by different groups of instances. Thus, in each group, we define different levels for the corresponding characteristic. In total, we have 260 random instances. The instances contain all warehouse parameters from the model presented in Section 3, including O, S, O_s, u_s, d, and p. For the non-collaboration scenario, we solve each instance separately. For the collaboration scenario, we combine inputs (orders, pickers and dock doors) of two instances into a larger instance containing data on two companies jointly using a shared warehouse. Next, we provide more details on different groups of instances and how they are generated.

4.1.1. Base case instances

The base case of instances is a scaled-down version of a real-life dataset, which has been provided by a large retailer with multiple operations in Western Europe. The dataset contains data of four warehouses that are operated by the retailer over a one-month period. These warehouses operate 24 h a day and seven days a week. The dataset includes the total workload picked in the warehouses and shipped by trucks per day. The truck departure times and the docks they depart from are also given in the dataset. For the non-collaborative setting, we consider a scaled-down version of the dataset by scaling down the main parameters by a factor of 1/5. In the collaborative scenario, we combine multiple of these companies. Scaling down the parameters reduces the computation complexity and helps us in speeding up the computational experiments. In addition, we envision medium-size companies for collaboration rather than large companies because large companies have sufficient economies of scale on their own and, therefore, are less motivated to start collaboration. Hence, it is reasonable to consider a scaled-down version of our empirical data.

Table 2 shows the parameters used in base case instances for the non-collaborative setting. In this table, $|O|$, $|S|$, $|T|$, and d are derived from the original dataset. However, we had no information about the labor in the warehouses. With the given parameters, the minimum number of pickers needed is calculated as $p = \left\lceil \frac{|O|}{|T|} \right\rceil = 7$. This value leads to utilization of 95% ($\frac{|O|}{|T| \times p} = \frac{160}{24 \times 7}$) for pickers. To moderate the workload and not overload the pickers, we should lower the picker utilization by increasing p. However, labor costs in manual order picking systems are high (Chang, Fu, & Hu, 2007), and having a too low picker utilization deviates from real-life situations. Therefore, we choose $p = 8$, resulting in picker utilization of 83%.

The original dataset does not provide the delivery due times of the retailer's customers, i.e., the stores. We, therefore, assume that the parted at their due times. We then randomly generate the due times based on the distribution of truck departure times. For this purpose, we divide the planning horizon of the original dataset (24 h) into four periods and calculate the percentage of truck departures in each period. In the original dataset, 25%, 30%, 40%, and 5% of trucks depart in the first to fourth period, respectively. We assume that in each period, the departure times of the trucks are uniformly distributed. We divide our planning horizon ($|T| = 24$) into four periods and assign a random due time to each truck so that the distribution of truck due times follows the distribution of truck departures in the original dataset. Finally, we generate 20 random instances with the given parameters as the base case instances.

4.1.2. Additional instances

One main research question that we need to answer is how the benefits of collaboration depend on the warehouse settings and how collaboration works in various settings, where each (or both) of the resources, i.e., order pickers and dock doors, is acting as a bottleneck. To answer this, we do our experiments on instances representing different warehouse settings. We consider three main characteristics in a warehouse; each defined by the utilization level of a specific resource in the warehouse. These characteristics are critical since they imply the bottlenecks of the system. For each characteristic, we define five different levels, varying from low to high. Therefore, we can simulate different settings in a warehouse. The characteristics are:

1. *Picker utilization*, indicated by the ratio $\frac{|O|}{p \cdot |T|}$. This characteristic shows how busy the pickers are for the picking process. Increasing (decreasing) the picker utilization makes the pickers more (or less) a constraint in the warehouse.
2. *Dock utilization*, shows how busy dock doors are, compared to the total time they are available. Each dock door is assumed to be busy from when the first pick order of the related truck is picked until the truck's departure time. Thus, this characteristic depends on the obtained solution for each instance and cannot be calculated based on the given parameters. Therefore, we choose an alternative to have a bound for this measure. To do so, we assume that each truck contains $\frac{|O|}{|S|}$ orders, which can be picked in $\frac{|O|}{p \cdot |S|}$ time slots. Since on average, we have $\frac{|S|}{d}$ trucks at each dock lane, the total time needed for picking the orders of a specific dock is equal to $\frac{|O|}{p \cdot d}$. In a planning time horizon with $|T|$ time slots, the average dock utilization can be estimated by $\frac{|O|}{p \cdot d \cdot |T|}$. Therefore, we choose the ratio of $\frac{|O|}{p \cdot d \cdot |T|}$ as an indicator of dock utilization. Increasing this value represents a setting where docks become more a bottleneck.
3. *Workload per truck*, denoted by the ratio $\frac{|O|}{|S|}$. This characteristic indicates the workload corresponding to a shipment. This will have an effect on both the required number of pickers as well as the required number of dock doors.

We define five different levels (including the base case level) for each characteristic and then generate 20 random instances for each level. Table 3 summarizes the characteristics of the different groups, where in each group, the base case is highlighted in bold.

In each group of instances, we define the level of characteristic by varying one key parameter while the other parameters and other characteristics remain fixed. In the first group, we modify p, and define four additional different levels for it so that $p \in \{7, 9, 10, 11\}$. We cannot have p lower than seven due to the feasibility constraint ($p \geq \frac{|O|}{|T|}$). In the second group of instances, we have d as the varying parameter and define four additional levels starting from the minimum possible value ($d \in \{3, 4, 6, 7\}$). We also

Table 3
The value of characteristics in additional instances. The value in the base case is highlighted in bold.

Group	Characteristic	Formula	Varying parameter	Parameter value	Level of characteristic
1	Picker utilization	$\frac{\lvert O\rvert}{p \cdot \lvert T\rvert}$	p	7	0.95
				8	**0.83**
				9	0.74
				10	0.67
				11	0.61
2	Dock utilization	$\frac{\lvert O\rvert}{p \cdot d \cdot \lvert T\rvert}$	d	3	0.28
				4	0.21
				5	**0.17**
				6	0.14
				7	0.12
3	Workload per truck	$\frac{\lvert O\rvert}{\lvert S\rvert}$	$\lvert O\rvert$	220	7.3
				190	6.3
				160	**5.3**
				130	4.3
				100	3.3

tested instances with $d = 1, 2$, but no feasible solution was found for most of them. In the third group of instances, we define different levels for the truck workload ($\frac{|O|}{|S|}$) by varying $|O|$. We put these values as 220,190,130,100, so that the average truck workload (which is 5.3 in the base case) has a one-unit increase or decrease between levels. We also need to keep other characteristics fixed; therefore, we define p as 11,10,7,5 to keep picker utilization closest to 83.3% which holds in the base case instances. Therefore, we have *picker utilization* $= 83.3\%, 79.2\%, 77.4\%, 83.3\%$ in the four additional levels defined for workload per truck.

In summary, we have a base case group, which is derived from real-life data and consists of 20 random instances, and 240 ($4 \times 3 \times 20$) additional instances, leading to 260 instances in total. We use these instances for both collaborative and non-collaborative scenarios. We first solve every two instances separately (non-collaborative scenario) and then combine them into one joint instance. So, we have 10 joint instances and compare their results in the case of collaboration and non-collaboration.

For our computations, we used Gurobi Optimizer version 9.0 on a server with an Intel® Xeon® Silver 4110 processor and 16 cores operating at 2.10 GHz base frequency. We applied the non-collaboration results as the initial starting solution for the collaboration scenarios to speed up the solution process. We set a time limit of 2 h to solve any instance. The 10 joint instances in each level are then compared for four different scenarios (collaboration, non-collaboration, shared pickers, and shared docks), leading to 40 cases in each level. In the base case, 5 out of 40 cases did not reach optimality within the given time limit, while the rest took about 3 min (on average) to get solved. For this 12.5% of cases that could not be solved in 2 h, the gap between the best-found solution and the lower bound is 20% on average. For these cases, we used the best-found solution in our computational study. It is worth mentioning that the non-optimal cases are mostly in the collaboration scenarios. As the main goal is to compare collaboration and non-collaboration scenarios, we believe that in the case of having the optimal solution (which is lower or equal to the best-found solution), the impact of collaboration is not less than what we report with the best-found solutions. Therefore, we use the best-found solution in cases that have not reached optimality since it would not lead to exaggerated results. In additional instances, about 20% of cases could not reach optimality within 2 h. However, the average gap in these instances is less than 5% in total. We observe that the average running time increases as the resource utilization increases as a result of decreasing resource availability. Within a specific level of resource utilization, the instances with a higher average of trucks due times usually take longer to get solved. This is caused by tighter space constraints at the dock doors because trucks cannot depart early.

Table 4
The average, minimum, maximum and 95% confidence intervals for improvement made in different scenarios of the base case instances compared to the non-collaboration scenario.

Scenario	Average	Min	Max	95% CI
Collaboration	61%	32%	100%	[47.4%,75.2%]
Shared Pickers	59%	32%	100%	[45.6%,72.0%]
Shared Docks	13%	0%	32%	[6.0%,19.3%]

4.2. Value of collaboration

In this section, we investigate the value of collaboration and study how collaboration affects the trucks' tardiness. For this purpose, we solve the base case instances in both collaborative and non-collaborative settings and compare the obtained results. We also consider two more scenarios, namely "Shared Pickers" and "Shared Docks". In the "Shared Pickers" scenario, we assume pickers are the only resource shared between the companies. Thus, each company uses its own dock doors independently but can share the pickers. In the "Shared Docks" scenario, we assume that pickers are not allowed to be used jointly, but the dock doors are shared between the companies.

Figure 2 provides the results of base case instances with two companies in different scenarios. A summary of these results is given in Table 4. In all instances, collaboration leads to at least a 32% decrease in the total tardiness of shipping trucks, with an average improvement of 61%. Although "Shared Docks" and "Shared Pickers" scenarios are not as effective as full collaboration, these scenarios can be helpful in cases where sharing both resources is not an option. We observe that sharing only the pickers has a larger impact than only sharing the dock doors. In 80% of the instances, sharing only the pickers results in the same improvement as full collaboration, i.e., the benefits of full collaboration can be gained by only sharing the pickers. However, sharing only the dock doors never leads to the improvement of full collaboration.

4.2.1. Picker utilization

In this section, we focus on the effect of the utilization of the pickers on the benefit of collaboration. Figure 3 depicts a summary of the results of group 1 instances. As it is shown, the maximum benefit of collaboration is obtained at medium-level picker utilization (about 60–70%). This can be explained by the fact that for a very high picker utilization, there is a limited idle capacity to share, whereas, for low utilization, the picking capacity is not

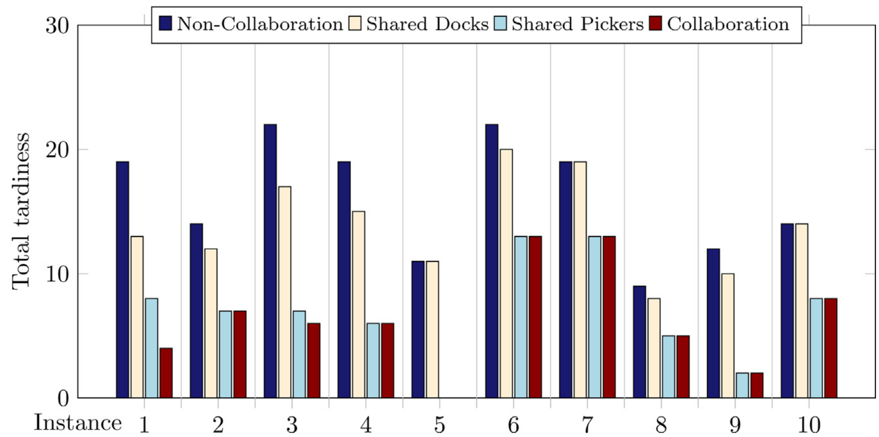


Fig. 2. Impact of collaboration in the joint instances of the base case group.

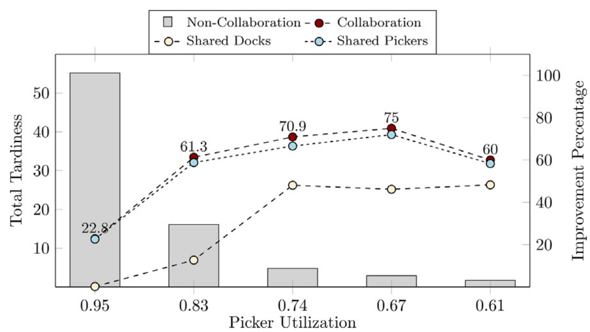


Fig. 3. Impact of collaboration on picker utilization. *Note:* The bars indicate the average total tardiness of instances for the non-collaboration case. The lines show the average percentage of improvement achieved by each scenario compared to the non-collaboration scenario.

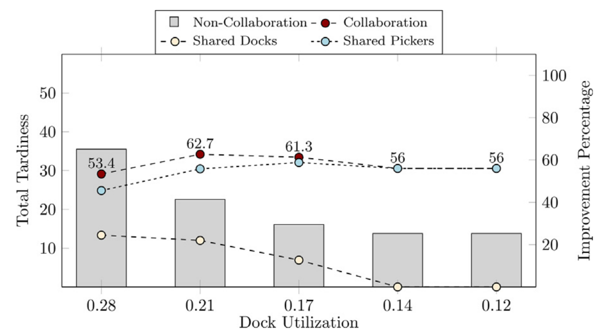


Fig. 4. Impact of collaboration on dock utilization. *Note:* The bars indicate the average total tardiness of instances for the non-collaboration case. The lines show the average percentage of improvement achieved by each scenario compared to the non-collaboration scenario.

the bottleneck in the warehouse. This trend is particularly evident when looking at the "shared picker" scenario. Here it can be seen that at a low level of picker utilization, the benefit of collaboration on pickers decreases, and the improvement resulting from collaboration mostly comes from sharing the dock doors rather than sharing the pickers.

The trend obtained for the "Shared Pickers" scenario is similar to the full collaboration scenario. However, the improvement resulting from the "Shared Docks" scenario differs. The result of this scenario is close to the "Shared Pickers" scenario at a low level of picker utilization. At this level, there are some idle pickers for each company. Hence, sharing only the pickers would not help in removing the bottleneck and does not lead to maximum improvement. However, sharing only the docks helps in speeding up the shipping process, while the previously idle pickers would make the order picking process faster simultaneously. Therefore, sharing docks is more beneficial at lower levels of picker utilization.

4.2.2. Dock utilization

Figure 4 depicts the results of collaboration at different levels of dock utilization. The trend of full collaboration is similar to the results obtained for picker utilization. The maximum improvement gained by collaboration occurs at a medium level of dock utilization. At lower dock utilization levels, the benefit of collaboration comes only from sharing the pickers, and sharing the docks does not affect the results. The improvement obtained by sharing only dock doors is also maximal at a medium level of dock utilization. However, this improvement can also be achieved by sharing only the pickers. In general, we can conclude that collaboration is most helpful in cases where the utilization of resources is at a medium level.

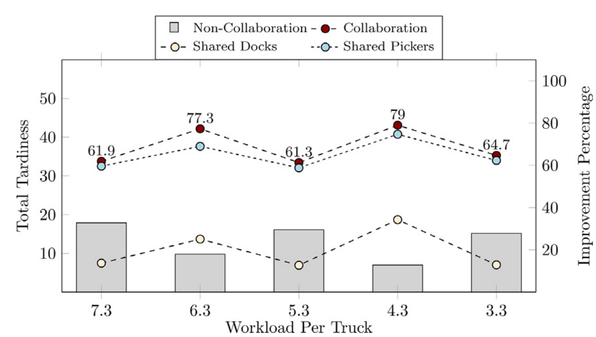


Fig. 5. Impact of collaboration on trucks workload. *Note:* The bars indicate the average total tardiness of instances for the non-collaboration case. The lines show the average percentage of improvement achieved by each scenario compared to the non-collaboration scenario.

4.2.3. Workload per truck

Figure 5 shows how collaboration performs at different levels of truck workload. The workload per truck does not seem to have a major impact on the effect of full or partial collaboration on truck tardiness reduction.

A more detailed overview of the results of the additional instances, including 95% confidence intervals, is given in Table 5 in the Appendix. We conclude that collaboration results in improvement, no matter what the warehouse settings are. However, the results reveal that sharing only the pickers leads to a higher improvement than sharing only dock doors. Besides, collaboration works best in cases with a medium level of resource utilization. In cases with low levels of picker/dock utilization, sharing only docks/pickers is more helpful. In these cases, there would be some

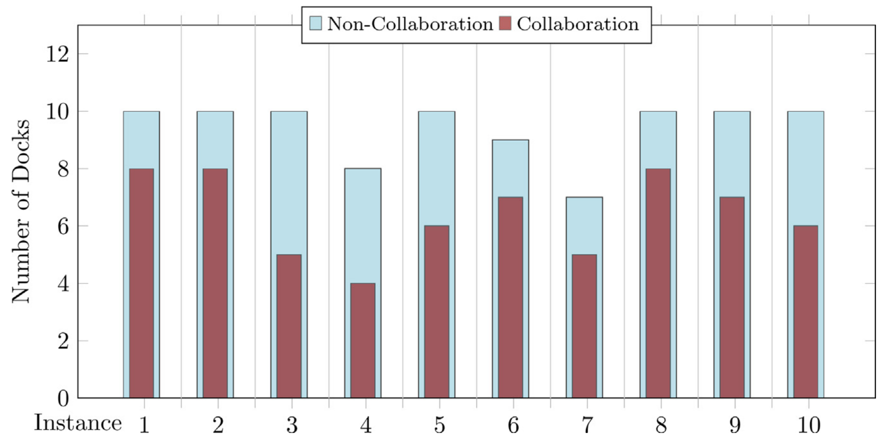


Fig. 6. Required number of docks to achieve a given service level the joint instances of the base case.

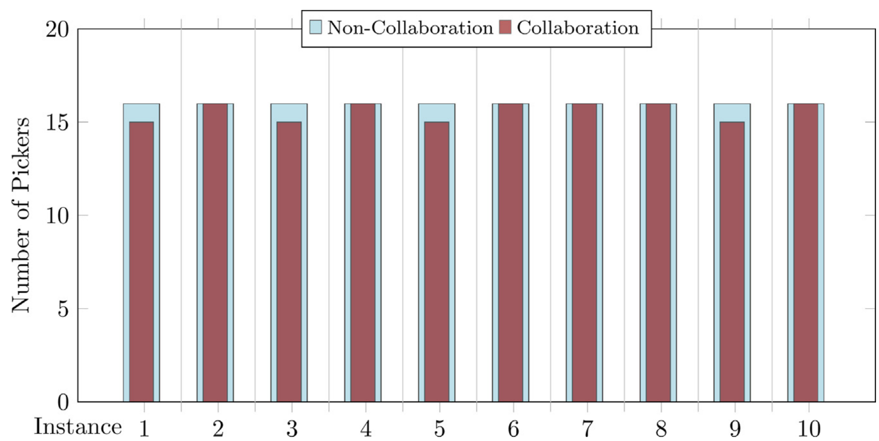


Fig. 7. Required number of pickers to achieve a given service level in the joint instances of the base case with 83% picker utilization.

pickers or docks idle, and sharing the other complementary resource can help more in speeding up the operations.

4.3. Impact of collaboration on the resource saving

This section investigates the savings in the resources that can be achieved by collaboration, given a certain service level (represented by total tardiness). In the base case group, we already have the tardiness of each instance (base tardiness). We now investigate how much savings can be achieved by the collaboration of two companies so that each company's tardiness is at most equal to the tardiness it has in the case of operating on its own (non-collaboration scenario). We analyze each resource separately. For all instances, we first calculate the exact amount of each resource that is needed for the base tardiness. We then consider collaboration on only one of the resources and check the total amount of that resource that is needed so that none of the companies would experience higher tardiness than the base value. We compare the required resources in non-collaboration and collaboration scenarios.

Figure 6 illustrates the difference in the number of dock doors needed when two companies of the base case instances are operating independently and when they jointly use their dock doors. As it is shown in this figure, in all the cases, at least 20% savings in the number of dock doors can be achieved when they are used jointly. On average, a decrease of 32% is obtained for all the instances.

Figure 7 shows the minimum number of pickers in both collaboration and non-collaboration scenarios required so that each company can achieve the base tardiness. A mean of 3% saving is achieved in the number of pickers if companies share this resource. As we mentioned in previous sections, picker utilization in the base case instances is 83%. In Section 4.2.1, we observed that in the middle levels of picker utilization, the positive effect of collaboration is more significant. Here, we investigate the resource-saving in the base case instance with 9 pickers (picker utilization = 74%). The results are depicted in Fig. 8.

The saving achieved by sharing pickers when their utilization is 74% is 7% on average. This result verifies the conclusion in Section 4.2.1. At very high picker utilization levels, there is limited idle capacity to share. Therefore, not much saving is gained by sharing this resource. However, the benefit of collaboration becomes significant at medium levels of picker utilization.

4.4. Analysis of demand patterns

In the instances we generated, the two companies engaged in collaboration have similar resources and demand patterns. In this section, we study the impact of collaboration in cases where companies have asymmetric demand patterns. We focus on the trucks due times, as the main objective of each company is on-time departure of trucks. We use the base case instances for this analysis and generate two groups of instances from them. In the first group, company 1 has its due times according to the original data set (25%, 30%, 40%, and 5% of trucks depart in the first to fourth period), while company 2 has the opposite due time distribution (5%, 40%, 30%, and 25% of trucks depart in the first to fourth period). In the second group, company 2 has the original due times'

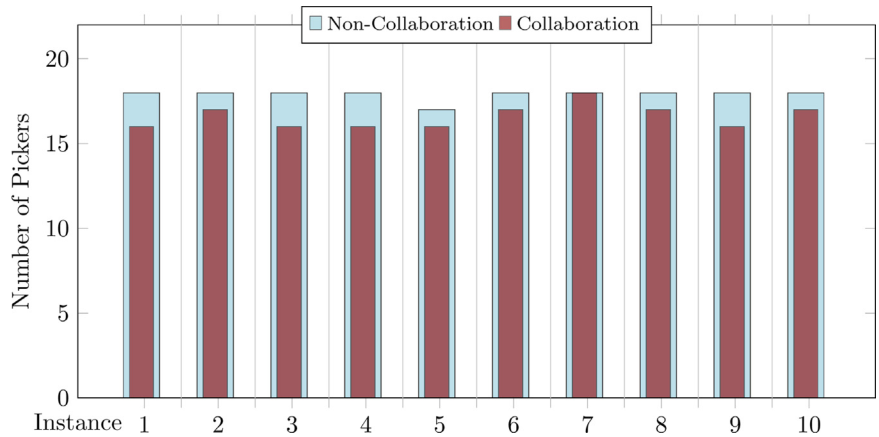
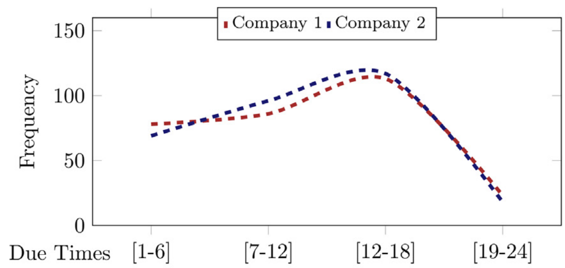
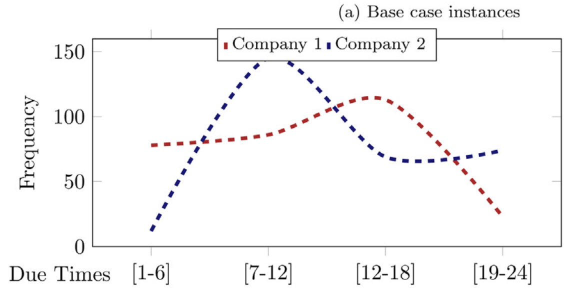


Fig. 8. Required number of pickers to achieve a given service level in the joint instances of the base case with 74% picker utilization.



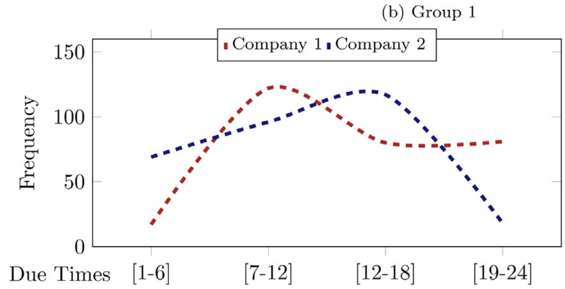
Scenario	Objective Improvement
Collaboration	61%
Shared Pickers	59%
Shared Docks	13%

(a) Base case instances



Scenario	Objective Improvement
Collaboration	82%
Shared Pickers	80%
Shared Docks	45%

(b) Group 1



Scenario	Objective Improvement
Collaboration	87%
Shared Pickers	75%
Shared Docks	32%

(c) Group 2

Fig. 9. Due time patterns and the results in different groups of instances.

pattern, and company 1 has the opposite. All other parameters in these groups remain the same as the base case instance. We then solve the two groups and compare the results with the base case instances where companies have symmetric demand patterns. Figure 9 shows the demand patterns in different groups and the obtained results.

The results show that collaboration helps more when companies have complementary demand patterns. On average, full collaboration leads to an 84% of improvement in the objective in cases with asymmetric demand patterns, which is much higher than the 61% objective improvement achieved in cases with similar demand patterns. Besides, the impact of the "Shared Docks" scenario is more significant in the case of complementary demand patterns. On average, 30% of the improvement made by full collaboration can be achieved by sharing only the docks. In summary, these results confirm the previous results stating that sharing only the pickers leads to bigger improvement than sharing only the docks, and collaboration is much more helpful when involved parties have complementary demand patterns and resource requirements, consequently.

4.5. Individual benefits

In order to investigate how the involved companies benefit from collaboration, we look into each instance to check whether the objective value of each company has improved as a result of collaboration. In general, the benefit of collaboration does not always result in benefits for all the involved partners. It is possible that in the optimal collaborative solution, one company would experience higher tardiness, while another company has a decrease in tardiness. This is particularly likely to occur in a situation where the companies have different demand patterns. Even though we consider symmetric companies, it can still occur. One possible solution would be to allow for financial compensation between the companies, where the company with increased tardiness receives money from the company with a tardiness reduction. We, however, take a different approach. In the optimization, we add a constraint to ensure that none of the involved parties experiences an increase in tardiness. Even stronger, for the case with more than two companies, we also ensure that the total tardiness of any subgroup of companies does not exceed the tardiness of this subgroup when collaborating together. This constraint ensures that the solution is in the core, a common concept introduced to game theory by Gillies (1959).

Note that adding these constraints requires solving $2^{|c|}$ instances of the ILP problem to obtain the objective values. In our problem, we want to obtain "fair" solutions in which no company is worse off after collaboration. The obtained results show that although improvement is made in each individual instance, not every individual company benefits from collaboration. In other words, in some instances, in the collaborative scenario, one of the two companies may experience higher tardiness as a result of the collaboration, despite the fact that the total tardiness is lower than the non-collaborative scenario. Therefore, for collaboration scenario, we add additional constraints to guarantee that companies would not experience an increase in their trucks' tardiness as a result of collaboration. Let us define each company by $c \in C$. We also have $N \subseteq C$ denoting a non-empty subset of C, and obj_N as the objective value (total tardiness of trucks) if collaboration is formed among all $c \in N$. We also have obj_c^{opt} denoting the objective value of company c in the optimal collaborative solution (i.e., without constraints (14)). We use the following constraint to the model and then solve it in the collaboration scenario where C companies are collaborating.

$$\sum_{c \in N} obj_c^{opt} \leq obj_N \qquad \forall N \subseteq C \qquad (14)$$

In our problem where collaboration happens between only two companies, constraints (14) lead to two constraints which can be presented as below, in which $C = \{1, 2\}$ is the set of companies involved in collaboration and S_1 and S_2 is the set of shipping trucks corresponding to "Company 1" and "Company 2", respectively. We define obj_1^{sep} and obj_2^{sep} as the objective values obtained for "Company 1" and "Company 2" in case of non-collaboration, which can be found by solving the optimization problem (with objective function (1) and constraints (2) to (13)) for a single company.

$$\sum_{s \in S_c} l_s \leq obj_c^{sep} \qquad \forall c \in C \qquad (15)$$

We run the model (1)–(13) updated with the constraint (15) on the base case instances. The new results reveal no changes in the cumulative results of collaborative scenarios in our test instances. Although the benefit of some companies has decreased as a result of adding this constraint, on aggregate, the benefit of the whole system has not changed. Thus, we can achieve "fair" solutions for our instances. It is also possible to change the constraint to have at least α% improvement for each participant to reduce differences between participants (for example, 10% saving for one participant and 0% for the other). By considering at least α% improvement for each company, differences in savings between companies can be reduced. This may motivate the participants to engage in collaboration.

We also study how individuals benefit in case of collaboration among more than two companies. For this purpose, we design a new set of instances based on the 20 base case instances we used before. We group every three instances together and consider a three-company collaboration scenario. Thus, we have six joint inputs for the collaboration scenario, in which $|O| = 480, |S| = 90, d = 15$, and $p = 24$. In the case of having more than two partners in the collaboration, we use the constraint (14) which is the generic version. The results reveal that adding this constraint does not change the objective value, i.e., even in collaboration among three companies, the benefit of the whole system does not change, and we can obtain fair solutions.

5. Conclusions

In this paper, we investigate the impact of collaboration on warehouse resources. We considered order pickers and docks doors as two main internal resources in warehouses. We studied a collaborative warehousing problem in which two companies jointly use internal resources. To evaluate the impact of collaboration, we focused on the total tardiness of shipping trucks of the warehouse and investigated how it changes in case of collaboration compared to the non-collaboration scenario, where each company independently operates its warehouse. We developed an ILP formulation that can be used the determine the tardiness in both the collaborative and non-collaborative setting. We generated the test instances based on a real-life dataset provided by a large retailer. Our results show an average of 61% improvement on the base case group of test instances, which was the scaled-down version of the original dataset, as a result of collaboration. We further found that sharing pickers has a considerably larger impact on the total tardiness than sharing dock doors. We also observed that for both resources, the maximum benefit of collaboration happens at the medium level of their utilization. At high levels of resource utilization, the resource can act as a bottleneck, and due to lack of idle resources, sharing does not cause the maximum benefit. On the other hand, at low levels of utilization, each partner already has enough resources to perform well on its own. As a consequence, the maximum improvement is not obtained at low levels of pickers utilization either. Finally, we proposed an approach to ensure that all of the involved parties benefit from the collaboration and that the benefit of one company does not come at another company's cost. For this purpose, we introduced additional constraints to the model inspired by the core concept from game theory. In the numerical experiment based on our instances, we see that without this constraint, it will occur that some of the companies are worse off as a result of the collaboration while adding the constraint can fix this without increasing the total tardiness.

For future research, we could consider collaboration on other warehouse resources. For example, we could include shipping trucks as a shareable resource and include the assignment of orders to the trucks into the internal operations of the problem. We can also investigate the impact of collaboration on the inventory storage space. A model can be developed to capture space-saving while using a specific ordering policy. This aspect will require inventory management modeling. We can also include the main costs of establishing a collaborative warehouse and study the cost-benefit trade-off to have a better overview of the problem.

Appendix

Table 5
Summary of results in different levels for resource utilization.

	Picker Utilization (Fig. 3)									
	0.95		0.83		0.74		0.67		0.61	
	Average	95% CI	Average	95% CI	Average	95% CI	Average	95% CI	Average	95% CI
Collaboration	22.8%	[17%,29%]	61.3%	[47%,75%]	70.9%	[46%,96%]	75.0%	[49%,100%]	60.0%	[28%,92%]
Shared Pickers	22.6%	[17%,29%]	12.7%	[46%,72%]	48.1%	[43%,90%]	46.2%	[47%,97%]	48.3%	[27%,90%]
Shared Docks	0.2%	[0%,1%]	12.7%	[6%,19%]	48.1%	[28%,68%]	46.2%	[20%,72%]	48.3%	[17%,80%]
	Dock Utilization (Fig. 4)									
	0.28		0.21		0.17		0.14		0.12	
	Average	95% CI	Average	95% CI	Average	95% CI	Average	95% CI	Average	95% CI
Collaboration	53.4%	[44%,63%]	62.7%	[51%,74%]	61.3%	[47%,75%]	56.0%	[42%,70%]	56.0%	[42%,70%]
Shared Pickers	45.6%	[37%,54%]	55.8%	[46%,66%]	58.8%	[46%,72%]	56.0%	[42%,70%]	56.0%	[42%,70%]
Shared Docks	24.5%	[20%,30%]	22.0%	[14%,30%]	12.7%	[6%,19%]	0.0%	[0%,0%]	0.0%	[0%,0%]
	Workload Per Truck (Fig. 5)									
	7.3		6.3		5.3		4.3		3.3	
	Average	95% CI	Average	95% CI	Average	95% CI	Average	95% CI	Average	95% CI
Collaboration	61.9%	[49%,74%]	77.3%	[67%,88%]	61.3%	[47%,75%]	79.0%	[65%,93%]	64.7%	[51%,79%]
Shared Pickers	59.6%	[48%,72%]	69.0%	[55%,83%]	58.8%	[46%,72%]	74.7.0%	[61%,88%]	62.3%	[49%,75%]
Shared Docks	13.7%	[7%,20%]	25.1%	[13%,37%]	12.7%	[6%,19%]	34.3%	[18%,51%]	12.9%	[4%,22%]

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