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Drone shipping versus truck delivery in a cross-docking system with multiple fleets and products

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ABSTRACT

We propose a new bi-objective multi-product combined cross-docking truck-scheduling model with direct drone shipping and multiple fleets.The proposed model considers two conflicting objective functions (scheduling cost and time) within a multi-objective mixed integer mathematical programming problem. Several constraint sets are also considered for both allocation and scheduling phenomena. An efficient multi-objective epsilon-constraint method is adapted to solve the proposed model. Several numerical examples and metrics are provided to demonstrate the applicability of the proposed model and exhibit the efficacy of the solution procedures and algorithms. The efficient frontiers of the numerical examples are estimated by generating non-dominated solutions. The effects that modifications in the costs associated with the direct shipping of products have on the corresponding Pareto frontiers are analyzed. Finally, sensitivity analysis is used to assess the robustness of the results of the model in the presence of uncertainty.

1. Introduction

1.1. Motivation

Cross-docking is an inventory management system for eliminating the inventory holding function and improving responsiveness in logistics and distribution networks. In a cross-docking system, materials are unloaded from inbound vehicles and loaded directly into outbound vehicles with very little or no storage. There are four different categories of cross-docking problems in inventory management including:(1) location (Mousavi & Tavakkoli-Moghaddam, 2013; Ross & Jayaraman, 2008); (2) vehicle routing (Dondo, Méndez, & Cerdá, 2011; Lee, Jung, & Lee, 2006; Liao, Lin, & Shih, 2010; Mousavi, Tavakkoli-Moghaddam, & Jolai, 2013; Mousavi, Tavakkoli-Moghaddam, Vahdani, & Hashemi, 2014; Santos, Mateus, & Salles da Cunha, 2011); (3) truck scheduling (Boysen & Fliedner, 2010; Van Belle, Valckenaers, & Cattrysse, 2012); and (4) truck door assignment (Shakeri, Low, Turner, & Lee, 2012).

The goal of the truck scheduling problem is to determine the optimal sequence of inbound and outbound trucks at the dock doors of a cross-dock. In the truck assignment problem, the trucks are assigned to dock doors within a short-term horizon. In this case, trucks with the same origin or destination can be assigned to different dock doors (Dondo et al., 2011).

It should be noted that the academic literature on truck-scheduling has not yet started to take into account the shipping capacity of drones as a last-mile resource for the supply chain. This is the case despite the substantial applicability to real-life scenarios that follows from such a possibility. In particular, Amazon and Walmart have both started considering the implementation of a drone delivery service, even though the USA federal law prohibits flying commercial drones over populated areas (Wang, 2016).

The emergence of drones as a transportation alternative to trucks is of particular relevance when considering last-mile deliveries in large cities, where the use of traditional truck-based methods, subject to traffic constraints and requiring sufficiently large docks to shift products between trucks, is becoming increasingly

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restrictive. These logistic restrictions in last-mile deliveries should be reflected in an increase in truck-based transportation costs relative to those derived from direct drone-based deliveries. When considering a formal cross-docking setting, these cost differentials may be due to difficulties in the allocation of trucks to the doors of the dock or the limited capacity of the dock to handle large numbers of shipments.

The substitution of trucks by drones will be mainly determined by the cost differences derived from their respective route density (number of drop-offs on a delivery route) and drop size (number of parcels delivered per drop-off) capacities. Amazon has stated that 86% of its packages weigh less than 5 pounds, which allows for direct drone transportation (Wang, 2016). In this regard, given the potential applicability of a fully operational last-mile drone delivery service, several contrasting reports based on the costs expected to be faced by Amazon have been published. These reports are mainly based on the limited capacity of drones to transport large numbers of packages per trip and range from optimistic scenarios, where a cost of 88 cents per delivery is obtained, to more pessimistic ones, where Amazon would be facing a cost of 10 to 17 dollars per delivery (Wang, 2016).

Thus, given the importance of delivery costs as a determinant factor of drone usage, we will develop a formal model describing the emergence of a direct delivery drone service that substitutes (either partially or totally) the standard truck-based one when companies are faced with different relative delivery costs between both alternatives. Moreover, we will also illustrate how companies may design different shipping strategies depending on the relative costs and delivery times obtained when defining the Pareto-efficient frontier.

1.2. Last-mile delivery logistics

Last- mile delivery in a business to customer environment is generally regarded as one of the more expensive, less efficient and most polluting sections of the logistics chain (Gevaers, Van de Voorde, & Vanelslander, 2014). Despite their considerable importance within the chain, the courier and parcel sectors defining last-mile and urban logistics remain mainly understudied (Ducret, 2014). However, several problems of the last-mile process are being currently analyzed in the literature:

- The uncertainty faced by couriers in terms of varying traffic and travel times has led to the design of novel logistic approaches to improve the reliability of the delivery process in city logistic models using different types of information available. Such approaches include the use of interval travel times (Groß, Ulmer, Ehmke, & Mattfeld, 2015), end-to-end information flows between couriers and customers (Petrovic, Harnisch, & Puchleitner, 2014), and coordinated planning between the courier and the city traffic control management (Köster, Ulmer, & Mattfeld, 2015).
- The substantial pollution emissions of the last-mile home-delivery process have led to the design of policies promoting direct customer pick-up, an option particularly supported in Europe within its seventh Framework Programme (Brown & Guiffrida, 2014). Pollution emissions per delivery can increase considerably given the fact that customers may not be at home at the time of the delivery (Dell'Amico & Hadjidimitriou, 2012).

The use of drones can reduce significantly the traffic-based uncertainty of the shipping process, providing a faster and more reliable service. Both these characteristics increase the probability that customers are home when the shipment is delivered, which, at the same time, helps reducing the pollution emissions.

However, the cross-docking literature seems to have obviated the potential relevance of the direct delivery process operated by drones. As we will illustrate in the literature review section, a considerable amount of papers focuses on variations of the standard cross-docking problem. To our knowledge, the only paper dealing explicitly with a comparison of direct shipment and cross-docking processes is that of Bányai (2012). The author analyses and compares both shipment strategies using cost functions but does not develop an optimization model deriving the corresponding choices that can be made by a courier.

1.3. Contribution

The aim of the current paper is to define a bi-objective model where both costs and delivery times must be minimized by a given decision maker. This is done in an environment where different types of products can be delivered and requested. At the same time, two types of strategies can be followed by the company, it can either use drones for direct transportation between the supplier and the consumer or it may use trucks through a standard cross-docking process. In the latter case, several constraints such as the number of delivery (outbound) trucks as well as the number of receiving and shipping doors within the dock must be considered by the firm when defining its optimization problem.

We will define the corresponding problem and illustrate how differences in costs between the direct drone-based transportation process and the traditional truck-based one lead to the partial or complete dominance of the former for sufficiently large costs differentials. The numerical evaluations of the optimization model will be used to illustrate different cost scenarios where direct shipping using drones emerges as a viable alternative to the standard cross-docking process. Therefore, logistic settings consisting of last-mile transportation within cities, where traditional cross-docking processes face relatively high costs, would be prone to the Pareto-dominance of the drone-based alternative.

It should be highlighted that the relative importance of costs is reduced when considering medical applications of drone delivery logistics within urban areas, where more feasible and faster deliveries can be provided in times of critical need (Lee, 2015; Thiels, Aho, Zietlow, & Jenkins, 2015). The same type of intuition applies to underdeveloped countries where drones can provide delivery services to remote hard-to-reach areas constrained by deficient road infrastructures that require high maintenance costs.

The remainder of this paper is organized as follows. In Section 2, we present a brief literature review regarding the truck scheduling problem. In Section 3, we formulate the basic model, while an extended version considering sequential delivery areas is described in Section 4. In Section 5, we introduce a solution procedure for generating non-dominated solutions on the Pareto front of the problem. Results, illustrative numerical examples, and a sensitivity analysis are provided in Section 6. Finally, we present our conclusions and suggest future research directions in Section 7.

2. Literature review: on the truck-scheduling problem

As explained in the introduction, the assignment of trucks to doors and the scheduling of trucks are two of the main operations defining the cross-docking problems analyzed in the literature.

One of the most influential papers is that of Yu and Egbelu (2008), who proposed a cross-dock with a single receiving and a single shipping door. Similar to a two-machine approach, their objective was to minimize the makespan while the products were assumed to be interchangeable. Consequently, the product assignments from the inbound trucks to the outbound trucks had to be determined additionally.Yu and Egbelu (2008) also considered a truck change overtime and assumed that the travel time between the receiving and the shipping doors was fixed. Chen and Lee (2009) proposed a two-machine cross-docking flow shop model.

Their objective was to sequence the inbound and outbound trucks, and minimize the makespan. This model was extended by Chen and Song (2009)to a two-stage hybrid cross-docking scheduling problem. In the problem proposed by Chen and Song (2009)multiple trucks were loaded or unloaded concurrently by considering parallel machines at the inbound and outbound platforms.

Vahdani and Zandieh (2010)used five meta-heuristic algorithms – genetic algorithm, tabu search, simulated annealing,electromagnetism-like algorithm, and variable neighborhood search – to solve the truck scheduling problem. They used the solution obtained by Yu and Egbelu (2008)as an initial solution in their proposed meta-heuristics. The computational experiments revealed that meta-heuristics improved the solutions obtained by the heuristic method of Yu and Egbelu (2008)at the expense of a slightly higher computation time. In this regard, Arabani, Ghomi, and Zandieh (2011) also presented five meta-heuristics–genetic algorithm, tabu search, particle swarm optimization, ant colony optimization, and differential evolution –designed for solving this problem.

We describe now several relevant variants of the Yu and Egbelu (2008) model. For example, Lim, Ma, and Miao (2006) considered a truck scheduling problem with a fixed time for window loading and unloading. Shakeri, Low, and Li, (2008, 2012) studied the truck scheduling problem in a cross-dock where products are exchanged between trucks. Chmielewski, Naujoks, Janas, and Clausen (2009) studied the scheduling of inbound trucks while simultaneously considering the assignment of the outbound trucks on a mid-term horizon. Forouhar-fard and Zandieh (2010) scheduled the inbound and outbound trucks in order to minimize the number of products that passed through temporary storage. Boysen, Fliedner, and Scholl (2010) divided the time horizon into discrete time slots. They assumed that the trucks can be completely loaded or unloaded within a time slot. Larbi, Alpan, Baptiste, and Penz (2011) presented a model to schedule the outbound trucks in a cross-dock with a single receiving and a single shipping door. They analyzed three cases with different levels of information about the inbound trucks. Their numerical experiments indicated that the total cost increased significantly when no information was available. Alpan, Larbi, and Penz (2011) extended the problem to a cross-dock with multiple receiving and shipping doors.

3. Mathematical formulation

The following assumptions are considered when modeling the bi-objective multi-product combined cross-docking truck allocation-scheduling model proposed in this study:

- All of Yu and Egbelu's (2008) assumptions are re-visited except for the multiple receiving/shipping (strip/stack) doors.
- There are P suppliers, Q customers, R inbound trucks, D outbound trucks, and K product types.
- There are multiple suppliers with different and fixed production capacities.
- It is possible for each supplier to produce n out of K product types ($n < K$).
- Suppliers can ship their products directly to customers, avoiding the cross-docking process.
- All demands are deterministic and known in advance.
- The cross-docking system includes Rinbound trucks that must be assigned to P suppliers at a minimum cost.
- Each truck is assigned to one supplier and each supplier is assigned to one truck.
- After loading the products, each inbound truck must choose between a direct and an indirect shipping alternative so as to minimize the total cost of the system.
- Each inbound truck can be assigned to a maximum of one receiving door.
- The unloading/loading time of commodities is equal to one unit of time per unit of commodity.
- The capacities of the inbound and outbound trucks are different.

Fig. 1 provides a schematic view of cross-docking operations including receiving, sorting, and shipping.

3.2. Problem formulation

3.2.1. Sets

P: Number of suppliers	$p \in P = \{1, 2 \ldots, P\}$
S: Number of receiving doors in cross-dock	$s \in S = \{1, 2 \ldots, S\}$
D: Number of shipping doors in cross-dock	$d \in D = \{1, 2 \ldots, D\}$
R: Number of inbound trucks	$r \in R = \{1, 2 \ldots, R\}$
J: Number of outbound trucks	$j \in J = \{1, 2 \ldots, J\}$
Q: Number of customers	$q \in Q = \{1, 2 \ldots, Q\}$
K: Variety of products	$k \in K = \{1, 2 \ldots, K\}$

3.2.2. Parameters

BM	A large positive number
$L_{k,p}$	Quantity of product k that is loaded from supplier p
$Demand_{k,q}$	Demands of customer q for product k
$Dcap_j$	Capacity of delivery truck j
$Rcap_r$	Capacity of inbound truck r
TCT	Truck changeover time
$V_{s,d}$	Time needed to transfer products from receivingdoor s to shipping door d
$DPA_{r,p}$	Assignment cost of inbound truck r to supplier p
$POA_{r,s}$	Assignment cost of inbound truck r to receiving door s
$PCA_{r,q}$	Assignment cost of inbound truck r to customer q
$OSA_{j,d}$	Assignment cost of outbound truck j to delivery door d
$SCA_{j,q}$	Assignment cost of outbound truck j to customer q
$C_{r,j,s,d}$	Product transfer cost from inbound truck$r$ in receiving-door s to outbound truck$j$ inshipping door d

3.2.3. Variables

$F_{r,j,s,d}$	1 if inbound truck r is assigned to receiving door s, outbound truck j is assigned to shipping door d and at least one product is transferred from truck r to truck j; else 0.
$B_{r,j}$	1 if at least one product is transferred from inbound truck$r$ to outbound truck$j$; else 0.
$AL_{r,j,s,d}$	1 if inbound truck r is assigned to receiving door s and outbound truck j is assigned to shipping door d; else 0.
$ISeq_{s,r,rr}$	1 if inbound truck r enters after inbound truck rr to the receiving door s; else 0.
$OSeq_{d,j,jj}$	1 if outbound truck j enter after outbound truck jj to the shipping door d; else 0.
$X_{r,p}$	1 if inbound truck r is assigned to supplier p; else 0.
$Y_{r,s}$	1 if inbound truck r is assigned to receivingdoor s; else 0.
$Z_{r,q}$	1 if inbound truck r is assigned to customer q; else 0.
$InDir_r$	1 if inbound truck r chooses an indirect path (goes to cross dock); else 0.
Dir_r	1 if inbound truck r chooses a direct path (goes directly to the customer area); else 0.
$W_{j,q}$	1 if outbound truck j is assigned to customer q.
$H_{j,d}$	1 if outbound truck j is assigned to shipping door d; else 0.
$ISD_{s,r,rr}$	1 if either inbound truck r or inbound truck rr is assigned to receiving door s; else 0.
$OSD_{d,j,jj}$	1 if either outbound truck j or outbound truck jj is assigned to shipping door d; else 0.
$PT_{k,r,j}$	Quantity of product k that is transferred from inbound truck r to outbound truck j.

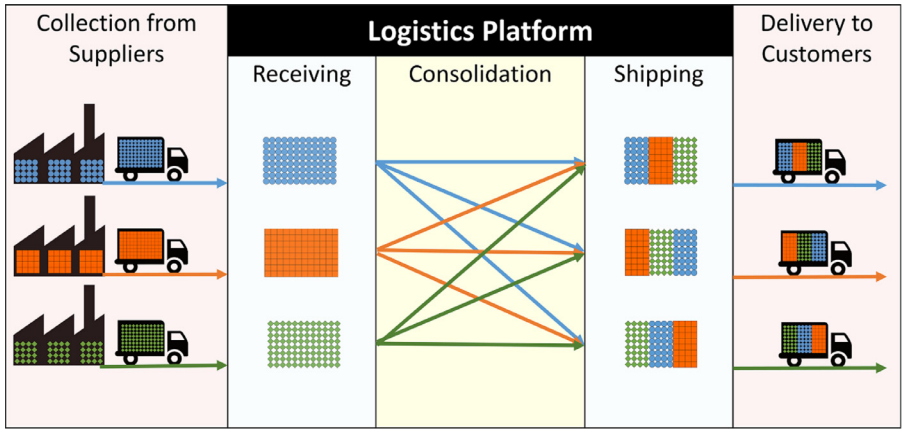

Fig. 1. Schematic view of the multiple door cross-docking problem and operations.

$DDel_{k,r,q}$	Quantity of product k that is delivered to customer q by inbound truck r.
$IDDel_{k,j,q}$	Quantity of product k that is delivered to customer q by outbound truck j.
$INV_{k,r}$	Inventory level of product k in inbound truck r.
$IiNnV_{k,j}$	Inventory level of product k in outbound truck j.
$IAT_{r,s}$	Arrival time of inbound truck r to receiving door s.
$IOT_{r,s}$	Exit time of inbound truck r from receiving door s.
$OAT_{j,d}$	Arrival time of outbound truck j to shipping door d.
$OOT_{j,d}$	Exit time of outbound truck j from shipping door d.
T	Completion time

3.3. Mathematical model

$$Min\,TC = \sum_{p=1}^{P}\sum_{r=1}^{R} X_{r,p} \times DPA_{r,p} + \sum_{s=1}^{S}\sum_{r=1}^{R} Y_{r,s} \times POA_{r,s} + \sum_{q=1}^{Q}\sum_{r=1}^{R} Z_{r,q} \times PCA_{r,q} + \sum_{d=1}^{D}\sum_{j=1}^{J} H_{j,d} \times OSA_{j,d} + \sum_{q=1}^{Q}\sum_{j=1}^{J} W_{j,q} \times SCA_{j,q} + \sum_{s=1}^{S}\sum_{s=1}^{S}\sum_{s=1}^{S}\sum_{r=1}^{R} C_{r,j,s,d} \times F_{r,j,s,d} \quad (1)$$

$$Min\,T \quad (2)$$

s.t.

$$\sum_{r=1}^{R} X_{r,p} = 1, \quad \forall p \in P \quad (3)$$

$$\sum_{p=1}^{P} X_{r,p} = 1, \quad \forall r \in R \quad (4)$$

$$\sum_{r=1}^{R} Y_{r,s} \le R, \quad \forall s \in S \quad (5)$$

$$\sum_{s=1}^{S} Y_{r,s} \le 1, \quad \forall r \in R \quad (6)$$

$$\sum_{r=1}^{R} Z_{r,q} \le R, \quad \forall q \in Q \quad (7)$$

$$\sum_{q=1}^{Q} Z_{r,q} \le Q, \quad \forall r \in R \quad (8)$$

$$\sum_{q=1}^{Q} Z_{r,q} + \sum_{s=1}^{S} Y_{r,s} \ge 1, \quad \forall r \in R \quad (9)$$

$$Indir_r + Dir_r = 1, \quad \forall r \in R \quad (10)$$

$$\sum_{q=1}^{Q} Z_{r,q} \le Dir_r \times BM, \quad \forall r \in R \quad (11)$$

$$\sum_{s=1}^{S} Y_{r,s} \le INDir_r \times BM, \quad \forall r \in R \quad (12)$$

$$\sum_{r=1}^{R} Z_{r,q} + \sum_{j=1}^{J} W_{j,q} \le R + J, \quad \forall q \in Q \quad (13)$$

$$\sum_{j=1}^{J} W_{j,q} \le J, \quad \forall q \in Q \quad (14)$$

$$\sum_{q=1}^{Q} W_{j,q} \le 1, \quad \forall j \in J \quad (15)$$

$$\sum_{d=1}^{D} H_{j,d} = 1, \quad \forall j \in J \quad (16)$$

$$\sum_{j=1}^{J} H_{j,d} \le J, \quad \forall d \in D \quad (17)$$

$$\sum_{r=1}^{R} DDel_{k,r,q} + \sum_{j=1}^{J} IDDel_{k,j,q} \ge Demand_{k,q}, \quad \forall k \in K, q \in Q \quad (18)$$

$$DDel_{k,r,q} \le Z_{r,q} \times BM, \quad \forall r \in R, q \in Q \quad (19)$$

$$IDDel_{k,j,q} \le W_{j,q} \times BM, \quad \forall j \in J, q \in Q \quad (20)$$

$$PT_{k,r,j} \le INDir_r \times BM, \quad \forall j \in J, k \in K, r \in R \quad (21)$$

$$INV_{k,r} = \sum_{p=1}^{P} L_{k,p} \times X_{r,p}, \quad \forall k \in K, r \in R \quad (22)$$

$$IiNnV_{k,j} = \sum_{r=1}^{R} PT_{k,r,j}, \quad \forall k \in K, j \in J \quad (23)$$

$$\sum_{k=1}^{K} IiNnV_{k,j} \le Dcap_j, \quad \forall j \in J \tag{24}$$

$$\sum_{k=1}^{K} INV_{k,r} \le Rcap_r, \quad \forall r \in R \tag{25}$$

$$\sum_{j=1}^{J} PT_{k,r,j} \le Inv_{k,r}, \quad \forall k \in K, r \in R \tag{26}$$

$$\sum_{q=1}^{Q} DDel_{k,r,q} \le INV_{k,r}, \quad \forall r \in R, k \in K \tag{27}$$

$$\sum_{q=1}^{Q} IDDel_{k,j,q} \le IiNnV_{k,j}, \quad \forall j \in J, k \in K \tag{28}$$

$$PT_{k,r,j} \le B_{r,j} \times BM, \quad \forall j \in J, k \in K, r \in R \tag{29}$$

$$IOT_{r,s} \le Y_{r,s} \times BM, \quad \forall s \in S, r \in R \tag{30}$$

$$IOT_{r,s} \ge IAT_{r,s} + \sum_{k=1}^{K}\sum_{j=1}^{J} PT_{k,r,j} - BM \times (1 - Y_{r,s}), \quad \forall s \in S, r \in R \tag{31}$$

$$IAT_{r,s} \ge IOT_{rr,s} + TCT - BM \times (1 - Iseq_{s,r,rr}), \quad \forall r, rr \in R, rr \ne r, s \in S \tag{32}$$

$$IAT_{rr,s} \ge IOT_{r,s} + TCT - BM \times (1 - Iseq_{s,rr,r}), \quad \forall r, rr \in R, rr \ne r, s \in S \tag{33}$$

$$Iseq_{s,r,r} = 0, \quad \forall r \in R, s \in S \tag{34}$$

$$ISD_{s,r,rr} \le Y_{r,s}, \quad \forall r, rr \in R, rr \ne r, s \in S \tag{35}$$

$$ISD_{s,r,rr} \le Y_{rr,s}, \quad \forall r, rr \in R, rr \ne r, s \in S \tag{36}$$

$$ISD_{s,r,rr} \ge Y_{rr,s} + Y_{r,s} - 1, \quad \forall r, rr \in R, rr \ne r, s \in S \tag{37}$$

$$ISeq_{s,r,rr} + ISeq_{s,rr,r} = ISD_{S,r,rr}, \quad \forall r, rr \in R, rr \ne r, s \in S \tag{38}$$

$$OOT_{j,d} \le H_{j,d} \times BM, \quad \forall d \in D, j \in J \tag{39}$$

$$OOT_{j,d} \ge OAT_{j,d} + \sum_{k=1}^{K} IiNnV_{k,j} - BM \times (1 - H_{j,d}), \quad \forall d \in D, j \in J \tag{40}$$

$$OAT_{j,d} \ge OOT_{jj,d} + TCT - BM \times (1 - Oseq_{d,j,jj}), \quad \forall j, jj \in J, jj \ne j, d \in D \tag{41}$$

$$OAT_{jj,d} \ge OOT_{j,d} + TCT - BM \times (1 - Oseq_{d,jj,j}), \quad \forall j, jj \in J, jj \ne j, d \in D \tag{42}$$

$$Oseq_{d,j,j} = 0, \quad \forall j \in J, d \in D \tag{43}$$

$$OSD_{d,j,jj} \le H_{j,d}, \quad \forall j, jj \in J, jj \ne j, d \in D \tag{44}$$

$$OSD_{d,j,jj} \le H_{j,d}, \quad \forall j, jj \in J, jj \ne j, d \in D \tag{45}$$

$$OSD_{d,j,jj} \ge H_{jj,d} + H_{j,d} - 1, \quad \forall j, jj \in J, jj \ne j, d \in D \tag{46}$$

$$OSeq_{d,j,jj} + OSeq_{d,jj,j} = OSD_{d,j,jj}, \quad \forall j, jj \in J, jj \ne j, d \in D \tag{47}$$

$$OOT_{j,d} \ge IAT_{r,s} + V_{s,d} + \sum_{k=1}^{K} PT_{k,r,j} - BM \times (1 - F_{r,j,s,d}), \quad \forall d \in D, j \in J, s \in S, r \in R \tag{48}$$

$$T \ge OOT_{j,d}, \quad \forall d \in D, j \in J \tag{49}$$

$$F_{r,j,s,d} \le B_{r,j}, \quad \forall d \in D, j \in J, s \in S, r \in R \tag{50}$$

$$F_{r,j,s,d} \le AL_{r,j,s,d}, \quad \forall d \in D, j \in J, s \in S, r \in R \tag{51}$$

$$F_{r,j,s,d} \ge AL_{r,j,s,d} + B_{r,j} - 1, \quad \forall d \in D, j \in J, s \in S, r \in R \tag{52}$$

$$AL_{r,j,s,d} \le Y_{r,s}, \quad \forall d \in D, j \in J, s \in S, r \in R \tag{53}$$

$$AL_{r,j,s,d} \le H_{j,d}, \quad \forall d \in D, j \in J, s \in S, r \in R \tag{54}$$

$$AL_{r,j,s,d} \ge Y_{r,s} + H_{j,d} - 1, \quad \forall d \in D, j \in J, s \in S, r \in R \tag{55}$$

$$F_{r,j,s,d}, B_{r,j}, AL_{r,j,s,d}, ISeq_{s,r,rr}, OSeq_{d,j,jj}, X_{r,p}, Y_{r,s}, Z_{r,q}, InDir_r, Dir_r, W_{j,q}, ISD_{s,r,rr}, OSD_{d,j,jj}, H_{j,d} \in \{0, 1\} \tag{56}$$

$$PT_{k,r,j}, DDel_{k,r,q}, IDDel_{k,j,q}, INV_{k,r}, IiNnV_{k,r}, IAT_{r,s}, IOT_{r,s}, OAT_{j,d}, OOT_{j,d}, T \ge 0 \tag{57}$$

Eqs. (1) and (2) present the "total cost of system" and "processing time" objective functions, respectively. Constraints (3) and (4) guarantee that only one truck is assigned to each supplier and that each supplier is assigned only to one truck, respectively. Constraints (5) and (6) represent the allocation of the trucks to the receiving doors of the docks. Constraints (7) and (8) introduce the possibility of direct shipping to the customers. Constraint (9)assures that an inbound truck is assigned either to a customer or to a receiving door. Constraint (10)requires each inbound truck to choose between the direct and the indirect shipping alternatives. Constraint (11) states that when an inbound truck is assigned to one customer, it has chosen a direct path. Similarly, Constraint (12) states that when inbound truck is assigned to a dock door, it has chosen an indirect path.

Note that Eqs. (5)–(12) allow us to divide the set of inbound trucks between regular trucks delivering through the cross-dock and drones providing direct shipping to customers. Indeed, only delivery by trucks will be considered when defining the time constraints implied by the door-assignment cross-docking process. Drones will not have to go through the cross-docking assignment process and their faster and less uncertain deliveries will be balanced in the model through the corresponding costs. That is, the temporal objective of the model will rely on the trucks and remain separated from the drones, which will be used to decrease the total completion time when substituting trucks as the main shipping method through the efficient frontier. In this regard, the explicit inclusion of drones in a parallel cross-docking process determined by the assignment of receiving doors and shipping platforms, together with the corresponding transfer process, constitutes an extension of the current model that should be considered in future research.

In order to simplify the presentation and concentrate on the effect that lower *delivery* costs have on the incentives of firms to

increase their use of drones, we have assumed that trucks and drones face the same *assignment* costs when being assigned to a supplier. Thus, *both of them have been treated as inbound trucks when being allocated to a supplier*. Note that this assumption could be modified and two different assignment cost lines, together with an explicit notation for drones, defined. However, implementing these changes would complicate the presentation of the model without affecting the results qualitatively.

Constraint (13)establishes that the maximum number of assignments to each customer consists of R inbound trucks plus J outbound trucks. Constraints (14)–(15) describe the allocation of the outbound trucks to the customers. Constraints (16)–(17)define the allocation of the outbound trucks to the shipping doors. Constraints (18) requires the demand of each customer to be satisfied. Constraint (19)guarantees that direct delivery to customer $q$takes place when inbound truck r is assigned to that customer. Constraint (20) indicates that indirect delivery to customer q takes place when outbound truck j is assigned to that customer. Constraint (21) guarantees that if the inbound truck r does not choose the indirect path, then the amount of load transferred from inbound truck r to outbound truck j will surely be zero.

Constraints (22) and (23)describe the inventory levels of product k loaded into inbound truck r and outbound truck$j$, respectively. Constraints (24) and (25) guarantee that trucks are not loaded over their respective capacities. Constraint (26) requires the quantity of product k transferred from inbound truck r to the outbound trucks to be lower than the inventory of the inbound truck. Constraints (27) and (28) guarantee that the total amount of products delivered to each customer q does not exceed the inventory of the trucks. Constraint (29) indicates that if product k is transferred from truck r to truck j, then there is a product relationship between these two trucks. Constraint (30) guarantees that the exit time of inbound truck$r$ from the receiving door $s$is zero if the truck is not assigned to door$s$. Constraint (31)requires the exit time of inbound truck$r$ from receiving door s to be greater than or equal to the sum of the arrival time of truck r to door $s$plus the time needed to move the products from truck r to each truck j(when truck r is assigned to door s). Constraint (32)requires the arrival time of inbound truck r to door s to be greater than or equal to the exit time of truck rr from door s plus the time needed for the change of the two trucks if truck r enters the door s after truck rr. Constraint (33) restates the same relationship when truck rr enters the door s after truck r.

Constraint (34) states that no inbound truck$r$ has priority over itself at door s. Constraints (35)–(37) define a situation in which both inbound trucks r and rr can be assigned to the same door. Constraint (38) indicates that for each truck$r$ and each truck rr assigned to door s, one has the priority to enter over the other. Constraints (39)–(47) have exactly the same descriptions as constraints (30)–(38), except that they are applied to outbound trucks. Constraint (48) requires the exit time of outbound truck j from door d to be greater than or equal to the sum of the arrival time of truck r to door$s$, the transfer time between the two doors,s and d, and the time needed to move every product from each inbound truck$r$ to outbound truck j when truck r is at door s, truck j is at door d and a product is being moved from truck r to truck j.

Constraint (49) requires the completion time at the dock to be greater than or equal to the exit time of each outbound truck$j$ from door d. Constraints (50)–(52) guarantee that in order to move a product from truck r to truck j, truck r must be assigned to door s, truck j must be assigned to door d and there must also be a product-relationship between these two trucks. Constraints (53)–(55) state that the decision variable $AL_{r,j,s,d}$ assumes a value of one if and only if the inbound truck$r$ is assigned to door s and the outbound truck j is assigned to door d. Constraints (56) and (57) define the decision variables of the proposed model.

The proposed model solves the integrated truck allocation-scheduling cross-dock problem in a cross-dock with two objective functions, multiple products, multi-doors, multiple fleets, and the possibility of shipping the products directly to the customer destinations. To the best of our knowledge, this type of model has not been studied in the cross-docking literature to this date.

4. Extending the basic model: sequential delivery areas

The model described in the previous section has been designed to separate the drone (direct) and the truck delivery processes across its objective functions. In particular, drones have been defined by their delivery costs while having an indirect effect on the total delivery time as trucks are substituted by drones across the Pareto frontier. Since drones do not have to go through the cross-docking process, they have been assumed to be faster than trucks and their temporal constraints - and efficiency - have not been explicitly defined in the model. This simplification allows us to focus on the effects of decreasing drone delivery costs on the resulting Pareto frontier.

On the other hand, trucks have been defined in terms of both cost and time requirements, the latter dimension described throughout the whole cross-docking process. As a result, all time-related constraints have been concentrated on the set of cross-docking operations, constituting the main difference between drones and trucks in the model.

The optimization environment described in the model aims at illustrating how an incremental cost advantage of the drones relative to the trucks favors the progressive introduction of the former. Among the potential extensions of this formal setting, we introduce below a more complex environment where drones and trucks must be allocated across different areas sequentially defined in terms of their relative delivery costs and times.

4.1. Drone delivery

4.1.1. Sequential costs

The potential extension considered requires differentiating among the costs derived from drone shipping when the relative distance from the supplier (or the cross-dock) is explicitly accounted for. Therefore, since we have assumed that the supplier allocation costs are the same for drones and trucks, we focus on the customer assignment costs included in Eq. (1)

$$\sum_{q=1}^{Q}\sum_{r=1}^{R} Z_{r,q} \times PCA_{r,q} \tag{58}$$

We assume now the existence of three sequential customer delivery areas denoted by qi, $i = 1, 2, 3$, each one imposing incremental costs on the drone as the distance from the supplier increases. It should be emphasized that the analysis is valid for any positive (and bounded) number of areas. The results obtained will therefore depend on the number of customers located per delivery area relative to the location of each supplier, Q_i, $i = 1, 2, 3$, which should be included as parameters of the model. Indeed, these values can be obtained or approximated using a geographical information system to analyze the population and demand density of the different city areas.

The following sequential delivery structure is defined to incorporate the different costs faced by the drones depending on the relative distance from the supplier. Consider first the delivery structure defined in Eq. (8)

$$\sum_{q=1}^{Q} Z_{r,q} \le Q, \quad \forall r \in R \tag{8a}$$

The costs defined in Eq. (8) must be modified and divided across three different potential delivery areas, $Z^i_{r,qi}$, $i = 1, 2, 3$, as follows

$$\sum_{q1=1}^{Q_1} Z^1_{r,q1} \le Q_1, \quad \forall r \in R$$
$$\sum_{q2=1}^{Q_2} Z^2_{r,q2} \le Q_2, \quad \forall r \in R \tag{8'}$$
$$\sum_{q3=1}^{Q_3} Z^3_{r,q3} \le Q_3, \quad \forall r \in R$$

Eq. (8′) limits the number of drones that can be assigned to the customers composing each delivery area. At the same time, a sequential condition could also be introduced where each drone is required to serve a customer in the precedent area before moving on to the next one. Such a constraint can be summarized as follows

$$\sum_{qi=1}^{Q_i} Z^i_{r,qi} \le Z^{i-1}_{r,qi-1}, \quad \forall r \in R, \ \forall qi \in Q_i \tag{59}$$

where $Z^i_{r,qi}$, $i = 1, 2, 3$, is a binary variable that takes a value of 1 if drone r is assigned to a customer in the $i-th$ area, and a value of zero otherwise. Note that Eq. (59) imposes quite a restrictive constraint, which could be softened if combined with specific cost requirements on the corresponding drones.

Alternatively, a set of exogenous constraints could be imposed to reflect the decreasing capacity of drones to serve customers located in relatively distant areas

$$\sum_{q3=1}^{Q_3} Z^3_{r,q3} \le \sum_{q2=1}^{Q_2} Z^2_{r,q2} \le \sum_{q1=1}^{Q_1} Z^1_{r,q1}, \quad \forall r \in R \tag{60}$$

Two potential ways of introducing the effects of costs within the corresponding model can be considered. First, the cost component of Eq. (1) described in Eq. (58) can be replaced with the sum of the costs incurred by all the drones

$$\sum_{q1=1}^{Q_1}\sum_{r=1}^{R} Z^1_{r,q1} \times PCA_{r,q1} + \sum_{q2=1}^{Q_2}\sum_{r=1}^{R} Z^2_{r,q2} \times PCA_{r,q2} + \sum_{q3=1}^{Q_3}\sum_{r=1}^{R} Z^3_{r,q3} \times PCA_{r,q3} \tag{61}$$

where

$$PCA_{r,q1} < PCA_{r,q2} < PCA_{r,q3}, \quad \forall r \in R \tag{62}$$

Note that this last condition can be defined in the model as follows

$$\begin{aligned} \gamma PCA_{r,q1} &\le PCA_{r,q2} \\ \gamma PCA_{r,q2} &\le PCA_{r,q3} \end{aligned} \tag{63}$$

where $\gamma > 1$ is a parameter that reflects the decreasing returns - or increasing costs - derived from covering a wider delivery area with the drone.

Second, the cost differences across delivery areas and the resulting constraints can be introduced by limiting the total cost that can be incurred by each drone, so as to restrict drones from serving too many customers

$$\sum_{q1=1}^{Q_1} Z^1_{r,q1} \times PCA_{r,q1} + \sum_{q2=1}^{Q_2} Z^2_{r,q2} \times PCA_{r,q2} + \sum_{q3=1}^{Q_3} Z^3_{r,q3} \times PCA_{r,q3} \le TPCA_r \quad \forall r \in R \tag{64}$$

In this case, the $TPCA_r$ parameter on the right hand side of Eq. (64) denotes the total delivery cost limiting the shipping capacity of the drone. Note that different types of drones could be defined in terms of the total costs they are endowed with, i.e. via $TPCA_r$.

Finally, it should be emphasized that suppliers can also be located in different areas of the city, which would imply extending the analysis presented above in order to differentiate among suppliers by location area. In this regard, the same type of constraints can be applied to differentiate across suppliers based on their relative distances from the cross-dock. It should also be initially assumed that suppliers and their reference delivery areas do not overlap, but such an assumption could be modified, leading to more complex delivery and potentially overlapping routes.

4.1.2. Time zones

We modify now the delivery schedule of the drones by introducing different time constraints determined by the distance covered. Intuitively, the delivery time required by the drones should be lower than that of the trucks. The model presented in this paper introduced this advantage by preventing drones from going through the cross-docking process. However, an extended version of the model could define a basic cross-docking process for the drones, which would still require a lower delivery time than trucks to reach their corresponding customers from the dock/shipping platform.

Despite the lower delivery time required by the drones, the resulting constraints introduced in the extended model should give place to a second - optimally defined - temporal structure. That is, even though a lower delivery time can be assumed for the drones, they must still behave efficiently and their respective completion time should be minimized. Adding a third objective function and the corresponding set of temporal constraints as follows would account for this fact

$$Min\ T' \tag{65}$$

$$T_r \ge \sum_{q1=1}^{Q_1} Z^1_{r,q1} \times TCA_{r,q1} + \sum_{q2=1}^{Q_2} Z^2_{r,q2} \times TCA_{r,q2} + \sum_{q3=1}^{Q_3} Z^3_{r,q3} \times TCA_{r,q3}, \quad \forall r \in R \tag{66}$$

$$T' \ge T_r, \quad \forall r \in R \tag{67}$$

where T' refers to the completion time of the drones, T_r represents the time required by each drone to complete its route, and $TCA_{r,\,qi}$ is the time required to reach a customer located in the $i-th$ area, $i = 1, 2, 3$. Clearly,

$$TCA_{r,q1} < TCA_{r,q2} < TCA_{r,q3}, \quad \forall r \in R \tag{68}$$

Alternatively, the autonomy time assigned to each drone for delivery could also be directly limited using a set of constraints such as

$$\sum_{q1=1}^{Q_1} Z^1_{r,q1} \times TCA_{r,q1} + \sum_{q2=1}^{Q_2} Z^2_{r,q2} \times TCA_{r,q2} + \sum_{q3=1}^{Q_3} Z^3_{r,q3} \times TCA_{r,q3} \le TTCA_r \quad \forall r \in R \tag{69}$$

$$T' \ge TTCA_r, \quad \forall r \in R \tag{70}$$

where the parameter $TTCA_r$ determines the maximum flying time assigned to each drone. Similarly to Eq. (64), several types of drones could be defined and different $TTCA_r$ values exogenously assigned to limit their respective autonomy times.

4.2. Truck delivery

4.2.1. Sequential costs

We shift our attention to the truck side of the extended model, focusing on the different cost-based constraints that determine the corresponding optimization objective. The extension of the truck environment to account for different delivery areas and their associated costs would be identical to the one defined for drones. For example, the limit imposed on the total shipping costs incurred by trucks through the three delivery areas adapts the drone shipping constraint defined in Eq. (64) as follows

$$\sum_{q1=1}^{Q_1} W^1_{j,q1} \times SCA_{j,q1} + \sum_{q2=1}^{Q_2} W^2_{j,q2} \times SCA_{j,q2} + \sum_{q3=1}^{Q_3} W^3_{j,q3} \times SCA_{j,q3} \leq TSCA_j \quad \forall j \in J \tag{71}$$

with $TSCA_j$ denoting the total delivery cost that limits the shipping distance that can be covered by each truck. Note that, as in the drone setting, the variables defined in Eq. (71) extend those in Eq. (1), i.e. $\sum_{q=1}^{Q}\sum_{j=1}^{J} W_{j,q} \times SCA_{j,q}$, to the three delivery areas considered.

Alternatively, the sum of the costs for all trucks could be incorporated in Eq. (1) when defining the total cost objective of the model. We concentrate our extended truck analysis on the temporal constraints that result from the introduction of different delivery areas, while noting that the same costs-based description as the one provided for drones in Section 4.1.1 applies to trucks.

4.2.2. Time zones

Consider now the temporal constraints imposed on the shipping trucks when different delivery areas are introduced in the model. In this case, instead of completion time at the dock, the variable T would represent the time required to complete all the truck deliveries up to the last customer. This modification would also allow the model to compare the truck completion time with that of direct drone shipping.

Given the different delivery areas incorporated to the analysis, the model has to consider not only the cross-dock completion process but also the deliveries taking place both per truck and shipping door. The formulation of the set of temporal constraints would be similar to that of the drones defined in Eq. (66)

$$T_{j,d} \geq OOT_{j,d} + \sum_{q1=1}^{Q_1} W^1_{j,d,q1} \times TCA_{j,q1} + \sum_{q2=1}^{Q_2} W^2_{j,d,q2} \times TCA_{j,q2} + \sum_{q3=1}^{Q_3} W^3_{j,d,q3} \times TCA_{j,q3}, \quad \forall j \in J, d \in D \tag{72}$$

However, when considering truck shipping the model would have to differentiate the assignment of customers both by truck and by shipping door, since different exit times are allocated to each door through the cross-dock process, as reflected by the variable $OOT_{j,\,d}$. As a result, a new binary variable has been defined per truck, door and delivery area, and has been denoted by $W^i_{j,d,qi}$, $i = 1, 2, 3$, in Eq. (72). The variable $W^i_{j,d,qi}$ takes a value of one if the outbound truck j is assigned to door d and to a customer located in the qi area, $i = 1, 2, 3$, and a value of zero otherwise.

The parameter $TCA_{j,\,qi}$ defines the time required to reach a customer located in the qi area, with $TCA_{j,\,q1} < TCA_{j,\,q2} < TCA_{j,\,q3}$. Note that a sequential condition similar to the one imposed on the drones can also be imposed on the trucks to reflect the complexity of serving customers located in relatively distant delivery areas, that is

$$\sum_{q3=1}^{Q_3} W^3_{j,d,q3} \leq \sum_{q2=1}^{Q_2} W^2_{j,d,q2} \leq \sum_{q1=1}^{Q_1} W^1_{j,d,q1}, \quad \forall j \in J, d \in D \tag{73}$$

Therefore, the extended model should incorporate the following expression in place of Eq. (49)

$$T \geq T_{j,d}, \ \forall j \in J, d \in D \tag{74}$$

Additionally, the different amounts of customers located per delivery area should be explicitly defined together with their respective product requirements, a potential extension that would complicate the design of the model considerably. However, the above description provides some basic insights regarding the direction on which the current model should be extended so as to identify and explicitly account for the costs and autonomy limits of drones and the temporal uncertainty inherent to truck delivery.

5. Solution method

The proposed model (1)–(57) is a multi-objective mixed integer linear programming optimization problem. The efficient epsilon-constraint method proposed by Mavrotas (2009) will be applied to solve this model. Thus, first we must briefly revisit the classic epsilon-constraint method and the efficient epsilon-constraint method proposed by Mavrotas (2009).

5.1. Epsilon-constraint method for multi-objective optimization

Assuming that k objective functions$f_j(x)$, $j \in \{1, ..., k\}$are to be optimized (in this case, to be minimized), we define the following problem:

$$\begin{aligned} &\min \left\{ f_1(x), ..., f_j(x), ..., f_k(x) \right\} \\ &s.t. \\ &x \in S \end{aligned} \tag{75}$$

where S is the feasible solution space including the constraints of the multi-objective decision making (MODM) problem.

According to classic epsilon-constraint method, the MODM model (75) is transformed into a single objective optimization problem such as Model (76) defined as follows:

$$\begin{aligned} &\min f_j(x) \\ &s.t. \\ &f_i(x) \leq \varepsilon_i, \quad \forall i \in \{1, ..., k\}, \quad i \neq j \\ &x \in S \end{aligned} \tag{76}$$

where$\varepsilon_i$is the upper-bound of objective function i, which is calculated using single objective optimization or determined by the decision maker experimentally.

This method can provide a representative subset of the non-dominated solutions. In this method, the decision maker chooses one objective out of n to be optimized (here$f_j(x)$); the remaining objectives (i.e.,$i \in \{1, ..., k\}, \quad i \neq j$) are then constrained to be less than or equal to given target values.

One advantage of the epsilon-constraint method is its ability to achieve efficient points in a non-convex Pareto curve. Therefore, the decision maker can vary the upper-bounds ε_i to obtain weak Pareto optima. It should be emphasized that when a multi-objective mathematical programming is changed into a single-objective mathematical programming, the computational effort of the solution procedure will decrease proportionally since there is no need to use non-dominant sorting procedures in order to achieve the non-dominated solutions. Unfortunately, the method is not computationally efficient for a large number of objective functions in the problem.

5.2. Efficient epsilon-constraint method for multi-objective optimization

Several methods have been proposed for improving the epsilon-constraint method (Mavrotas, 2009). More formally, the epsilon-constraint method has three shortcomings that need to be addressed regarding its implementation: (a) the calculation of the range of the objective functions over the efficient set, (b) the guarantee of efficiency of the solution obtained and, (c) the increased solution time for problems with several objective functions. Mavrotas (2009) addressed these issues with an efficient version of the epsilon-constraint method, called efficient epsilon constraint (EEC). After implementing the EEC method, the MODM model (75) can be converted into Model (77) as follows:

$$\begin{aligned}
&Min \quad Z = f_j(x) + \varepsilon \times \left(\frac{S_1}{(f_1^U - f_1^L)} + \ldots + \frac{S_{j-1}}{(f_{j-1}^U - f_{j-1}^L)} \right. \\
&\left. + \frac{S_{j+1}}{(f_{j+1}^U - f_{j+1}^L)} + \ldots + \frac{S_k}{(f_k^U - f_k^L)} \right) \\
&s.t. \\
&f_i(x) + S_i = f_i^U + e_i \times (f_i^U - f_i^L), \quad \forall i \in \{1, \ldots, k\}, \quad i \neq j \\
&x \in S \\
&e_i \in [0, 1], \quad \forall i \in \{1, \ldots, k\}, \quad i \neq j \\
&S_i \geq 0, \quad \forall i \in \{1, \ldots, k\}, \quad i \neq j
\end{aligned} \tag{77}$$

where S_i, $i \in \{1, ..., k\}$, $i \neq j$ are slack variables associated with those objective functions that have been transformed into constraints;e_i, $\forall i \in \{1, ..., k\}$, $i \neq j$are parameters; the terms$(f_i^U - f_i^L)$, $\forall i \in \{1, \ldots, k\}$, $i \neq j$ are the associated ranges of the objective functions that have been transformed into constraints;f_i^L and f_i^U, $\forall i \in \{1, \ldots, k\}$, $i \neq j$ are the lower and upper bounds of the *ith* objective function, respectively.

As stated above, the EEC method has been successfully utilized in several settings. Additional features regarding its successful implementation are widely documented in the literature (Hafezalkotob & Khalili-Damghani, 2015; Khalili-Damghani & Amiri, 2012; Khalili-Damghani, Tavana, & Sadi-Nezhad, 2012; Khalili-Damghani, Tavana, Abtahi, & Santos-Arteaga, 2015; Khalili-Damghani, Abtahi, & Ghasemi, 2015; Khalili-Damghani, Abtahi, & Tavana, 2013a; Khalili-Damghani, Abtahi, & Tavana, 2013b; Khalili-Damghani, Nojavan, & Tavana, 2013; Mavrotas, 2009; Tavana, Abtahi, & Khalili-Damghani, 2014; Tavana, Khalili-Damghani, & Abtahi, 2013).

5.3. EEC method for multi-objective integrated allocation-scheduling cross-dock problems

Two distinctive objective functions were described in Eqs. (1) and (2). Taking into account the constraints (3)–(57), and using the efficient epsilon-constraint model (77), the following single objective mathematical programming problem (78) is proposed:

$$\begin{aligned}
&Min \quad Z = \; TCs(X) + \varepsilon \times \left(\tfrac{S_2}{(T^U - T^L)} \right) \\
&s.t. \\
&TCs(X) + S_2 = T^L + e_2 \times (T^U - T^L) \\
&x \in S
\end{aligned} \tag{78}$$

where S_2 is a slack variable associated with the second objective function, *which has been transformed into a constraint*;εis a very small positive value (i.e., 0.00001) that is used to determine the priority assigned to the minimization of $TCs(X)$ and to the slack variable of the second objective function; T^L and $T^U$are, respectively, lower and upper bounds associated to the second objective function; e_2 is a parameter chosen from the interval [0, 1], and$x \in S$ refers to the constraints (3)–(57) of the original model.

Table 1
Problem data.

Number of suppliers (P)			3
Number of customers (Q)			3
Receiving trucks (R)			3
Delivering trucks (J)			4
Number of Receiving docks (s)			2
Number of Shipping docks (d)			2
Number of products (k)			3
Customer demand	**Q3**	**Q2**	**Q1**
$K1$	60	120	0
$K2$	40	0	110
$K3$	70	80	60
Available Inventory of product *k* at supplier *p*	**P3**	**P2**	**P1**
$K1$	60	60	60
$K2$	40	50	60
$K3$	70	80	60
Receiving trucks capacity			270
Delivering trucks capacity			210

Table 2
Pay-off matrix.

F(x)	Cost	Time
Cost	924	600
time	3741	0

It should be noted that the upper and lower bounds of the second objective function are determined by optimizing a single objective mathematical model in which the second objective function is optimized subject to constraints (3)–(57).

6. Experimental results and sensitivity analysis

In this section, we start by verifying the validity of the proposed mathematical model using small benchmark instances. Then, several additional instances are generated and the corresponding non-dominated solutions computed. Within this latter setting, we will illustrate how direct shipping using drones arises as a viable alternative to trucks as the transportation costs of drone delivery decrease. The accuracy of the non-dominated solutions is discussed. All the models proposed have been coded using LINGO software.

6.1. Validation of the proposed mathematical model

In order to check the validity of the proposed mathematical model, a basic extreme benchmark instance is considered. The size and parameters of this instance are selected so that the solution can be intuitively validated without formally running the model. This allows us to verify whether or not the results are meaningful and the model achieves its goals. The extreme instance is presented in Table 1.

Table 2 shows the pay-off matrix that results from running the single objective problems separately. Each column represents the minimum and maximum values associated with each objective function. The epsilon value associated to each function should determine the intensity between the minimum and the maximum of the corresponding objective function so that the Pareto bound is obtained for the multi-objective problem.

The step-size epsilon value used to form the Pareto front is assumed to be 0.01. After running the codes developed using LINGO, the different Pareto solutions are obtained and presented in Fig. 2.

Each point on the Pareto front of Fig. 2 suggests a planning in the cross-dock with its own total cost and processing time. In Fig. 2, solutions P1 and P2 are the start and end point of the regenerated Pareto front. In solutionP1 the cost is maximized and the time is minimized. In this solution, each truck uses direct shipping for customer delivery. That is, drones are costly but guaran-

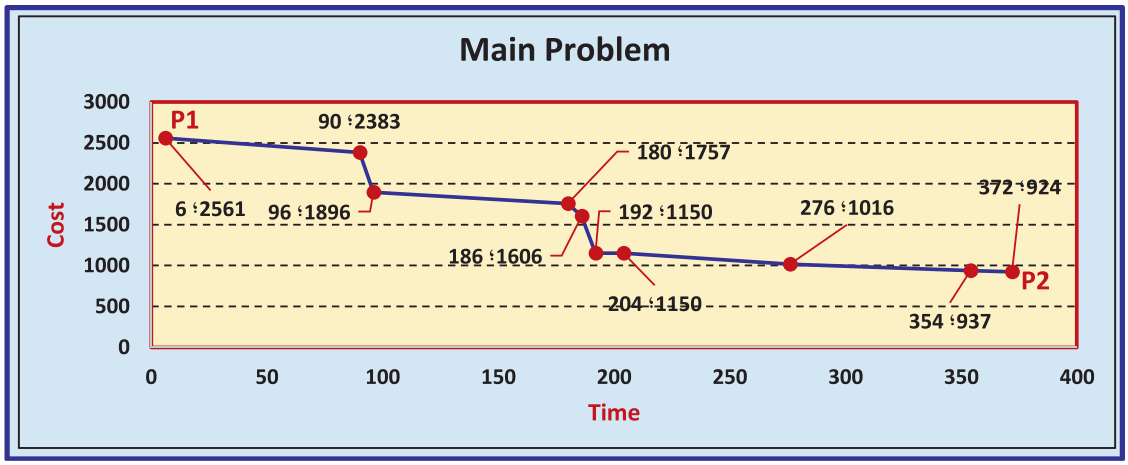

Fig. 2. Pareto front of the main test problem.

Table 3
Sensitivity analysis of parameters.

Type of change	Problem number
50% increase in allocation cost of truck r to door S	1
50% increase in allocation cost of truck j to customer p	2
50% increase in shipping cost of product from truck r at door S to truck j at door d	3
50% increase in allocation cost of truck r to customer q	4
Reduction in receiving doors S	5
Reduction in shipping/sending doors D	6

Table 4
Value of objective functions at the extreme points of the Pareto front of test problems.

Problem	Point P1		Point P2	
	Time	Cost	Time	Cost
Main problem	6	2561	372	924
Problem 1	6	2561	372	972
Problem 2	6	2667	372	1027
Problem 3	6	2561	552	1010
Problem 4	6	3730	372	924
Problem 5	6	2561	546	962
Problem 6	6	2561	546	957

Table 5
Percentual changes of the objective functions at the extreme points of the Pareto front.

Problem	Cost changes (%)		Time changes (%)	
	Point P1	Point P2	Point P1	Point P2
Problem 1	0%	0%	0%	3%
Problem 2	1%	1%	0%	3%
Problem 3	0%	0%	0%	3%
Problem 4	9%	0%	0%	3%
Problem 5	0%	3%	0%	52%
Problem 6	0%	2%	0%	52%

tee fast and timely deliveries. In solution P2 trucks are assigned to the dock and the corresponding receiving and shipping operations are performed. In this case, the completion time is high but the total cost of the system is very low. The results of this test problem reveal that both the proposed model and solution method can achieve their goals and obtain several non-dominated solutions for the problem.

6.2. Sensitivity analysis on the parameters of the proposed model

Changes in the parameters defined in Table 1 are made in order to carry out a sensitivity analysis, the details of which are shown in Table 3.

Based on the changes described in Table 3, six new instances are generated. All of these numerical instances are solved and the results analyzed. The Pareto frontiers obtained for each one of these instances are represented in Fig. 3.

Table 4 shows the values of the cost and time objective functions for the extreme points of the Pareto front in each one of these instances. In this regard, Table 5 displays the percentual changes in the values of the two extreme points – P1 and P2 – of the cost and time objective functions relative to those of the main problem for all test instances.

As illustrated in Table 5, a reduction in the number of receiving or shipping doors has a significant impact on the working time in the dock. It is also obvious that the costs associated with the direct shipping of products to customers, i.e. those defining Problem 4,are one of the most important parameters of the model. Thus, we have analyzed the effects that modifications in the costs associated with the direct shipping of products have on the corresponding Pareto frontiers.

Fig. 4 illustrates the progressive introduction of drones (direct shipping) that takes place through the Pareto frontier as the costs of drone delivery decrease by 25% and 50% relative to the main setting presented in Fig. 2. The total completion time and the resulting costs are defined in the horizontal axes, while the number of direct deliveries, $\sum_{r=1}^{R} Dir_r$, out of a total of three trucks is presented in the vertical axis. The simulation results defining the Pareto frontiers represented in the figure are provided in Table 6.

Note that a direct consequence of these modifications is the decrease observed in total costs as drones start being used to provide direct delivery to customers. Note also how a 50% decrease in the cost of drone delivery makes it a viable option to start introducing drones almost all the way through the frontier, with the sole use

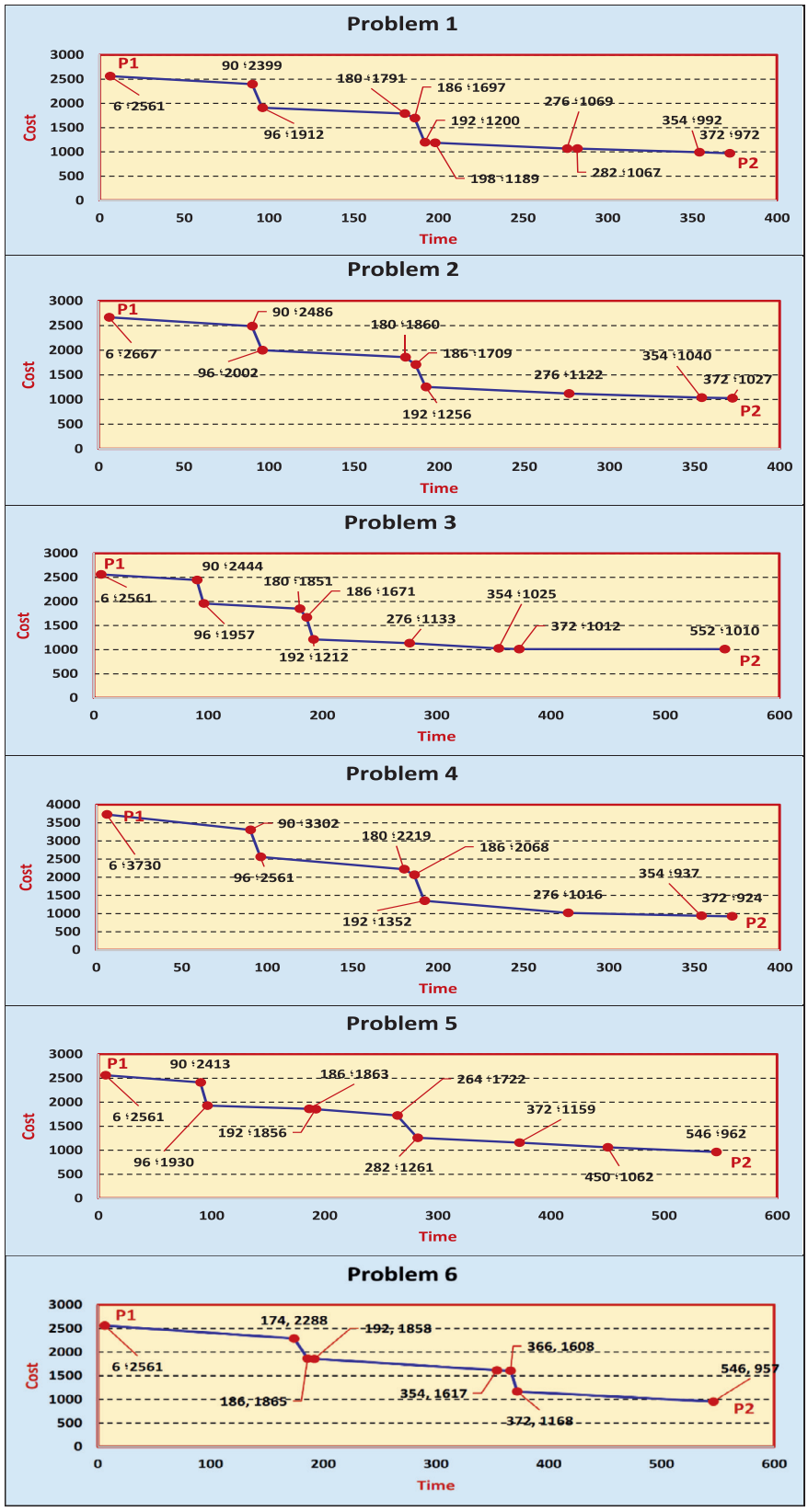

Fig. 3. Pareto Frontier of Problems 1–6.

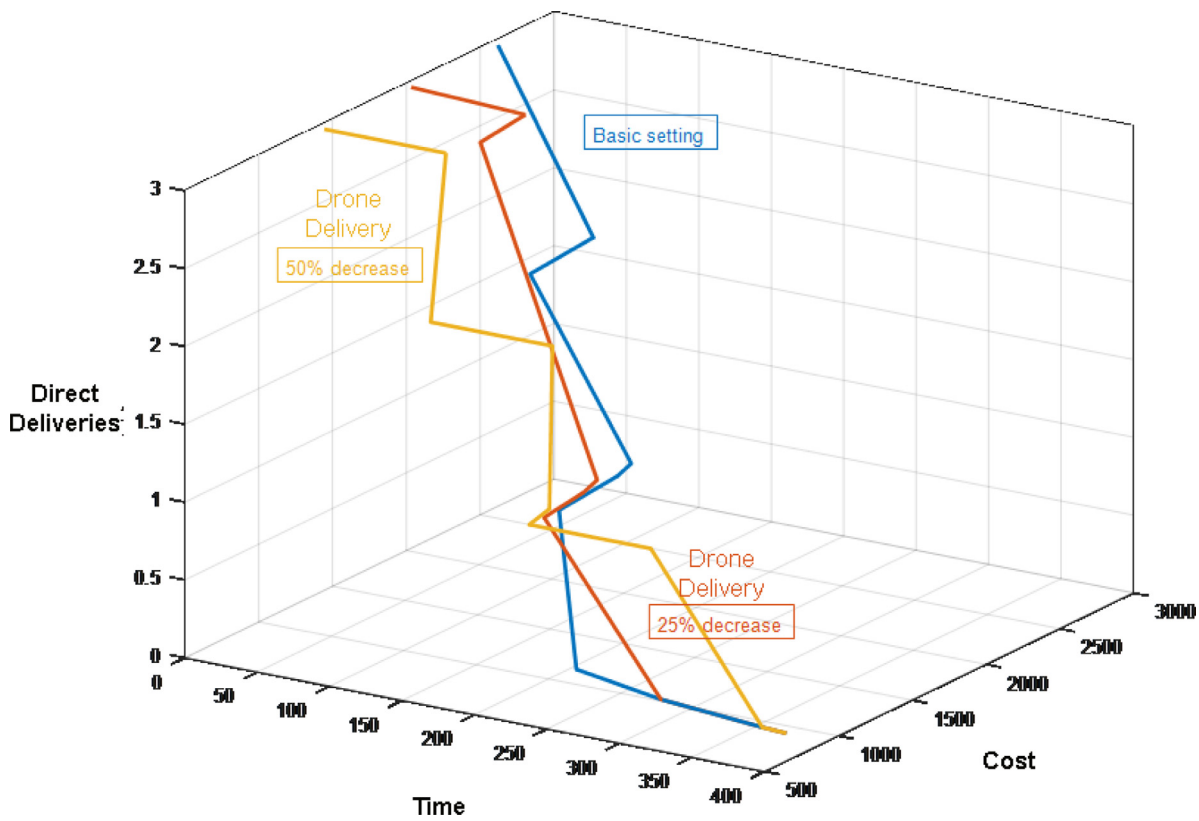

Fig. 4. Decrease in direct shipping costs:Pareto frontiers and number of drones used in the delivery process.

Table 6
Decrease in direct shipping costs: Pareto frontiers and number of drones used in the delivery process.

Time	Basic model		25% decrease in direct shipping costs		50% decrease in direct shipping costs	
	Cost	$\sum_{r=1}^{R} Dir_r$	Cost	$\sum_{r=1}^{R} Dir_r$	Cost	$\sum_{r=1}^{R} Dir_r$
6	2561	3	1973.25	3	1385.5	3
90	2383	2	1923.75	3	1385.5	3
96	1896	2	1559.75	3	1223.5	2
180	1757	1	1526	1	1223.5	2
186	1606	1	1375	1	1144	1
192	1150	1	1049	1	948	1
204	1150	0	–	–	–	–
276	1016	0	1016	0	948	1
354	937	0	937	0	937	0
372	924	0	924	0	924	0

of drones becoming a dominant alternative as relatively fast deliveries are required.

An additional comparison in terms of cost modifications is provided in Fig. 5, which illustrates the different Pareto frontiers derived from the progressive (and simultaneous) increase in truck shipping costs, i.e. $OSA_{j,\,d}$ and $SCA_{j,\,q}$. The simulation results defining the Pareto frontiers represented in the figure are provided in Table 7. As can be observed, drones are not progressively introduced through the Pareto frontier, with a single exception arising as the costs of outbound truck docking and delivery increase by 50% relative to the main setting presented in Fig. 2.

A direct consequence of these modifications is the increment observed in total costs as trucks become increasingly used in the delivery process. The current setting assumes that the inbound door assignment and product transfer costs remain unchanged through the cross-docking process. Note that, if drones would be departing from the cross-dock, these costs would also be part of their delivery process. Thus, these numerical results are based on the increment in the shipping door and customer assignment costs of the outbound trucks, while keeping the remaining costs involved in the cross-docking process constant.

The intuition justifying the current structure of the model follows from the complete separation between cost and time objectives per transportation mode, with drones focusing on the former and trucks mainly on the latter. That is, the introduction of drones saves delivery time as less trucks are send through the cross-dock, but no temporal constraint on the drones has been introduced in the model. As highlighted in the previous section, allowing drones to leave from the cross-dock would require defining specific time-based constraints for the drones, which would complicate the model considerably. Moreover, the main emphasis of the current model has been placed on the decrease in the operational costs of the drones as the main mechanism that triggers their progressive introduction.

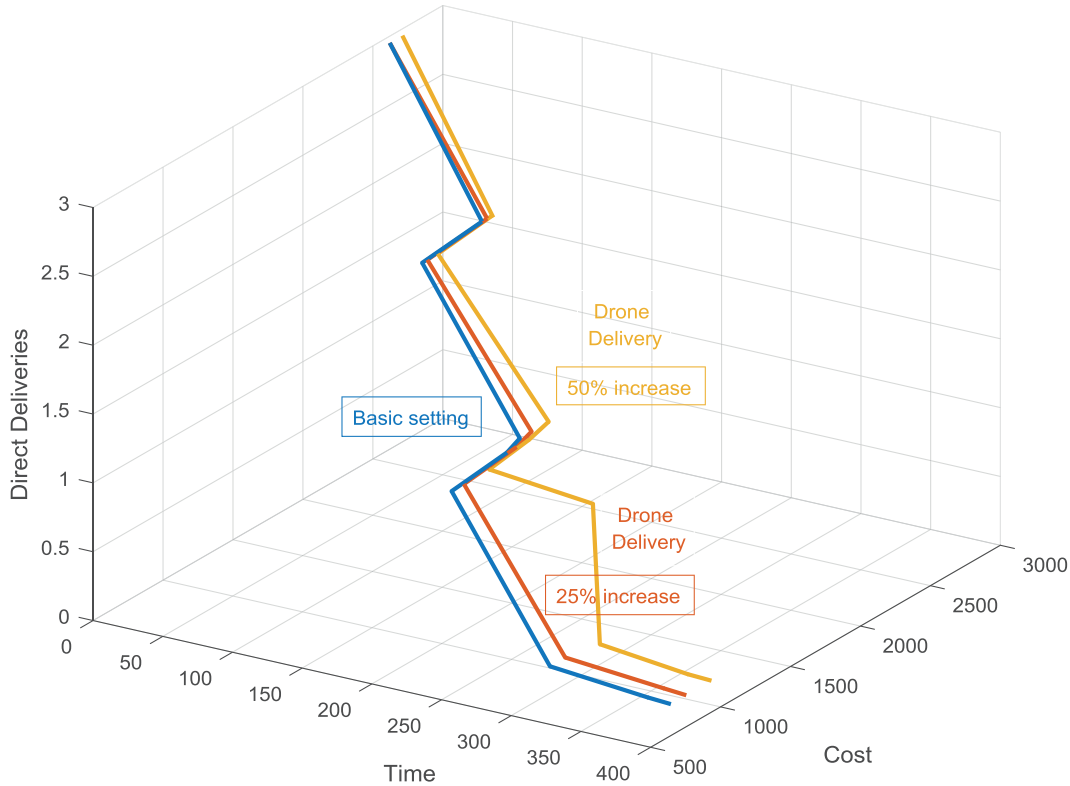

Fig. 5. Simultaneous increase in $OSA_{j,\,d}$ and $SCA_{j,\,q}$:Pareto frontiers and number of drones used in the delivery process.

Table 7
Simultaneous increase in $OSA_{j,\,d}$ and $SCA_{j,\,q}$:Pareto frontiers and number of drones used in the delivery process.

Time	Basic model		25% simultaneous increase in: $OSA_{j,\,d}$ and $SCA_{j,\,q}$		50% simultaneous increase in: $OSA_{j,\,d}$ and $SCA_{j,\,q}$	
	Cost	$\sum_{r=1}^{R} Dir_r$	Cost	$\sum_{r=1}^{R} Dir_r$	Cost	$\sum_{r=1}^{R} Dir_r$
6	2561	3	2561	3	2651	3
90	2383	2	2420.25	2	2457.5	2
96	1896	2	1933.25	2	2008.75	2
180	1757	1	1841.5	1	1963.75	1
186	1606	1	1674.25	1	1763.75	1
192	1150	1	1238	1	1419	1
204	1150	0	–	–	–	–
276	1016	0	1125	0	1323.5	1
354	937	0	1050.75	0	1224.5	0
372	924	0	1034.25	0	1214.5	0

Finally, we conclude by emphasizing that if we were to include the loading process of the drones within the cross-dock, two new parameters should be defined, one of them related to the costs of transferring the product from an inbound truck r in receiving door s to a drone α located in a shipping platform p, $DC_{r,\,\alpha,\,s,\,p}$. In this case, the platform entry sequence should also be defined and would differ from the door assignment process of trucks. At the same time, the time needed to transfer products from receiving door s to shipping platform p, which could be denoted by $DV_{s,\,p}$, would also have to be defined.

Table 8
DM for test problems.

Problem	DM
Main problem	111.0424
Problem 1	121.7412
Problem 2	111.1082
Problem 3	116.8568
Problem 4	144.3408
Problem 5	120.2726
Problem 6	100.8803

6.3. Dispersion criteria

Dispersion criteria are used to study the dispersion and the covering degree of the non-dominated solutions generated by the proposed efficient epsilon-constraint method. In this paper, a Distance Metric (DM) is used to study the dispersion of the Pareto front. First, the Euclidean distance of each solution from the others is calculated and the maximum distance is chosen. Then, the DM is obtained by taking the square root of the sum of the differences between the maximum distance and those of all the other solutions. The DMs obtained for all the test problems performed are presented in Table 8.

As illustrated in Table 8, the DM is sufficiently large given the scale and values of the objective functions in all test problems,

which means that the regenerated Pareto frontier is dispersed over the real Pareto front of the test problems.

7. Conclusions and future research directions

This study has focused on a combination of two main problems, i.e. allocation and scheduling of the trucks in cross-docks. To make the model more practical from a business stand point and account for the potential implementation of drone deliveries by firms, the assumption of direct shipping from the suppliers to the demand points was introduced. Moreover, multiple transportation fleets with various capacities and types of products were also considered, together with multiple receiving and delivery doors in the cross-dock.

A new bi-objective multi-product multiple-door combined cross-docking truck allocation-scheduling problem allowing for direct shipping and multiple fleets was proposed. The problem was modeled using multi-objective mixed integer mathematical programming. Two conflictive objective functions, the total cost of allocation and scheduling and the time of scheduling, were optimized, concurrently. Several sets of constraints, motivated by real allocation-scheduling situations, were also considered for both allocation and scheduling phenomena. Then, an efficient multi-objective solution method, called epsilon-constraint, was adapted to solve the proposed mathematical model.

Several numerical examples and metrics have been supplied in order to illustrate the mechanism of the mathematical model and the efficacy of the solution procedure. The efficient frontiers of the numerical examples were estimated by generating non-dominated solutions. Finally, a sensitivity analysis was conducted in order to check the variations of the solutions resulting from changes in the parameters of the model. The reduction of the number of dock's doors (receiving or shipping) had the most impact on the time increase and the change in the costs associated with the direct shipping of products had the most impact on the increase in costs.

Several immediate possibilities arise when considering potential extensions of the current model. For example, despite the manageable size and weight of most last-mile parcels, the capacity of the drones remains considerably below that of the trucks. Thus, even though the larger capacity assigned to drone shipping in our simulations could be justified in terms of costs differentials, a cross-docking process for the drones should be explicitly defined.

Moreover, given the space constraints faced in last-mile deliveries and the substantial effects that modifications in the number of receiving and shipping doors have on the efficient frontier, the consequences from limiting the capacity of the cross-dock should be further examined. In this regard, companies promising timely last-mile deliveries may consider the assignment of drones to suppliers prior to direct customer delivery, as described in the current model.

Finally, adding other criteria like earliness or tardiness shipping, considering multi-period and dynamic situations, as well as the triple of allocation-scheduling-routing in cross-docks are also interesting ways to extend the model. In this regard, solving large-size real case studies using Meta-heuristic methods constitutes another interesting extension that should be considered in future research.

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