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ABSTRACT

This paper addresses the optimization of the truck to door assignment problem in cross-docks. It defines a new form of horizontal collaboration between suppliers by sharing the platform's resources in order to enhance service level and reduce economical costs. Moreover, this study proposes to solve the problem considering uncertainty in transfer time that is frequently observed in real-world cross-docks. Due to imprecise arrival time of trucks, equipment breakdown, or workload variation, etc, the actual transfer time tends to be shorter or longer than the prefixed one. This uncertainty is modeled as a triangular fuzzy number then a Fuzzy Chance Programming model has been proposed to solve the problem using possibilistic measures. The efficiency and robustness of both (deterministic and fuzzy) proposed models are tested empirically and obtained results confirm the positive effect of collaboration and uncertainty handling.

1. Introduction

Inspired by Silk Road supply chains (Ertek, 2011), cross-docking (CD) is one of the most growing trends in supply chain management. It defines a distribution center that can be seen as a very high-speed warehouse: goods arrive from suppliers (origins) to the terminal by inbound trucks. They are received, sorted, and then directly transferred from inbound (receiving) docks to outbound (shipping) docks to be shipped to customers (destinations) onto outbound trucks. This logistics strategy aims to reduce, if not eliminating, intermediate storage that cannot exceed 24h anyway. These particularities, enable to reduce delivery times, transportation costs, order picking costs, and inventory holding costs (Apte and Viswanathan, 2000). Successful cross-docking experiences of Wal-Mart retail chain (Stalk et al., 1992), UPS mailing company (Forger, 1995), and Toyota Automobile producer (Witt, 1998) have witnessed the success of this logistics technique and have motivated more and more companies to adopt this practice.

However, making the move to a cross-dock distribution center requires companies to have a mature supply-chain organization and an efficient Information Technology (IT) system. Besides, cross-docking involves many decisions that cover different time scales and different stakes. Authors such as (Napolitano, 2000; Gue, 2007; Vogt, 2010) have considered this problem and have provided practical guidelines for successful implementation and use of a cross-dock. They have afforded key factors to improve services' quality and to achieve economies of scale by considering decisions relative to the cross-dock planning, designing, implementing, and running. These decisions can be classified according to three different levels: strategic decisions concern essentially terminal location and layout design. Tactical decisions are relative to cross-docking networks and operational decisions comprise vehicle routing, temporary storage, dock door assignment, and truck scheduling problem (Van Belle et al., 2012).

In this work, we consider the operational cross-docking decisions that concern the optimization of short-term decisions that are directly related to transit of goods from (unloading) inbound trucks to (loading) outbound trucks. We focus especially on the optimization of the Truck to Door Assignment (TDA) which is one of the key issues in cross-docking. It attempts to find an optimal assigning of each incoming inbound or outbound truck to the appropriate inbound or outbound dock with regards to the cross-dock characteristics. These characteristics have been classified by Van Belle et. al. (Van Belle et al., 2012) into three groups: physical characteristics (like the number of docks, shape, internal transportation), operational characteristics (as the service mode, pre-emption) and flow characteristics (such as arrival/departure time, product interchangeability, temporary storage). Solving this problem is known to be NP-Hard (Chen and Song, 2009), it requires perfect synchronization of operational processes (receiving, sorting, and shipping goods) taking into account internal as well as external parameters. Hence, a good TDA system greatly influences the whole cross-docking performances. It may considerably enhance cross-dock service efficiency, improve delivery quality, and reduce the transshipment processing costs and delays.

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Many research efforts have been conducted in this direction. Studied objectives in these works are commonly the minimization of time-based objective functions, utilization-based objective functions, and cost-based objective functions. The considered assumptions could be classified into six categories: costs and penalties-related assumptions, facility-related assumptions, freight-related assumptions, layout-related assumptions, truck-related assumptions, and finally, other assumptions (Ghomi, 2019). The majority of these studies have been performed under the assumption of a deterministic environment that supposes a certain and perfect knowledge about the problem's parameters. However, this is unfortunately seldom in real-world cross-docking. Because of traffic congestion, engine failures, broken forklift, and, many other contingencies the problem's parameters such as arrival and departure time of trucks, or service time are always subject to uncertainties. In these cases, applying a deterministic planned assignment may not be relevant and can economically cause substantial losses. Hence, the necessity to deal with such unusual or unforeseen circumstances in cross-docks as noticed for the first time by (Boysen and Fliedner, 2010). Few proposals have been developed to address this need such as the studies (Yu and Egbelu, 2008; Acar et al., 2012) and more recently (Fatthi, 2016).

From a practical point of view, to bear with uncertainty and increase their ability to absorb risks, companies are increasingly opting for collaboration. This allows generally a significant cost reduction and enables the achievement of desired common objectives (enhance the service level, customer satisfaction, innovation, and sustainability). Some studies have concurred that collaboration in cross-docks has many advantages at the strategical (Moutaoukil et al., 2013; Makaci et al., 2017; Sitadewi et al., 2018), tactical (Badea et al., 2014; Vanovermeire et al., 2014) and operational decision level (Serrano-Hernandez et al., 2018; Nataraj et al., 2019). However, none of the existing works in the literature has considered the impact of collaboration on the truck to door assignment problem. The present paper tries to address this issue considering both deterministic and uncertain environments. We first have proposed a mathematical model to consider collaboration in cross-docks and then we have adapted it to deal with uncertainty. After that, we have illustrated through a well-elaborated experimental study the positive impact of both considerations on the total cost efficiency. It is organized as follows: The next section is devoted to a review of TDA related literature. In Section 3 we propose a clear description of the problem and we define a relative mathematical integer programming formulation. Section 4 presents a Fuzzy Chance Constrained (FCC) adaptation of the mathematical model to deal with uncertain transfer time. The picture is finally completed by an experimental study, presented in Section 5, to investigate the efficiency and robustness of proposed models.

2. Related work

Over the last decade, a lot of attention has been paid to tackle cross-docking related decisions (such as cross-dock location, vehicle routing, truck scheduling, goods transshipment,...) from different theoretical points of view. Some literature reviews have been developed to offer an in-depth grasp of the problem, to compare and synthesize prior research works. Among the most frequently cited, the survey of Boysen and Fliedner (Boysen and Fliedner, 2010) performed in 2010 where the authors have addressed the question of deterministic truck scheduling optimization programming and have classified studied works using the tuple notation for machine scheduling (Graham et al., 1979). Besides, in their study, the authors have raised the need for further research and have identified the most relevant issues related to the implementation of real-world cross-docking applications. Agustina et al. (Agustina et al., 2010) have considered a more global view of cross-docking mathematical models and have classified them based on their decision levels (strategic, tactical, or operational). Stephan et al. (Stephan and Boysen, 2011) have proposed a different classification scheme for structuring the cross-dock applications according to the location in the distribution network, the technical support of inner cross-dock transport, and whether or not value-adding services are provided. The authors have detailed the decision problem structure defined in (Boysen and Fliedner, 2010) and have suggested integrating the cross-docking concept to other business functions.

A bit later, Van Belle et al. (Van Belle et al., 2012) have conducted a more exhaustive study on cross-docking problems. They have studied the physical, operational, and flow characteristics of a cross-dock terminal to distinguish between the various cross-docking types and techniques. This categorization has been used to classify existing works according to the decision problem level: strategical, tactical, and operational. Then, the authors have made suggestions to improve and extend the cross-docking research field. Ladier and Alpan (Ladier and Alpan, 2016) have concentrated their efforts to highlight the shortcomings between literature and industry practice captured through cross-docking platform visits and interviews with their managers. They identify the main issues and challenges met in real-world cross-docking operations. More recently, a new survey on cross-docking (Theophilus et al., 2019) has been published in 2019 to fill the gap of literature from different standpoints. It identifies the new cross-docking trends with a particular

focus on the truck scheduling problem. The studied works have been categorized into four major classes: general CD truck scheduling, multi-objective truck scheduling, uncertainty modeling truck scheduling, and miscellaneous works. Then, the evaluation has been performed with regards to the major attributes of cross-docking operations defined in (Boysen and Fliedner, 2010).

All these studies agree that Truck Scheduling (TS) and Truck to Door Assignment (TDA) represent the main activities in a cross-docking terminal and are the most challenging operational problems. These optimization issues have been widely studied in the literature from different viewpoints. The contributions differ according to the cross-dock characteristics (shape, number of doors, intermediate storage, service mode,...) and also according to the considered objectives, assumptions, and performance measures. However, it's rather difficult to provide a clear classification of these works and explicitly clarify the limits between both problems. As stated in (Ladier and Alpan, 2014), different terms (such as door assignment, truck dock assignment, dock door assignment, truck scheduling, cross-dock scheduling, truck sequencing ....) could be used in different papers to qualify the same issue and there are no standard names to designate distinctively these problem variants. In our sense, "Truck to Door Assignment" (TDA) consists of assigning a set of trucks present at a given time to a set of available dock doors. This problem is generally restricted to a single time moment and considers only the spatial dimension to provide the best assignment. Truck Scheduling (TS) adds a time dimension to the Truck to Door Assignment where the cross-dock manager has to assign incoming trucks to available docks over time.

In this work, we focus on Truck to Door Assignment Problem that has been formulated for the first time by Peck (Peck, 1983). The author has developed a greedy heuristic approach for assigning inbound and outbound trailers to the dock doors in the objective to minimize the total shipment transfer time from inbound to outbound docks. Tsui et al. (Tsui and Chang, 1990, 1992) have tackled the minimization of total traveled distance within the terminal and have proposed a bilinear integer programming to model the problem and a branch and bound algorithm to solve it. Their proposed formulation is nowadays by far the most cited model for cross-dock assignment. Besides, in these works, the authors have proved that the problem at hand is a special case of the Quadratic Assignment Problem (QAP), and thereby like all QAP problems, this is an NP-complete problem. In his thesis dissertation (Brown, 2003), Brown has considered a case study to investigate the trailers to dock doors assignment and sequencing of the shipments' unloading at hubs. The used performance measures are bottleneck time, total labor time, and total travel distance. The tests have been performed considering two different hub layouts (semi-permanent and dynamic) and five freight sequencing approaches (trailer-at-a-time, trailer-at-a-time with offloading, nearest neighbor within a group, nearest neighbor within a shared group, and nearest neighbor).

Later, Oh et al. (Oh et al., 2006) have addressed the problem of assigning destinations to shipping doors in a Korean mail distribution center. In such platforms, clustering destinations into groups and defining the optimal number of these groups is mandatory to ensure the proper activity of the center. To this end, the authors have proposed a nonlinear integer program to model the problem and have developed a decomposition heuristics and genetic algorithm to solve the problem with the objective of minimizing the travel distance of shipments. Bozer et al. (Bozer and Carlo, 2008) have proposed a linear mixed-integer program formulation for the general rectilinear-quadratic assignment problem and have developed a Simulated Annealing (SA)-based heuristic for the optimization of inbound and outbound door assignment in less-than-truckload cross-docks. The effectiveness of this method has been verified through experiments performed on data sets from Con-way company. Cohen et al. (Cohen and Keren, 2009) have considered capacity constraints on the weight of each truck and have suggested a new mathematical formulation and a new heuristic approach for assigning cross-dock doors to trailers.

The majority of the previous literature has been proposed under the assumption stating that an equal number of docks and destinations can easily be ensured (Zenker and Boysen, 2018). Lim et al. (Lim et al., 2006a,b) have considered such restrictions and have proposed a more realistic version of the problem, with a number of trucks that exceeds the number of docks, for a given time horizon instead of a single moment. They have formulated an over-constrained problem version with limited capacity and pre-fixed processing time windows. They have proposed a MIP model formalization of the problem aiming to minimize the total shipping distance between docks and have performed tabu search and genetic algorithm to solve it. In the same direction, Miao et al. (Miao et al., 2009) have resumed the mathematical representation of the problem and have considered the same heuristics to minimize the operational cost of the cargo shipment and the number of unfulfilled shipments. Alpan et al. (Alpan et al., 2011) have studied the same problem in a cross-dock with multiple dock doors and have proposed its resolution using a graph-based dynamic programming approach. The objective has been also the minimization of the total cost (handling cost + penalty cost). Later, Miao et al. (Miao et al., 2014) have adapted the formulation to a more realistic case and have distinguished

between inbound docks and trucks from outbound docks and trucks.

Another strand of the literature concerns the generalized assignment problem in cross-docking systems. Zhu et al. (Zhu et al., 2009) have addressed the issue as a Generalized Quadratic 3-dimensional model aiming to optimize the traveled distance between inbound and outbound docks. Based on this model, Guignard et al. (Guignard et al., 2012) have proposed a local search algorithm, and the Convex Hull Relaxation (CH) meta-heuristic to optimize the assignment of inbound and outbound dock doors. More recently, Nassief et al. (Nassief et al., 2016) have studied the problem with the objective of minimizing the total material handling cost. They have defined a new linear MIP formalism based on Zhu et al. (Zhu et al., 2009) model and have proposed a Lagrangean relaxation (LR) and local search to solve the problem. Comparing with Guignard et al. (Guignard et al., 2012) experimental results, performed tests confirm the efficiency of the proposed solution. In 2018, the same authors (Nassief et al., 2018), have presented two new mixed-integer programming for door assignment and have compared them with previously existing ones. The used solution methods have been column generation and tabu search. Finally, Gelareh et al. (Gelareh et al., 2020) have performed a more extensive empirical comparative study considering 11 MIP formulations for the assignment of inbound and outbound dock doors. Eight of these models have been introduced for the first time and have been compared with Nassief et al. models to prove their equivalence under some integrality requirements.

Studies presented above as almost all studies on the truck to door assignment have been performed assuming perfect knowledge about the problem. Variations in available resources, workload, or possible disruptions in the cross-docking process have been often neglected. Yu et al. (Yu and Egbelu, 2008) were the pioneers to consider uncertainty in such optimization problems. In their work, authors have supposed that uncertainty may concern the number of inbound trailers, their arrival times, their contents, or the time needed to unload them. They have developed an on-line policy for inbound trailers door allocations aiming to minimize the expected man-hours for goods consolidating. Besides, they have proposed a stochastic linear program to model the destination door allocation and two heuristic methods (namely the local search and genetic algorithm) to solve the problem. Thereafter, just a few proposals have been performed in this sense. We may cite Acar et al. (Acar et al., 2012) where the authors have considered uncertainty on truck arrival and departure time as well as freight flow. They have introduced a new mixed-integer quadratic formulation for the problem and have proposed to solve it using a Door Assignment Heuristic (DAH) that distributes the idle times at doors between trailer service times to absorb uncertainty. Fattahi et al. (Fatthi, 2016) have developed a mixed-integer programming model for a real-time truck-to-door assignment and scheduling problem in the inbound phase with the objective to minimize the total service time of trucks. They have considered a dynamic arrival time of trucks and an estimated value of unloading time (see (Walha et al., 2014) and (Ardakani and Fei, 2020) for further details on cross-docking under uncertainty).

As uncertainty handling, collaborative supply chains is one of the latest logistics trends in the literature. In perpetual search for evolution and improvement, nowadays several companies have opted for this solution to meet customer requirements and confront economic, environmental, and social challenges. Researches conducted in this area distinguish between two forms of collaboration: vertical or horizontal collaboration. The former defines collaboration between logistic entities from two or more different levels of the same supply chain (exp. customers and suppliers). The latter refers to the collaboration between actors from the same layer of the supply chain (exp. competitors for different logistic chains) (Mrabti et al., 2019). Collaboration implies the sharing of information, resources but also risks and enables collaborators to satisfy and optimize their common objectives. This aspect can take place at several stages of the chain and with different levels of interaction (Gonzalez-Feliu and Morana, 2011). It may concern several logistic activities such as network design (Moutaoukil et al., 2013; Makaci et al., 2017) and partner selection (Sitadewi et al., 2018) for the strategical decision level. The allocation of costs and emissions of CO2 (Badea et al., 2014; Vanovermeire et al., 2014) for tactical level and transport planning (Serrano-Hernandez et al., 2018; Nataraj et al., 2019) for the operational decision level (Allaoui et al., 2019). However, to the best of our knowledge, no work considers collaboration when dealing with the optimization of the truck to door assignment as illustrated in Table 1. This is the major contribution of this paper that introduces a new form of shared cross-docks and studies its impact on service efficiency and economic costs under the assumption of a fully known environment and then considering uncertainty in transfer time.

3. Problem statement and mathematical formulation

The objective of this paper is the optimization of trucks assignment to multiple inbound and outbound dock doors under time windows constraints. This matter has been previously studied by (Lim et al., 2006a,b).

Context	Proposed model	Author(s) (year)	Objective(s)	Solution method
Non-Collaborative	D	Peck (1983)	TT	Heuristic
		Tsui and Chang (1990, 1992)	TD	Exact method
		Brown (2003)	BT, LT, TD	Heuristic
		Oh et al. (2006)	TD	Meta-heuristic
		Lim et al. (2006a,b)	TD	Meta-heuristic
		Bozer and Carlo (2008)	TD	Meta-heuristic
		Cohen and Keren (2009)	TD	Heuristic
		Miao et al. (2009)	TC	Meta-heuristic
		Zhu et al. (2009)	TC	Heuristic
		Alpan et al. (2011)	TC	Exact method
		Guignard et al. (2012)	TD	Meta-heuristic
		Miao et al. (2014)	TC	Meta-heuristic
		Nassief et al. (2016)	TC	Meta-heuristic
		Fatthi (2016)	TT	Simulation
		Nassief et al. (2018)	TC	Meta-heuristic
		Gelareh et al. (2020)	TC	Exact method
		Yu and Egbelu (2008)	TT	Meta-heuristic
		Acar et al. (2012)	TT	Heuristic
Collaborative	**F**	**This paper**	**TC**	**Exact method**

TT = transfer time, TD = traveled distance, BT = bottleneck time, LT = labor time, TC = Total (economic) cost
D = deterministic, F = fuzzy

Table 1
Overview of reviewed papers on the truck to door assignment

After that, Miao et al. (Miao et al., 2009, 2014) have considered the same problem with the objective to minimize the total handling cost (operational cost + penalty cost). The operational cost depends on the transfer time of pallets from inbound docks to outbound docks. This transfer time varies essentially according to the cross-dock shape and the distance between inbound and outbound docks: the greater is the distance, the higher is the unit cost. The penalties are extra costs for unfulfilled shipments: when it is not possible to serve the client, he receives a payment compensation relative to uninsured order. This is due to a no assignment of the inbound or the outbound truck or a reduced time window that does not allow to make the transfer. These trucks are later rescheduled to complete their job.

Our proposal tries to elaborate a new horizontal form of collaboration between suppliers by extending Miao et al. model (Miao et al., 2014) to a "shared cross-dock". We attempt first to show the positive impact of collaboration to make cost-saving and then in the next section, we will adapt the model to handle uncertainty. We assume that the platform, illustrated by Figure 1, is used by m suppliers (or any involved supply chain actor), rather than a single one and each of them possesses at least one inbound dock. However, since they have the same customers we suppose that outbound docks are commonly shared. Also, the collaboration allows sharing of inbound docks between suppliers but this engenders extra costs relative to docks' rental fees: when a new inbound truck n^I of supplier s is to be docked, it is assigned to a dock k belonging to s if possible otherwise it is assigned to any other available dock for an additional rental cost. Nevertheless, these additional costs are generally absorbed by the generated saving costs of collaboration. Actually, the cross-docking system is supposed to provide the optimal assignment and ordering that generates less global costs. Sometimes, even if truck i_1 belonging to m_1 and truck i_2 belonging to m_2 are candidates for the same available inbound dock k_1 belonging to m_1, it may be more advantageous to assign i_2 to this dock door in order to minimize the total cost of penalties.

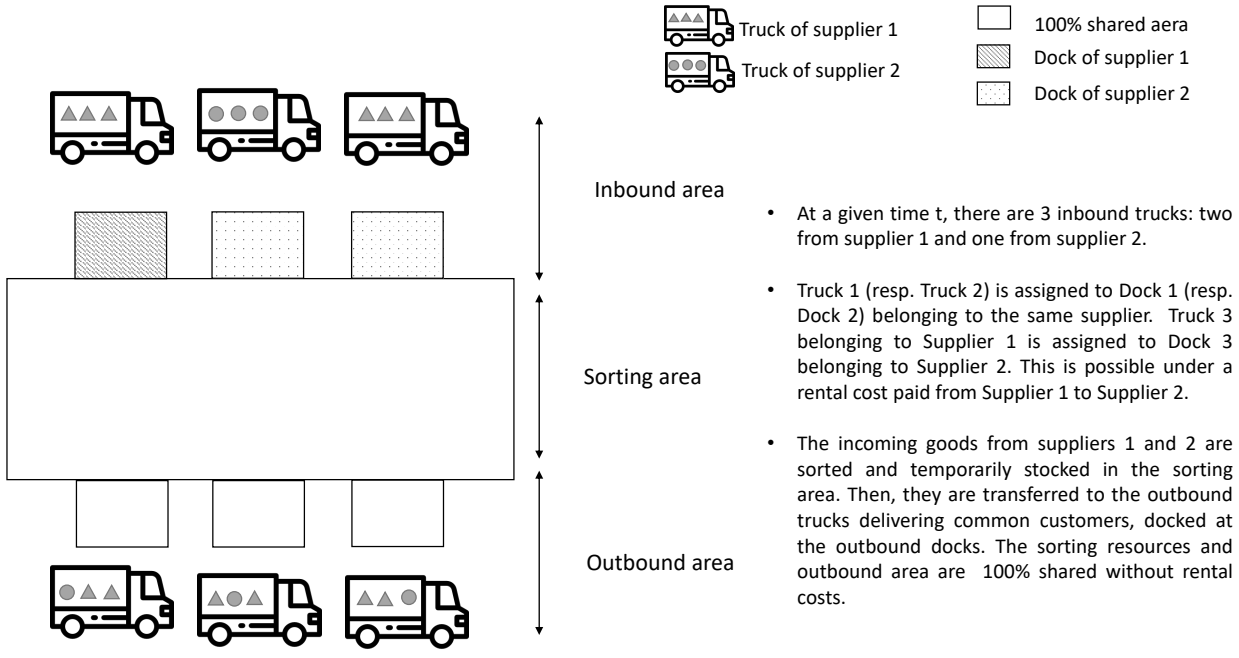


Figure 1: Illustration of shared a cross-dock

The mathematical integer programming model for the given problem can be formulated as follows:

- **Variables and parameters**

S: set of suppliers, $|S| = s$;
N^I: set of inbound trucks arriving at the cross-dock, $|N^I| = n^I$;
M^I: set of inbound docks available in the cross-dock, $|M^I| = m^I$, where $n^I > m^I$;
N^O: set of outbound trucks departing from the cross-dock, $|N^O| = n^O$;
M^O: set of outbound docks available in the cross-dock, $|M^O| = m^O$, where $n^O > m^O$;
a_i^I: arrival time of inbound truck i $(1 \le i \le n^I)$;
d_i^I: departure time of inbound truck i $(1 \le i \le n^I)$;
a_j^O: arrival time of outbound truck j $(1 \le j \le n^O)$;
d_j^O: departure time of outbound truck j $(1 \le j \le n^O)$;
$q_{i,j}$: number of pallets transferred from inbound truck i to outbound truck j $(1 \le i \le n^I, 1 \le j \le n^O)$;
$t_{k,l}$: operational time per pallet from inbound dock k to outbound dock l $(1 \le k \le m^I, 1 \le l \le m^O)$;
$c_{k,l}$: operational cost per pallet from inbound dock k to outbound dock l $(1 \le k \le m^I, 1 \le l \le m^O)$;
$p_{i,j}$: penalty cost per pallet from inbound truck i to outbound truck j $(1 \le i \le n^I, 1 \le j \le n^O)$;
$f_{m,i}$: indicates that inbound truck i belongs to supplier m $(1 \le m \le s, 1 \le i \le n^I)$;
$g_{m,k}$: indicates that inbound dock k belongs to supplier m $(1 \le m \le s, 1 \le k \le m^I)$;
$h_{m,k}$: rental fees per unit time for inbound dock k from supplier m $(1 \le m \le s, 1 \le k \le m^I$, if $f_{m,i} = g_{m,k} = 1$, then $h_{m,k} = 0)$;

We also define a pre-processing parameters $x^I_{ii'}$ and $x^O_{jj'}$ that define the arriving order between inbound and outbound trucks respectively. It takes 1 if $a_{i'} \geq d_i$ (resp. $a_{j'} \geq d_j$) i.e. the inbound (resp. outbound) truck i' (resp. j') arrives after the departure of inbound (resp. outbound) truck i (resp. j); 0 otherwise.

- **Decision variables**

$$y^I_{i,k} = \begin{cases} 1, if\ inbound\ truck\ i\ is\ assigned\ to\ inbound\ dock\ k \\ 0, otherwise \end{cases}$$

$$y^O_{j,l} = \begin{cases} 1, if\ outbound\ truck\ j\ is\ assigned\ to\ outbound\ dock\ l \\ 0, otherwise \end{cases}$$

$$z_{i,j,k,l} = \begin{cases} 1, if\ q_{i,j}\ pallets\ are\ transferred\ from\ inbound\ dock\ k\ to\ outbound\ dock\ l \\ 0, otherwise \end{cases}$$

$$v_{i,m,k} = \begin{cases} 1, if\ inbound\ truck\ i\ belonging\ to\ m\ is\ assigned\ to \\ inbound\ dock\ k\ not\ belonging\ to\ m \\ 0, otherwise \end{cases}$$

- **Objective function**

$$Minimize: \ Operational_{\ cost} + Penalty_{\ cost} + Rental_{\ cost}$$

where:

$$Operational_{\ cost} = \sum_{k=1}^{m^I}\sum_{l=1}^{m^O}\sum_{i=1}^{n^I}\sum_{j=1}^{n^O} c_{k,l}\ q_{i,j}\ z_{i,j,k,l}$$

$$Penalty_{\ cost} = \sum_{i=1}^{n^I}\sum_{j=1}^{n^O} q_{i,j}\ p_{i,j}\ (1 - \sum_{k=1}^{m^I}\sum_{l=1}^{m^O} z_{i,j,k,l})$$

$$Rental_{\ cost} = \sum_{m=1}^{a}\sum_{k=1}^{m^I}\sum_{i=1}^{n^I} v_{i,m,k}\ h_{m,k}\ (d^I_i - a^I_i)$$

- **Constraints**

$$\sum_{k=1}^{m^I} y^I_{i,k} \leq 1, \forall i \in N^I \tag{1}$$

$$\sum_{l=1}^{m^O} y^O_{j,l} \leq 1, \forall i \in N^O \tag{2}$$

$$y^I_{i,k} + y^I_{i',k} - 1 \leq 2\ (x^I_{i,i'} + x^I_{i',i}), \forall k \in M^I, \forall i, i' \in N^I, i \neq i' \tag{3}$$

$$y^O_{j,l} + y^O_{j',l} - 1 \leq 2\ (x^O_{j,j'} + x^O_{j',j}), \forall l \in M^O, \forall j, j' \in N^O, j \neq j' \tag{4}$$

$$y^I_{i,k} + y^O_{j,l} \leq 2\ z_{i,j,k,l}, \forall i \in N^I, \forall i \in N^O, \forall k \in M^I, \forall l \in M^O \tag{5}$$

$$(d^O_j - a^I_i - (t_{k,l} * q_{i,j}))\ z_{i,j,k,l} \geq 0, \forall i \in N^I, \forall i \in N^O, \forall k \in M^I, \forall l \in M^O \tag{6}$$

$$v_{i,m,k} = y^I_{i,k} * |f_{m,i} - g_{m,k}|, \forall i \in N^I, \forall m \in S, \forall k \in M^I \tag{7}$$

$$y^I_{i,k} \in \{0,1\}, y^O_{j,l} \in \{0,1\}, z_{i,j,k,l} \in \{0,1\}, v_{i,m,k} \in \{0,1\}, \forall i \in N^I, \forall j \in N^O, \forall k \in M^I, \forall l \in M^O, \forall m \in S \tag{8}$$

The objective of this mathematical model is to find an optimal assignment of trucks in a shared cross-dock that minimizes simultaneously the operational cost of the cargo shipments, the total number of unfulfilled shipments and the rental cost of docks loaning. These objectives are combined into one term, namely the total cost. Hence, the objective function is defined by the sum of the $Operational_{cost}$, the $Penalty_{cost}$, and the $Rental_{cost}$. The first one is relative to the handling cost of pallets from inbound to outbound docks. The second corresponds to the sum of payment compensations due to unfulfilled transshipment. The last is a new proposed cost paid by any supplier using a dock that does not belong to him. Thus, the minimization of the total cost comes back to the minimization of each of the three generated costs. These costs are all expressed in the same monetary unit (in instance euro) and computed on the basis of the predefined unit costs, namely $c_{k,l}$, $p_{i,j}$ and $h_{m,k}$. As shown in the experimental study, the proportion relating each of these costs may change depending on the problem instance. However, as a general rule we have the operational costs > penalty costs > rental costs.

Constraints (1) and (2) impose that each inbound or outbound truck is assigned at most to one dock. Constraints (3) and (4) ensure that at a given time, two different trucks can not be assigned simultaneously to the same dock. Constraint (5) specifies the decision variable z and the logical relationship between it and y^I and y^O. Constraint (6) guarantees that the transfer process between inbound truck i and inbound truck j should be performed within the arrival of i and departure of j. Finally, we added constraint (7) to define the variable v that represents if truck i owned by m is assigned to a dock belonging or not to the same supplier.

This model resumes almost the same formulation and notations as in (Miao et al., 2014). We have performed some modifications and have adapted the model to deal with collaboration. Miao et al. consider the same transfer time between inbound dock k and outbound dock l for any goods' quantity in their papers (Miao et al., 2009, 2014). However, in our case, we suppose that it is more appropriate to define a unit transfer time $t_{k,l}$ per pallet for variable quantity (q_{ij}) of transferred goods. This modification has engendered the adjustment of constraint (7) allowing the verification that the time window between the arrival of the inbound truck i and the departure of the outbound truck j is sufficient for handling the ordered goods. Moreover, to deal with shared cross-dock, new variables, and parameters have been added such S the set of suppliers, $f_{m,i}$ that indicates if truck i belongs or not to supplier m, $g_{m,k}$ that defines if dock k belongs or not to supplier m and $h_{m,k}$ relative to the rental fees of dock k that have to be paid by supplier m. Besides, it was necessary to propose a new variable decision $v_{i,m,k}$ that receives 1 if a truck i belonging to m is assigned to a dock k not belonging to the same supplier and 0 otherwise. This variable is indispensable for the computation of the rental cost.

Finally, in order to illustrate the impact of collaboration, we assume that outbound docks as well as internal resources (materials, workforce, ...) are totally shared in the platform. But, for inbound docks, we define two different cases. The first one is detailed above ensures inbound docks sharing for a rental cost between suppliers. In the second one, each supplier uses only its own inbound docks. This scenario is formulated using the following additional constraint:

$$\sum_{m=1}^{s} v_{i,m,k} \leq 0, \forall i \in N^I, \forall k \in M^I \tag{9}$$

The constraint (9) forces each supplier to use only its own docks. An inbound truck i belonging to supplier m can be assigned only to a dock k belonging to the same supplier.

4. Fuzzy Chance Constrained Optimization (FCCO) for truck assignment

Even if cross-docking allows companies to enhance their shipping process by saving time and costs, this process inevitably generates costs. The amount of these costs depends essentially on the structure of the cross-dock platform (number of inbound and outbound docks, capacity, distance between docks, available human and material resources,

etc.) and the characteristics of goods' flow to be transferred (quantity of goods, number of inbound and outbound trucks,...). An efficient truck assignment may considerably help to minimize generated fees. The efficiency of such a strategy is very sensitive to external and/or internal changes that may occur. Actually, in real-world problems, no one can predict with certainty neither the availability of resources (equipment breakdown, the absence of staff, ...) nor the exact arrival time of inbound and/or outbound trucks due to unforeseen circumstances (road traffic, weather conditions,...). In our case, we focus on internal operations such as loading, unloading, sorting, and labeling. In practice, these operations are typically subject to perturbations and due to an incident, the service may be slowed down or even interrupted.

Given such uncertainties, deterministic optimization reaches its limits and the planned solution becomes obsolete. To better address such circumstances, one may consider stochastic optimization. However, the use of the latter imposes that the knowledge about the problem is rich enough to be modeled using a large number of probabilistic scenarios. When available information defines only imprecise or vague values and cannot be quantified in a probabilistic way the fuzzy set theory (Zadeh, 1965) and fuzzy mathematical programming (FMP) (Tanaka et al., 1973) are natural alternatives to consider. This representation form is currently in vogue in the field of logistics and supply chain management. It is used to model uncertainties associated with cross-docking location planning (Mousavi et al., 2019), production planning (Darvishi et al., 2020), vehicle-routing (Baniamerian et al., 2019), and many other cross-docking problems, embedded with uncertainty. In these models, fuzziness may arise in the parameters of the objective function and/or constraints. Or, it may be related to the flexibility of constraints or predefined target values in the objective function (Inuiguchi and Ramık, 2000).

In our study, we consider an uncertain transfer time parameter modeled using a triangular form of fuzzy numbers. Then, based on the possibility theory (Dubois and Prade, 2012), we propose a Fuzzy Chance Constrained programming to carry out the defuzzification of the fuzzy model and generate its crisp and linear reformulation that can be effectively solved by an exact solution algorithm. Specifically, We express uncertain transfer time by allowing a negative and positive variation of 20 % of initially established transfer time. Instead of a single (crisp) value, this variable will be defined as a triangular fuzzy number denoted by $\tilde{t}_{k,l}$. It is characterized by a triplet $(t_{k,l}, \widehat{t_{k,l}}, \overline{t_{k,l}})$ where $\widehat{t}_{k,l}$ defines the average transfer time, $\underline{t}_{k,l}$ and $\bar{t}_{k,l}$ represent, respectively, the minimal $(\widehat{t}_{k,l} - 20\ \%\ \widehat{t}_{k,l})$ and maximal $(\widehat{t}_{k,l} + 20\ \%\ \widehat{t}_{k,l})$ values of $\tilde{t}_{k,l}$. Hence, the definition of a new Fuzzy Truck to Door Assignment (FTDA) problem. To model this uncertainty, we have adjusted the mathematical representation, detailed in Section 3 in order to encompass uncertainty. More precisely, the modification concerns, constraint (6) that refer to the time needed to transfer goods from inbound dock k to outbound dock l with regards to the arrival time of inbound trucks and departure of outbound ones. This constraint has been defined in the crisp model as follows:

$$(d_j^O - a_i^I - (t_{k,l} * q_{i,j}))\ z_{i,j,k,l} \geq 0 \tag{10}$$

To represent the transfer time's fuzziness, constraints (6) can be redefined in such terms:

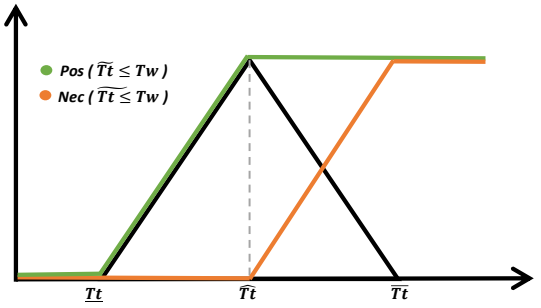
$$(\tilde{t}_{k,l} * q_{i,j}) * z_{i,j,k,l} \tilde{\leq} (d_j^O - a_i^I) \tag{11}$$

For notation convenience, we designate by $Tw_{i,j}$ the time window $(d_j^O - a_i^I)$ between the arrival of inbound truck i and departure of outbound truck j and we denote by $(\tilde{t}_{k,l} * q_{i,j}) * z_{i,j,k,l}$ the needed transfer time to transfer goods from inbound truck i docked at k to outbound truck j docked at l by $\tilde{Tt}_{i,j,k,l}$. Then, we obtain:

$$\tilde{Tt}_{i,j,k,l} \tilde{\leq} Tw_{i,j} \tag{12}$$

where $\tilde{Tt}_{i,j,k,l}$, by definition of t_{kl}, can be denoted by $(\underline{Tt}_{i,j,k,l}, \widehat{Tt}_{i,j,k,l}, \overline{Tt}_{i,j,k,l})$, and it is equal to the triplet $\{(\underline{t}_{k,l} * q_{i,j}) * z_{i,j,k,l}\}, \{(\widehat{t}_{k,l} * q_{i,j}) * z_{i,j,k,l}\}, \{(\bar{t}_{k,l} * q_{i,j}) * z_{i,j,k,l}\}$.

According to Farrokh et al. (Farrokh et al., 2017), the possibility theory is very appropriate to handle constraints with fuzzy parameters. Hence, the use of possibilistic chance constrained programming to solve the problem. The satisfaction of such constraints can be formulated using the possibility and necessity measures (Dubois and Prade, 2012). Formally, Constraints (12) can be defined as follows:



$$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) = \begin{cases} 1,\ \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j} \\ \frac{Tw_{i,j} - \underline{Tt}_{i,j,k,l}}{\widehat{Tt}_{i,j,k,l} - \underline{Tt}_{i,j,k,l}},\ \underline{Tt}_{i,j,k,l} \leq Tw_{i,j} < \widehat{Tt}_{i,j,k,l} \\ 0,\ Tw_{i,j} \leq \underline{Tt}_{i,j,k,l} \end{cases}$$

$$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) = \begin{cases} 1,\ \overline{Tt}_{i,j,k,l} \leq Tw_{i,j} \\ \frac{Tw_{i,j} - \widehat{Tt}_{i,j,k,l}}{\overline{Tt}_{i,j,k,l} - \widehat{Tt}_{i,j,k,l}},\ \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j} < \overline{Tt}_{i,j,k,l} \\ 0,\ Tw_{i,j} \leq \widehat{Tt}_{i,j,k,l} \end{cases}$$

Possibility and necessity measures relative to Constraints 12

Therefore, the satisfaction of Constraints 12 depends on the values of the possibility and necessity measure. The possibility measure evaluates to what extent the satisfaction of the constraints is consistent with the knowledge (the event is possible). Oppositely, the necessity measure evaluates at which level the constraints satisfaction is certain (the event is compulsory). Specifically, the satisfaction of Constraints 12 can be expressed as follows:

$$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq \alpha$$

$$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq \beta$$

These inequalities imply that the possibility (resp. necessity) measure corresponding to the satisfaction of the constraints must be at least equal to the threshold α (resp. β). These values; α and β; are stated in a linearly ordered scale, exemplified by the unit interval [0, 1]. They are chosen by the decision-maker and implicitly express his attitude towards risk. Generally, a low possibility degree α describes an adventurous, risk-taking (optimistic) attitude and allows certain flexibility of the constraints satisfaction. However, a high necessity degree β implies hard constraints and reflects a risk-averse (pessimistic) attitude of the decision-maker. It should be noted that if the satisfaction of the constraints is certain to some degree β it is necessary totally possible ($\alpha = 1$). According to the choice of values α and β we can distinguish 5 possible combinations:

1. $\alpha = 0$ and $\beta = 0$, For this case, we obtain:

   $$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq 0$$

   $$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq 0$$

   Since possibility and necessity degrees are between 0 and 1, these two inequalities are always satisfied. The results in this case are similar to the solution provided for the crisp model.

2. $0 < \alpha < 1$ and $\beta = 0$, Hence, we have:

   $$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq \alpha$$
   $$\Rightarrow \alpha\ \widehat{Tt}_{i,j,k,l} + (1-\alpha)\ \underline{Tt}_{i,j,k,l} \leq Tw_{i,j}$$
   $$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq 0$$
   $$\Rightarrow \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j}$$

   The necessity measure is always satisfied for any β in [0,1]. We just need to check the satisfaction of the constraints with regards to the possibility measure.

3. $\alpha = 1$ and $\beta = 0$, This case implies that:

$$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) = 1$$
$$\Rightarrow \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j}$$
$$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq 0$$
$$\Rightarrow \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j}$$

This always holds for any β in [0,1]. We have to check the satisfaction of the constraints only for the possibility measure.

4. $\alpha = 1$ and $0 < \beta < 1$, This means that:

$$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) = 1$$
$$\Rightarrow \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j}$$
$$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) \geq \beta$$
$$\Rightarrow \beta\, \overline{Tt}_{i,j,k,l} + (1-\beta)\, \widehat{Tt}_{i,j,k,l} \leq\ Tw_{i,j}$$

The constraints is totally possible and certain with a necessity degree equals to β. Its satisfaction is insured by the satisfaction of the necessity measure.

5. $\alpha = 1$ and $\beta = 1$, This implies that:

$$Pos\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) = 1$$
$$\Rightarrow \widehat{Tt}_{i,j,k,l} \leq Tw_{i,j}$$
$$Nec\ (\tilde{Tt}_{i,j,k,l} \leq Tw_{i,j}) = 1$$
$$\Rightarrow \overline{Tt}_{i,j,k,l} \leq Tw_{i,j}$$

This is the most challenging case. To satisfy the constraints $\overline{Tt}_{i,j,k,l}$ (i.e. the worst scenario happens) must be inferior to $Tw_{i,j}$.

These different combinations show that the value of the transfer time considered for fuzzy planning depends essentially on the definition of α and β. Instead of the prefixed average value t_{kl}, this parameter will be defined in the interval $[\underline{t}_{k,l}, \bar{t}_{k,l}]$.

5. Experimental study

In this section, we attempt to test the efficiency and the robustness of the proposed models and compare the fuzzy model with its deterministic version by considering the presence or absence of collaboration. On one hand, our experiments aim to evaluate the effect of collaboration in the context of fully known information: is collaboration profitable for suppliers? does it allow saving costs? Without any doubt, sharing a cross-dock significantly reduces installation costs. However, in this work, we want to show that collaborating may offer better service and may generate less operational process costs. On the other hand, we address the question of the optimization of the truck to door assignment under uncertainty, taking into account variability in transfer time. In fact, we believe that planning by considering uncertainty allows a better managing of unforeseen changes and thus reduces economical losses. Thereby, we study the robustness of the fuzzy model compared to its deterministic version for collaborative or non-collaborative suppliers. This gives rise to four different configurations as illustrated in Figure 2.

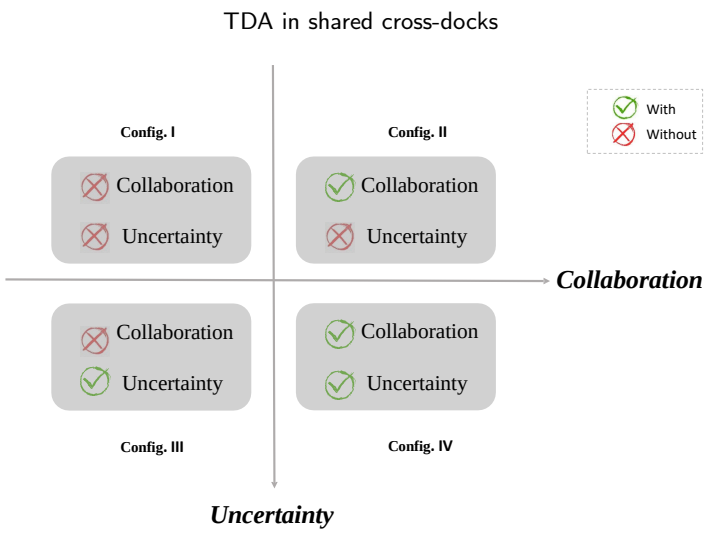


Figure 2: The different experimental configurations

5.1. Experimental setting and data generation

The experiments have been complimented on Intel(R) Core(TM) Duo i5-6300CPU 2.4 GHz, 2.5 GHz processor, 8 Gb RAM memory and under Windows 10 operating system with 64 bits architecture. They have been solved using MIP on the IBM ILOG CPLEX solver v.12.8. Our benchmark has been generated as follows: We resume the same cross-dock layout as in (Miao et al., 2014) with two sets of terminals where inbound and outbound docks are symmetrically located. The distance between docks has been computed using the Manhattan metric (assuming 1 unit between adjacent docks and 3 units for parallel ones). The remaining parameters of the model have been generated using the protocol defined by the same authors, except for the transfer time that has been generated per pallet and not globally. Its value has been defined by $t_{kl} = c_{kl}/10$.

Besides, since we are dealing with shared cross-docks it was necessary to define additional parameters relative to collaboration that do not exist in Miao et al. model. In addition to the number of inbound docks and inbound trucks, our data generation program requires the number of suppliers that we have set to 3. The unit rental fees have been assumed the same for all suppliers such as $h_{mk} = min_{ij}\{pij\}/10$. Regarding the apportionment of inbound trucks and inbound docks between suppliers, we have considered either a fair distribution (if it is possible) or a majority/minority distribution. For the first case, each supplier owns the same number of inbound trucks (resp. inbound docks) as his collaborators. In the second case, there is a majority supplier that owns the maximal number of inbound trucks (resp. inbound docks) and a minority supplier that owns the minimal number of inbound trucks (resp. inbound docks). Each of these suppliers (i.e. the majority or minority supplier) is chosen randomly and independently for inbound docks and trucks. The majority (resp. minority) supplier for docks is not necessarily the same for trucks.

In our study, we consider only MIP optimization to solve the assignment problem. So, only small and medium instances have been generated to test the models. We have conducted 30 instances sorted into 12 groups. Each group is denoted by m^I-n^I the number of inbound docks (ranging from 3 to 6) and respectively the number of inbound trucks (ranging from 6 to 15). The maximal number of docks and trucks have been chosen according to an arbitrary computational time limit of 2 hours for CPLEX solver to obtain optimal solutions. The instances in the same group vary according to the docks and trucks apportionment as mentioned above. So, each group contains 2 or 4 instances depending on the number of possible distribution combinations: Equal docks - Equal trucks, Equal docks - Majority / Minority trucks, Majority / Minority docks - Equal trucks, and Majority / Minority docks - Majority / Minority trucks. (e.g., we consider 3 suppliers, 4 inbound docks, and 6 inbound trucks. For docks apportionment, we can only consider the Majority / Minority distribution (since 4 is not divisible by 3). For trucks, we consider a fair distribution with 2 trucks for each supplier and a Majority / Minority with 3 trucks (resp. 1 truck) for a randomly chosen majority (resp. minority) supplier and 2 trucks for the third one.) In our experiments, each of the tested instances has been executed 5 times to compute the average run time.

5.2. Deterministic optimization

The first step of our tests consists in evaluating the impact of collaboration in a fully known environment. To do so, we have considered the two deterministic cases Config. I and Config. II defined in Figure 2. Both of them do not consider uncertainty. Yet, Config. I supposes that each supplier can use only his inbound doors to dock his inbound trucks and there is no collaboration. The second (Config. II) assumes that the use of inbound docks is shared between all suppliers. Any incoming truck may be docked to any available inbound dock which reduces the global costs regardless of its ownership (the fact that a truck and the dock, to which it is assigned, belong or not to the same supplier is taken into account only to compute the rental cost). We define the optimal strategy $\delta^*()$ as the best truck to door assignment of all the inbound and outbound trucks as well as the optimal goods' flow obtained by the decision variables y^I_{ik}, y^O_{jl}, z_{ijkl}, and v_{imk}.

This strategy may vary for the same problem depending on the service mode: with or without collaboration or even for the same configuration according to the docks and trucks apportionment. This variation can be also noticed in terms of temporal performances, as shown in Figure 3 and Table 2[1]. Obviously, whatever the docks and trucks apportionment the CPU time increases with the size of the problem, especially for the most tricky cases 5-15 and 6-15. Besides, it can be easily checked that no-collaboration optimization is always faster than the collaboration configuration. This is visible especially for 5-15 instances where the average CPU time for the Config. I is about 125 times slower than Config.II. However, it remains below the prefixed limit time of 7200 sec. Regarding the dock and truck apportionment, the tests do not offer a conclusive answer. But, at least for medium instances, the tests verify that the Maj-Min dock appointment and Equal truck appointment is the most time-consuming combination.

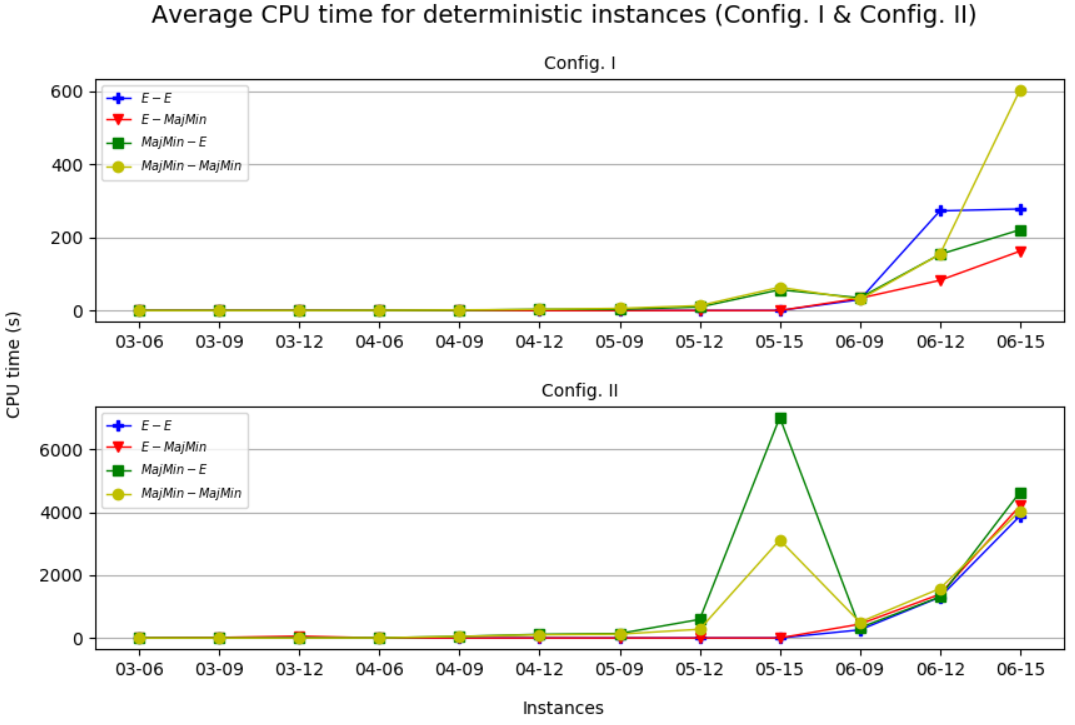


Figure 3: Average CPU time, in seconds, for deterministic instances (Config. I and Config. II) according to the size of the problem

Concerning the solution quality, the CPLEX solver generates an optimal solution that minimizes the global cost for each instance. This cost comprises the operational cost relative to goods transfer, penalty cost for unfulfilled shipments, and a rental cost; paid only in the collaborating case; by suppliers who use docks not belonging to them. Details about

[1] For the sake of clarity and for better reading comprehension an appendix have been dedicated for all result tables.

these generated costs are summarized in Figure 4 and Table 3 that translate economically the optimal solutions of different instances regarding Config. I and Config. II. The results show that the collaboration makes it possible to save costs. In 100% of cases, the total cost relative to Config.I (without collaboration) is higher than the one obtained for Config. II (with collaboration). Savings are at least equal to 2.78% for the 03-09 group of instances and reach 26.29% for 06-09. This gain results generally from the satisfaction of more demands that reduces considerably the penalty costs. Or, even if the penalties remain the same an optimal truck assignment considering all the terminal's docks allows a more advantageous truck assignment which reduces operational cost and thus the total cost. Obviously, collaboration involves an additional rental cost. But, it is usually absorbed by the total saving costs.

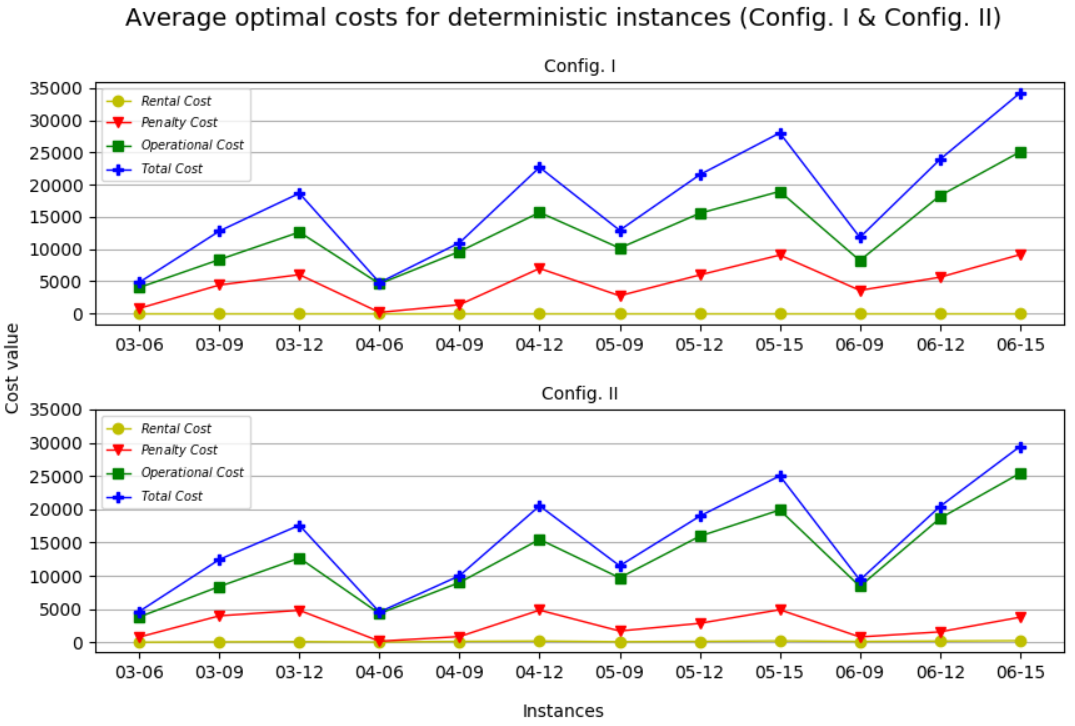


Figure 4: Average optimal cost values for deterministic instances (Config. I and Config. II) according to the size of the problem

The obtained results enable us to deduce that collaboration allows reducing costs. However, it is important to note that these results are extremely sensitive to the variation in the values of the unit transfer cost c_{kl}, the unit penalty cost p_{ij}, and especially the unit rental fees h_{mk}. For example, to illustrate the impact of the variability of the rental cost on the optimal solution, we have considered the instance 3E-6E and have varied the value of this parameter (h_{mk}) upwards and downwards. By decreasing the value of the rental cost each time by 1%, we have noted that the optimal solution δ^* remains the same until $h_{mk} = h_{mk} - 29\%$. Of course, subtracting 1% of the rental cost value each time (from 33 to 23.43) has impacted the value of generated total cost which has slightly felt by 0.2% (from 4656 to 4646.43). However, the decision variables, the operational cost, and penalties remain unchanged. Below 29%, the solver offers new solutions that further reduce costs and promote collaboration. In the opposite sense, by increasing the rental cost even by 100% the solution remains the same. In this case, the optimal solution is insensitive to the increase in the rental cost until rising it to 7 times its initial value. Beyond that, the solver generates less interesting solutions with increased costs until reaching the limit where the collaboration is no longer advantageous. This limit is obtained in our case when the rental cost is equal to 10 times its initial value (330 instead of 33).

5.3. Fuzzy optimization

As previously mentioned, in real-world problems the transfer time can not always be predicted with certainty. Several factors can intervene to affect the presupposed period. To handle this uncertainty, we model uncertain transfer time $\tilde{t}_{k,l} = (\underline{t_{k,l}}, \widehat{t_{k,l}}, \overline{t_{k,l}})$ as a fuzzy number and provide a fuzzy chance constrained model to solve the problem (Section 4). We assume that $\widehat{t}_{k,l}$ is the presupposed transfer time period (a reference scenario) and consider a 20% less or more variation ($\underline{t}_{k,l}$ and $\overline{t}_{k,l}$ respectively the best and worst scenarios). The optimal solution is obtained according to the possibility α and necessity β degrees, given by the decision-maker. These values define the decision-maker attitude toward risk and allow a certain degree of flexibility to the constraints satisfaction.

For sake of simplicity and to facilitate the comparison with the deterministic cases (Config. I and Config. II), the fuzzy optimization considering Config. III (uncertainty without collaboration) and Config. IV (both uncertainty and collaboration), has been performed only on the most challenging group of instances 6-15. Config. I and Config. II can be considered as special cases of Config. III and Config. IV respectively by assuming that $\alpha = \beta = 0$.

Regarding the temporal performance, the results present in Figure 5 and Table 4 show that Config. IV is more time consuming than Config. III. But, both of them are slower than the deterministic cases. For each instance and each configuration, the average execution time increases by 17% at least. However, the CPU time remains affordable. In terms of quality of solutions, we notice as for the deterministic case that the collaboration between suppliers allows the reduction of costs. Optimal solutions generated for Config. IV (when suppliers collaborate) are more interesting than those relative to Config. III (when suppliers do not collaborate) and this is valid for all instances. Besides, we observe that generated costs for Config. III presents a relatively remarkable variation according to the trucks and docks apportionment for the same problem. Unlike, this is not the case for Config. IV where the variability of trucks and docks apportionment does not really affect the optimal solution.

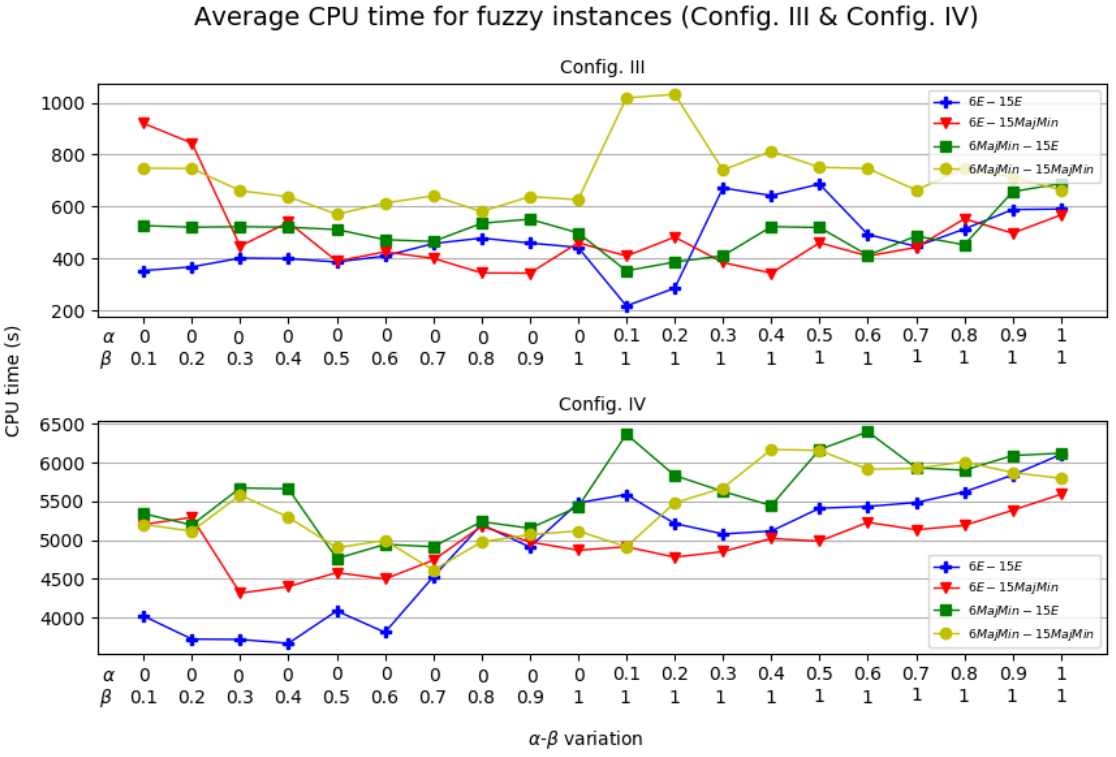


Figure 5: Average CPU time, in seconds, for fuzzy 6-15 group of instances (Config. III and Config. IV)

Furthermore, as illustrated in Figure 6 and Table 5, our tests show that the obtained optimal solution and the relative generated costs are very sensitive to the values of possibility and necessity degrees α and β for both configurations. For each instance, the minimal global cost is obtained considering a null necessity degree and a low possibility degree

(generally $\alpha \leq 0.3$). In such situations, the decision-maker adopts an optimistic attitude toward risk and presume a needed transfer time below average. Contrariwise, when the decision-maker is pessimistic, he considers the worst scenario with the maximal value of transfer time and reinforces the constraints by assuming that is totally possible and totally certain ($\alpha = \beta = 1$). Hence, we obtain the maximal generated cost. For intermediate cases, when the possibility degree is fairly possible ($\alpha = 1$ or almost) with a low necessity degree ($\beta = 0$ or a little bit higher) we obtain the same results as for the deterministic case where the average value of transfer time has been used to compute the optimal solution.

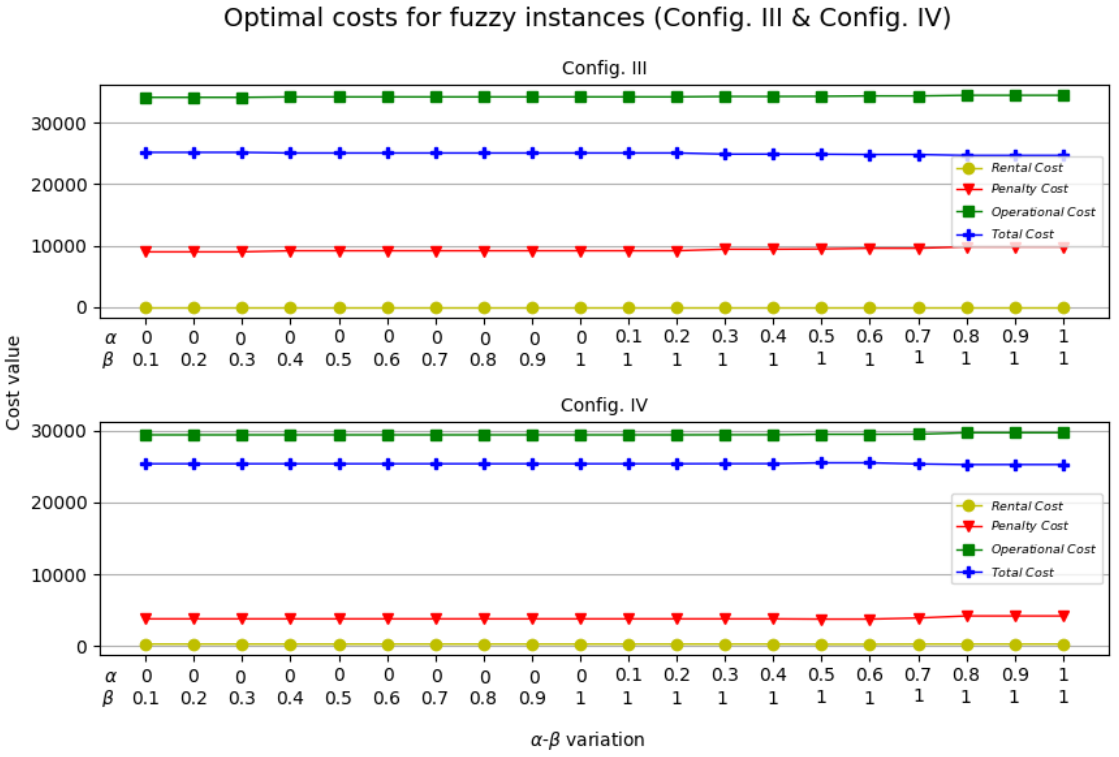


Figure 6: Optimal cost values for 6-15 group of instances (Config. III and Config. IV) with regards to α and β

In conclusion, we can say that by increasing the values of α and β the decision-maker develops an increasingly risk-averse attitude that reinforces the constraints and allows us to have a more robust, but more expensive solution against changes. Conversely, decreasing these values allows having a more economically advantageous solution, based on an optimistic view of the problem. The effective gains or losses will depend on the scenario that will actually occur. Hence, it is relevant to test the robustness of obtained solutions as we have performed in the next section.

5.4. Solutions robustness

In this subsection, we want to test the robustness of obtained solutions in presence of changes and provide a comparison between deterministic optimal solutions and fuzzy ones. For different reasons, things may not go as planned and the transshipment process can be performed in a shorter or a longer-term. To this purpose, we first resume 6-15 group of instances and consider three different scenarios: the average transfer time $\widehat{t}_{kl}$ is identified as the reference scenario and we define the best and the worst scenarios BS and WS by considering 20% positive and negative variations of average time. For BS the transfer time is equal to $\underline{t}_{kl}$ and it is equal to $\overline{t}_{kl}$ for WS. To perform the tests, we re-execute the optimal truck to assignment for deterministic as well as fuzzy cases and we consider once BS and then WS to determine the optimal flow of goods and generated costs for each situation.

5.4.1. Deterministic solutions

The deterministic optimal solutions obtained in Section 5.2 have been computed on the basis of a crisp transfer time value. We suppose that the best or the worst scenario may occur and we study the consequence of these changes on the planned solution, with regards to Config. I and Config. II. The test reveals that the occurrence of the optimal scenario BS does not really impact the optimal solution i.e. if the transshipment process takes less time than expected, the optimal solution and relative generated costs remain the same. Except for the instance 6E-15E where the time saving can be translated into financial savings equal to (174 units) 0.5% of generated costs regarding Config. I. However, when the worst scenario WS occurs the optimal solution becomes irrelevant and generates losses for each instance. As shown in Figure 7 and Table 6, these losses stem from unfulfilled shipments that increase considerably the penalties. Nevertheless, we notice that the collaboration helps to better cope with such situations since losses for Config. I (between 278 and 595 units) are about 1.6% of planned solutions, which is higher than losses observed for Config. II (between 303 and 399 units, 1% of expected costs). Hence, we can deduce that collaboration does not only make it possible to have better-planned solutions but also allows us to cope with changes when unforeseen events occur.

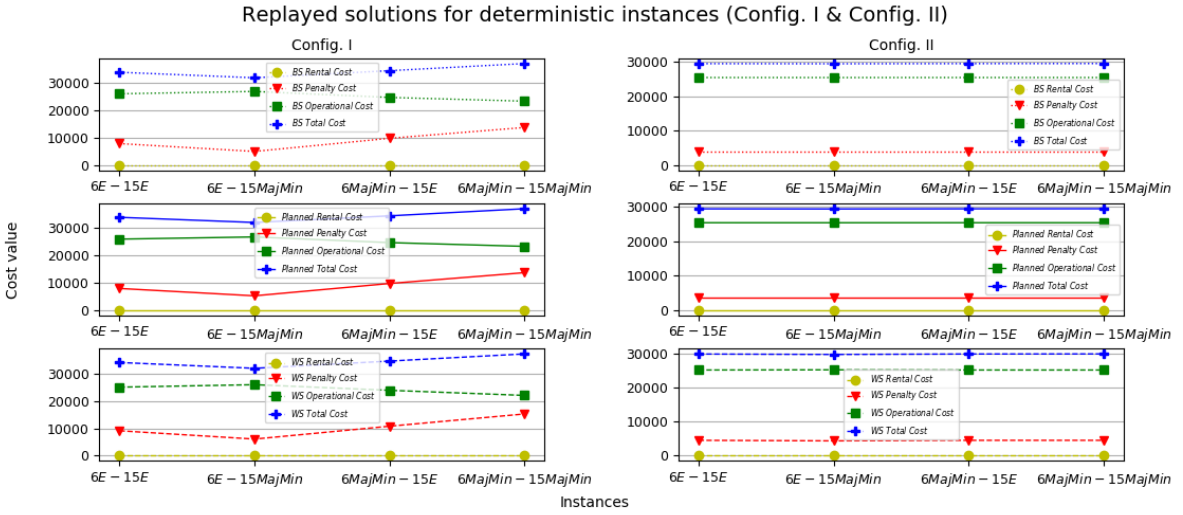


Figure 7: Best and Worst scenarios vs Reference scenario (Config.I and Config. II)

5.4.2. Fuzzy solutions

For fuzzy optimization, uncertainty is already considered for the planned solutions. We want to check if this enables or not better handling of unforeseen events. In fact, the results outlined in Figure 8 and Table 7 for Config. III as well as Config. IV, show that the optimal solution and effective generated costs obtained when the shipments' transfer needs less time than expected are almost the same as the planned ones. This is especially true when the necessity degree β is null and the possibility degree α is below 1. Beyond that, the time reduction creates an increasing gap between the planned solution and that of the possible obtained solution for best scenario BS. For each instance, this gap attains the maximal value when the constraint is supposed to be totally possible and totally necessary or almost ($\alpha = 1$, $\beta \geq 0.8$). Regarding Config. III, this gap varies from 0.26% (96 units) for 6MajMin-15MajMin to 0.76% (256 units) for 6E-15MajMin. For Config. VI, the total cost decreases by 0.96% (203 units) for 6E-15E to 1.02% (299 units) for 6MajMin-15MajMin, 6E-15MajMin, and 6MajMin-15E.

Conversely, when the worst scenario WS occurs, it generates losses if the planned solution has been performed considering an optimistic attitude (with low degrees of α and β). These losses decrease considerably by reinforcing the constraints by assuming high possibility and necessity degrees α and β, to attain 0 losses when $\alpha = \beta = 1$. Besides, we denote that the average losses when suppliers do not collaborate (Config. III) is more important than the case where they collaborate (Config. IV). On one hand, these results demonstrate that fuzzy planning allows better handling of unforeseen changes. Especially when bad situations occur and the decision-maker adopts a realistic attitude (not too optimistic) fuzzy optimization can be seen as a good solution to avoid considerable losses. On the other hand, the

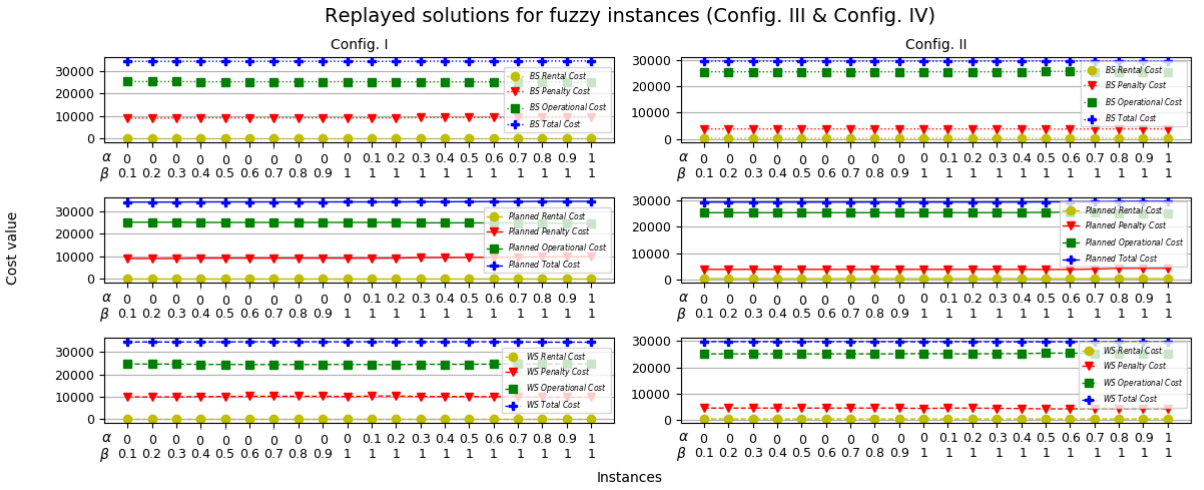


Figure 8: Best and Worst scenarios vs Reference scenario (Config.III and Config. IV)

tests prove that collaboration is always profitable for suppliers. Furthermore, considering both collaboration and fuzzy planning, the obtained solutions may be robust and more advantageous.

6. Conclusion

This paper can be seen as a first attempt to truck to door assignment in shared cross-docks. In addition to the savings that may be done in the installation phase of a shared cross-dock, our idea is to prove that resources' sharing allows to improve the service's quality and reduce costs (especially penalty costs). When everything goes well, as expected, collaboration could prove to be cost-effective and a mutually beneficial solution. However, we can never predict future events with certainty in real-world situations. In fact, unforeseen changes may considerably affect the planned solution and engender additional costs and economical losses. To cope with such circumstances, we consider an uncertain transfer time and propose a fuzzy chance constrained model to deal with this issue. Our experiments confirm that uncertainty handling better copes with unexpected changes especially when decision-maker is rather realistic (not too pessimistic neither too optimistic). Besides, it illustrates that collaboration provides further economic gain.

As future work, we may first consider the experiments on large scale instances. In such cases, it is not possible to obtain optimal solutions in a reasonable time. So, it is more appropriate to consider meta-heuristic methods such as (genetic algorithm, tabu search, ...) in order to come up with good trade-offs between computational time and quality of solutions. Later, we can address the problem of cost-sharing and try to find the most appropriate method (50%/50%, Shepley, etc.) that ensures a fair distribution of saving costs.

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7. Appendix

	D-T dist.	Instances											
		03-06	03-09	03-12	04-06	04-09	04-12	05-09	05-12	05-15	06-09	06-12	06-15
Config. I	E-E	0.022	0.068	0.102	-	-	-	-	-	-	29.866	272.84	278.05
	E-MajMin	0.012	0.060	0.110	-	-	-	-	-	-	33.610	82.698	162.48
	MajMin-E	-	-	-	0.290	0.936	3.292	3.234	9.546	56.956	34.776	153.740	220.920
	MajMin-MajMin	-	-	-	0.488	1.544	3.188	5.912	13.454	63.834	30.316	153.890	603.670
Config. II	E-E	0.928	17.408	20.536	-	-	-	-	-	-	257.390	1297.900	3884.400
	E-MajMin	0.916	15.644	57.458	-	-	-	-	-	-	440.330	1392.200	4204.800
	MajMin-E	-	-	-	4.522	49.102	116.300	141.640	591.080	7016.400	325.76	1309.100	4636.500
	MajMin-MajMin	-	-	-	4.098	48.968	101.360	121.730	277.690	3120.200	502.320	1571.600	4042.900

D-T dist.= Distribution of Docks and Trucks between suppliers

Table 2
Average CPU time, in seconds, for deterministic cases (Config. I & Config. II) according to the size of the problem

	Costs	Instances											
		03-06	03-09	03-12	04-06	04-09	04-12	05-09	05-12	05-15	06-09	06-12	06-15
Config. I	RC	0	0	0	0	0	0	0	0	0	0	0	0
	PC	798	4430	6035.5	175	1373	7009.5	2761	5989	9083.5	3597	5634.3	9150
	OC	4043	8372.5	12646	4622.5	9627.5	15705	10163	15566	18971	8230.8	18291	25099
	TC	4841	12803	18681	4797.5	11001	22714	12924	21555	28054	11828	23925	34249
Config. II	RC	25.2	74.7	106.8	50.75	149.1	198.1	94.4	148.8	224	136.58	198	256.5
	PC	798	3988	4821	175	871	4847	1706	2863	4909	814	1579	3775
	OC	3825	8394	12672	4332	9000	15472	9701	15949	19896	8415.3	18631	25407
	TC	4648.2	12457	17600	4557.8	10020	20517	11501	18961	25029	9365.8	20408	29439

RC = rental cost, PC = penalty cost, OP = operational cost, TC = Total (economic) cost

Table 3
Average optimal costs for deterministic cases (Config. I & Config. II) according to the size of the problem

	D-T dist.	Variation of α and β																			
		$\beta = 0$										$\alpha = 1$									
		$\alpha =$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	$\beta =$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Config. III	6E-15E		353	367	401	399	386	409	457	478	459	442		217	285	671	642	686	492	446	513	588	590
	6E-15MajMin		920	844	447	539	389	425	400	344	343	460		409	482	384	343	460	409	442	552	497	567
	6MajMin-15E		526	520	522	520	511	472	465	535	551	498		352	386	410	522	519	412	486	452	657	688
	6MajMin-15MajMin		747	746	661	637	570	613	641	580	638	626		1018	1032	740	813	751	746	663	746	713	663
Config. IV	6E-15E		4022	3725	3720	3671	4088	3812	4528	5202	4912	5481		5588	5215	5080	5117	5412	5435	5485	5623	5839	6105
	6E-15MajMin		5203	5294	4317	4403	4582	4500	4742	5180	4977	4871		4914	4781	4853	5021	4987	5230	5135	5190	5386	5591
	6MajMin-15E		5342	5195	5673	5661	4764	4945	4916	5238	5154	5429		6366	5834	5628	5446	6168	6398	5932	5902	6091	6121
	6MajMin-15MajMin		5203	5117	5582	5294	4903	4997	4614	4977	5071	5119		4914	5481	5673	6168	6158	5915	5926	6009	5872	5798

D-T dist.= Distribution of Docks and Trucks between suppliers

Table 4
Average CPU time, in seconds, for fuzzy instances (Config.III and Config. IV) of 6-15 group of instances

	Costs	Variation of α and β																			
		$\beta = 0$										$\alpha = 1$									
	$\alpha =$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	$\beta =$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Config. III	RC	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0
	PC	8970	8970	8970	9150	9150	9150	9150	9150	9150	9150		9150	9150	9400	9400	9440	9556	9556	9796	9796	9796
	OC	25198	25198	25198	25094	25094	25094	25094	25094	25094	25099		25099	25099	24912	24912	24896	24849	24849	24710	24710	24710
	TC	34168	34168	34168	34244	34244	34244	34244	34244	34244	34249		34249	34249	34313	34313	34337	34405	34405	34506	34506	34506
Config. IV	RC	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5		256.5	256.5	256.5	256.5	232	232	256.5	256.5	256.5	256.5
	PC	3775	3775	3775	3775	3775	3775	3775	3775	3775	3775		3775	3775	3775	3775	3741	3741	3895	4185	4185	4185
	OC	25407	25407	25407	25407	25407	25407	25407	25407	25407	25407		25407	25407	25417	25422	25540	25540	25379	25292	25292	25292
	TC	29439	29439	29439	29439	29439	29439	29439	29439	29439	29439		29439	29439	29449	29454	29513	29513	29531	29734	29734	29734

RC = rental cost, PC = penalty cost, OP = operational cost, TC = Total (economic) cost

Table 5
Optimal cost values for fuzzy cases (Config.III and Config. IV) of 6-15 group of instances with regards to α and β

	D-T dist.	Cost value											
		Rental cost			Penalty cost			Operational cost			Total cost		
		PS	BS	WS	PS	BS	WS	PS	BS	WS	PS	BS	WS
Config. I	6E-15E	0	0	0	5256	4966	6052	26671	26787	26153	31927	31753	32205
	6E-15MajMin	0	0	0	7931	7821	9119	25875	25935	25234	33806	33756	34353
	6MajMin-15E	0	0	0	9735	9735	10804	24603	24603	24070	34338	34338	34874
	6MajMin-15MajMin	0	0	0	13678	13678	15332	23247	23247	22188	36925	36925	37520
Config. II	6E-15E	229.5	229.5	229.5	3775	3775	4290	25401	25401	25189	29405.5	29405.5	29708.5
	6E-15MajMin	252.9	252.9	252.9	3775	3775	4450	25409	25409	25133	29436.9	29436.9	29835.9
	6MajMin-15E	260.1	260.1	260.1	3775	3775	4450	25409	25409	25133	29444.1	29444.1	29843.1
	6MajMin-15MajMin	283.5	283.5	283.5	3775	3775	4450	25409	25409	25133	29467.5	29467.5	29866.5

D-T dist.= Distribution of Docks and Trucks between suppliers
PS = planned scenario, BS = best scenario, WS = worst scenario

Table 6
Cost values for Best and Worst scenarios vs Reference scenario (Config.I and Config. II) of 6-15 group of instances

			Variation of α and β																			
	Sc	Cost	$\beta = 0$										$\alpha = 1$									
		$\alpha =$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	$\beta =$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Config.III	BS	RC	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0
		PC	8970	8970	8970	9078	9078	9078	9078	9078	9078	9050		9050	9050	9203	9203	9203	9203	9203	9286	9286	9286
		OC	25198	25198	25198	25123	25123	25123	25123	25123	25123	25143		25143	25143	25058	25058	25058	25078	25078	25044	25044	25044
		TC	34168	34168	34168	34200	34200	34200	34200	34200	34200	34193		34193	34193	34261	34261	34261	34280	34280	34330	34330	34330
	PS	RC	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0
		PC	8970	8970	8970	9150	9150	9150	9150	9150	9150	9150		9150	9150	9400	9400	9440	9556	9556	9796	9796	9796
		OC	25198	25198	25198	25094	25094	25094	25094	25094	25094	25099		25099	25099	24912	24912	24896	24849	24849	24710	24710	24710
		TC	34168	34168	34168	34244	34244	34244	34244	34244	34244	34249		34249	34249	34313	34313	34337	34405	34405	34506	34506	34506
	WS	RC	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0
		PC	9923.75	9923.75	9923.75	10098.5	10098.5	10222.25	10222.25	10222.25	10222.25	10066.77		10326.75	10326.75	10105	10105	10105	10025.25	10025.25	9796.25	9796.25	9796.25
		OC	24669.25	24669.25	24669.25	24521.5	24521.5	24460.5	24460.5	24460.5	24460.5	24581.38		24411.25	24411.25	24582	24582	24582	24643.5	24643.5	24709.5	24709.5	24709.5
		TC	34593	34593	34593	34620	34620	34682.75	34682.75	34682.75	34682.75	34648.15		34738	34738	34687	34687	34687	34668.75	34668.75	34505.75	34505.75	34505.75
Config.IV	BS	RC	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5		256.5	256.5	256.5	256.5	232	232	256.5	256.5	256.5	256.5
		PC	3775	3775	3775	3775	3775	3775	3775	377	5 3775	3775		3775	3775	3775	3775	3701	3701	3775	3775	3775	3775
		OC	25407	25407	25407	25407	25407	25407	25407	25407	25407	25407		25407	25407	25407	25417	25422	25563	25563	25427	25427	25427
		TC	29439	29439	29439	29439	29439	29439	29439	29439	29439	29439		29439	29439	29449	29454	29495	29495	29459	29459	29459	29459
	PS	RC	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5		256.5	256.5	256.5	256.5	232	232	256.5	256.5	256.5	256.5
		PC	3775	3775	3775	3775	3775	3775	3775	3775	3775	3775		3775	3775	3775	3775	3728	3728	3895	4185	4185	4185
		OC	25407	25407	25407	25407	25407	25407	25407	25407	25407	25407		25407	25407	25417	25422	25548	25548	25379	25292	25292	25292
		TC	29439	29439	29439	29439	29439	29439	29439	29439	29439	29439		29439	29439	29449	29454	29507	29507	29531	29734	29734	29734
	WS	RC	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	256.5	252.04		256.5	256.5	256.5	256.5	231.975	231.975	256.5	256.5	256.5	256.5
		PC	4410	4410	4410	4410	4410	4410	4410	4410	4410	4247.25		4410	4410	4297.5	4241.25	4105.5	4105.5	4185	4185	4185	4185
		OC	25147	25147	25147	25147	25147	25147	25147	25147	25147	25265.88		25147	25147	25219.5	25255.75	25420.25	25420.25	25292	25292	25292	25292
		TC	29813.5	29813.5	29813.5	29813.5	29813.5	29813.5	29813.5	29813.5	29813.5	29765.17		29813.5	29813.5	29773.5	29753.5	29757.725	29757.725	29733.5	29733.5	29733.5	29733.5

RC = rental cost, PC = penalty cost, OP = operational cost, TC = Total (economic) cost
Sc: scenario, BS: best scenario, PS: planned scenario, WS: worst scenario

Table 7
Best and Worst scenarios vs Reference scenario (Config.III and Config. IV)

References

Acar, K., Yalcin, A., Yankov, D., 2012. Robust door assignment in less-than-truckload terminals. Computers & Industrial Engineering 63, 729–738.

Agustina, D., Lee, C., Piplani, R., 2010. A review: Mathematical modles for cross docking planning. International Journal of Engineering Business Management 2, 13.

Allaoui, H., Guo, Y., Sarkis, J., 2019. Decision support for collaboration planning in sustainable supply chains. Journal of Cleaner Production 229, 761 – 774.

Alpan, G., Larbi, R., Penz, B., 2011. A bounded dynamic programming approach to schedule operations in a cross docking platform. Computers & Industrial Engineering 60, 385–396.

Apte, U.M., Viswanathan, S., 2000. Effective cross docking for improving distribution efficiencies. International Journal of Logistics 3, 291–302.

Ardakani, A.A., Fei, J., 2020. A systematic literature review on uncertainties in cross-docking operations. Modern Supply Chain Research and Applications 2, 2–22.

Badea, A., Prostean, G., Goncalves, G., Allaoui, H., 2014. Assessing risk factors in collaborative supply chain with the analytic hierarchy process (ahp). Procedia-Social and Behavioral Sciences 124, 114–123.

Baniamerian, A., Bashiri, M., Tavakkoli-Moghaddam, R., 2019. Modified variable neighborhood search and genetic algorithm for profitable heterogeneous vehicle routing problem with cross-docking. Applied Soft Computing 75, 441–460.

Boysen, N., Fliedner, M., 2010. Cross dock scheduling: Classification, literature review and research agenda. Omega 38, 413 – 422.

Bozer, Y.A., Carlo, H.J., 2008. Optimizing inbound and outbound door assignments in less-than-truckload crossdocks. IIE Transactions 40, 1007–1018.

Brown, A.M., 2003. Improving the efficiency of hub operations in a less-than-truckload distribution network, in: IIE Annual Conference. Proceedings, Institute of Industrial and Systems Engineers (IISE). p. 1.

Chen, F., Song, K., 2009. Minimizing makespan in two-stage hybrid cross docking scheduling problem. Computers & Operations Research 36, 2066–2073.

Cohen, Y., Keren, B., 2009. Trailer to door assignment in a synchronous cross-dock operation. Int. J. Logistics Systems and Management Int. J. Logistics Systems and Management 5, 574–590.

Darvishi, F., Yaghin, R.G., Sadeghi, A., 2020. Integrated fabric procurement and multi-site apparel production planning with cross-docking: A hybrid fuzzy-robust stochastic programming approach. Applied Soft Computing , 106267.

Dubois, D., Prade, H., 2012. Possibility theory: an approach to computerized processing of uncertainty. Springer Science & Business Media.

Ertek, G., 2011. Cross-Docking Insights from a Third-Party Logistics Firm in Turkey.

Farrokh, M., Azar, A., Jandaghi, G., Ahmadi, E., 2017. A novel robust fuzzy stochastic programming for closed loop supply chain network design under hybrid uncertainty. Fuzzy Sets and Systems 341.

Fatthi, W.N.A.W.A., 2016. A mixed integer programming model for solving real-time truck-to-door assignment and scheduling problem at cross docking warehouse.

Forger, G., 1995. Ups starts world's premiere cross-docking operations. Modern Material Handling 36, 36–38.

Gelareh, S., Glover, F., Guemri, O., Hanafi, S., Nduwayo, P., Todosijević, R., 2020. A comparative study of formulations for a cross-dock door assignment problem. Omega 91, 102015.

Ghomi, V., 2019. Cross-Docking: A Proven LTL Technique to Help Suppliers Minimize Products' Unit Costs Delivered to the Final Customers. Ph.D. thesis. University of Mississippi.

Gonzalez-Feliu, J., Morana, J., 2011. Collaborative transportation sharing: from theory to practice via a case study from france, in: Technologies for supporting reasoning communities and collaborative decision making: Cooperative approaches. IGI Global, pp. 252–271.

Graham, R., Lawler, E., Lenstra, J., Kan, A., 1979. Optimization and approximation in deterministic sequencing and scheduling: a survey, in: Hammer, P., Johnson, E., Korte, B. (Eds.), Discrete Optimization II. Elsevier. volume 5 of *Annals of Discrete Mathematics*, pp. 287 – 326.

Gue, K.R., 2007. Warehouses without inventory. International Commerce Review: ECR Journal 7, 124–132.

Guignard, M., Hahn, P.M., Pessoa, A.A., da Silva, D.C., 2012. Algorithms for the cross-dock door assignment problem, in: Proceedings of the fourth international workshop on model-based metaheuristics, pp. 145–162.

Inuiguchi, M., Ramık, J., 2000. Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem. Fuzzy sets and systems 111, 3–28.

Ladier, A.L., Alpan, G., 2014. Cross-docking operations planning. Ph.D. thesis. University of Grenoble.

Ladier, A.L., Alpan, G., 2016. Cross-docking operations: Current research versus industry practice. Omega 62, 145 – 162.

Lim, A., Ma, H., Miao, Z., 2006a. Truck dock assignment problem with operational time constraint within crossdocks, in: Ali, M., Dapoigny, R. (Eds.), Advances in Applied Artificial Intelligence, Springer Berlin Heidelberg, Berlin, Heidelberg. pp. 262–271.

Lim, A., Ma, H., Miao, Z., 2006b. Truck dock assignment problem with time windows and capacity constraint in transshipment network through crossdocks, pp. 688–697.

Makaci, M., Reaidy, P., Evrard-Samuel, K., Botta-Genoulaz, V., Monteiro, T., 2017. Pooled warehouse management: An empirical study. Computers & Industrial Engineering 112, 526–536.

Miao, Z., Cai, S., Xu, D., 2014. Applying an adaptive tabu search algorithm to optimize truck-dock assignment in the crossdock management system. Expert Systems with Applications 41, 16 – 22.

Miao, Z., Lim, A., Ma, H., 2009. Truck dock assignment problem with operational time constraint within crossdocks. European Journal of Operational Research 192, 105 – 115.

Mousavi, S.M., Antuchevičienė, J., Zavadskas, E.K., Vahdani, B., Hashemi, H., 2019. A new decision model for cross-docking center location in logistics networks under interval-valued intuitionistic fuzzy uncertainty. Transport 34, 30–40.

Moutaoukil, A., Derrouiche, R., Neubert, G., 2013. Modeling a logistics pooling strategy for agri-food smes, in: Working Conference on Virtual Enterprises, Springer. pp. 621–630.

Mrabti, N., Hamani, N., Delahoche, L., 2019. Vers un modèle de simulation de la mutualisation logistique 4.0. Logistique & Management , 1–15.

Napolitano, M., 2000. Making the move to cross docking: A practical guide to planning, designing, and implementing a cross dock operation. Warehousing Education and Research Council.

Nassief, W., Contreras, I., As' ad, R., 2016. A mixed-integer programming formulation and lagrangean relaxation for the cross-dock door assignment problem. International Journal of Production Research 54, 494–508.

Nassief, W., Contreras, I., Jaumard, B., 2018. A comparison of formulations and relaxations for cross-dock door assignment problems. Computers & Operations Research 94, 76–88.

Nataraj, S., Ferone, D., Quintero-Araujo, C., Juan, A., Festa, P., 2019. Consolidation centers in city logistics: A cooperative approach based on the location routing problem. International Journal of Industrial Engineering Computations 10, 393–404.

Oh, Y., Hwang, H., Cha, C.N., Lee, S., 2006. A dock-door assignment problem for the korean mail distribution center. Computers Industrial Engineering 51, 288 – 296. Special Issue: Logistics and Supply Chain Management.

Peck, K.E., 1983. Operational analysis of freight terminals handling less than container load shipments. Ph.D. thesis. University of Illinois at Urbana-Champaign.

Serrano-Hernandez, A., Hirsch, P., Faulin, J., Fikar, C., 2018. The role of horizontal cooperation to improve service quality in last-mile distribution. International Journal of Simulation and Process Modelling 13, 299–309.

Sitadewi, D., Okdinawati, L., Farmaciawaty, D.A., Rahadi, R.A., 2018. The conceptual framework of horizontal collaborative transportation management in indonesian trucking industry. International Journal of Modern Trends in Business Research 3, 42–58.

Stalk, G., Evans, P., Shulman, L., 1992. Competing on capabilities: the new rules of corporate strategy. Harvard business review 70, 57—69.

Stephan, K., Boysen, N., 2011. Cross-docking. Journal of Management Control 22, 129.

Tanaka, H., Okuda, T., Asai, K., 1973. On fuzzy-mathematical programming. Journal of Cybernetics 3, 37–46.

Theophilus, O., Dulebenets, M.A., Pasha, J., Abioye, O.F., Kavoosi, M., 2019. Truck scheduling at cross-docking terminals: A follow-up state-of-the-art review. Sustainability 11, 5245.

Tsui, L.Y., Chang, C.H., 1990. A microcomputer based decision support tool for assigning dock doors in freight yards. Computers Industrial Engineering 19, 309 – 312.

Tsui, L.Y., Chang, C.H., 1992. An optimal solution to a dock door assignment problem. Computers Industrial Engineering 23, 283 – 286.

Van Belle, J., Valckenaers, P., Cattrysse, D., 2012. Cross-docking: State of the art. Omega 40, 827 – 846. Special Issue on Forecasting in Management Science.

Vanovermeire, C., Sörensen, K., Van Breedam, A., Vannieuwenhuyse, B., Verstrepen, S., 2014. Horizontal logistics collaboration: decreasing costs through flexibility and an adequate cost allocation strategy. International Journal of Logistics Research and Applications 17, 339–355.

Vogt, J.J., 2010. The successful cross-dock based supply chain. Journal of Business Logistics 31, 99–119.

Walha, F., Chaabane, S., Bekrar, A., Loukil, T., 2014. The cross docking under uncertainty: State of the art, in: 2014 International Conference on Advanced Logistics and Transport (ICALT), pp. 330–335.

Witt, C.E., 1998. Crossdocking: Concepts demand choice. Material Handling Engineering 53, 44–49.

Yu, W., Egbelu, P.J., 2008. Scheduling of inbound and outbound trucks in cross docking systems with temporary storage. European Journal of Operational Research 184, 377 – 396.

Zadeh, L., 1965. Fuzzy sets. Information and Control 8, 338 – 353.

Zenker, M., Boysen, N., 2018. Dock sharing in cross-docking facilities of the postal service industry. Journal of the operational research society 69, 1061–1076.

Zhu, Y.R., Hahn, P.M., Liu, Y., Guignard, M., 2009. New approach for the cross-dock door assignment problem, in: in Proceedings of the XLI Brazilian Symposium on Operations Research.