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ScienceDirect

Procedia Manufacturing 42 (2020) 488–497

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

International Conference on Industry 4.0 and Smart Manufacturing (ISM 2019)

Using drones for parcels delivery process

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Abstract

Parcels delivery is the most expensive phase of the distribution logistics. Everyday, several vehicles, usually internal combustion engine vehicles, have to serve a high number of customers spatially distributed in an urban area. Their presence generates several negative externalities, such as, noise, congestion and pollutant emissions. Drones have become a valid alternative to support the delivery process and several big companies, such as, Amazon and DHL, have started to use them for parcels deliveries. On the one hand, drones drastically reduce negative externalities, allowing a more sustainable delivery process. On the other hand, several technical aspects must be carefully taken into account. In particular, they have a limited flight endurance and capacity. In addition, several restrictions related to safety and flight area must be considered. Indeed, not all countries allow the use of drones in the urban area. In this work, we provide a qualitative and quantitative analysis on benefits and drawbacks in using drones in the parcels delivery process. We analyze three different transportation systems with incremental use of drones for the delivery. In particular, we address the problem of delivering parcels without drone, known as vehicle routing problem, the problem in which the deliveries are performed by a fleet of drones starting from the central depot, and a hybrid transportation system where the classical vehicles are equipped with drones. In the latter case, the classical vehicles perform the deliveries and the drones can get in charge some deliveries. The drone takes off from the vehicle, carries out the delivery, and lands to the same vehicle at a randevouz-location. During the drone delivery, the classical vehicle continues its work. The three transportation systems are formalized via mathematical programming models. The solutions obtained by solving the models via a general-purpose solver are compared and insights on the use of drones in the urban area are provided.

Keywords: urban transportation; last-mile delivery; drones; vehicle routing problem

1. Introduction

The last-mile delivery is the "end node" of the logistic chain. It refers to the delivery of parcels to the customers and it is the most expensive process in distribution logistics. Indeed, the cost ranges from 13% to 73% with respect to the total distribution cost [12]. The entity of such a cost depends on quality of service, dangerous nature of the materials delivered, geographic area, market share, and typologies of vehicles used.

Retailers which operate in e-commerce face several challenges. Indeed, on-line shopping is becoming very common and the demand of same-day deliveries has exponentially grown in the last years. More and more people prefer to use shopping on-line instead to buy items from conventional shop. In this context, the expectation of the customers has begun high in terms of quality of service. In addition, the number of online retailers is constantly growing and customers can easily change their on-line shop if they are not completely satisfied. Therefore, fulfilling customers' needs is one of the biggest challenge for on-line retailers. Thus, on the one hand, the shopping on-line increases the possibility of the retailers to increment their revenue, on the other hand, high operational costs have to be paid in order to guarantee the expected customers' satisfaction. This trend force the logistic operators to efficiently manage the delivery process; therefore, the implementation of novel distribution paradigms is a key success factor. Since a high number of delivery requests have to be satisfied in the same-day and in the same urban area, it is expected a high number of delivery vehicles on the roads at any time of the day. As a result, the increase of same-day deliveries in the urban area causes several negative externalities. Indeed, the presence of this high number of vehicles on the urban road system increases congestion, noise, and has a bad impact on the air quality in the urban area, due to the CO_2 emissions. In order to face the negative environmental impacts of the traditional deliveries, some companies have

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2351-9789
10.1016/j.promfg.2020.02.043

started to introduce the use of alternative vehicles. Electric vehicles are common in several urban areas. They reduce noise and CO_2 emissions ([18, 19]) but the use of these vehicles continue to generate congestion and do not solve the problem of efficiency in last-mile delivery process.

With the aims of gaining from the possibility offered by the new behavior of the customers, managing in a profitable way the own resources and finding new eco-friendly solutions, several big on-line retailers, such as Amazon and DHL, have started to promote new delivery processes.

One of the most promising distribution paradigm is based on crowd-shipping. Ordinary people accept to deliver parcels to other people for a small compensation ([6, 20, 21, 22]). Recently, Amazon and DHL have started to use unmanned aerial vehicles, common known as drones, for same-day last-mile delivery process [30]. On the one hand, the use of drones in the delivery process reduces noise and avoids both the increase of congestion in the urban area and CO_2 emissions. On the other hand, drones have a lower capacity (they can carry low weight parcels) and working time (low flight endurance) than classical vehicles. Overall, drones have a positive impact. Indeed, their use reduces the lead time and both the makespan [28] and the transportation costs [8] of the delivery process.

The scientific literature refers to the routing of vehicles for delivering parcels as routing problems (RPs). The RPs are classified into two main classes, i.e., travelling salesman problem (TSP) when a vehicle without capacity constraint is used, and vehicle routing problem (VRP) when several capacitated vehicles are considered. Several variants of both TSP and VRP have been studied by considering pickup and delivery operations, multi trip assumptions, the presence of one or more central depots, intermediate depots, and time window constraints that impose the interval of time in which each customer has to be served. For more details on both TSP and VRP and their variants, the reader is referred to [4, 10, 14, 15, 17].

The RPs with the aid of drones was introduced in [28] where the cooperation of trucks and drones was studied under a theoretical point of view. In particular, the authors provided bounds on the makespan for the TSP with drones (TSP-D) and the VRP with drones (VRP-D). A comparison with the TSP and VRP was carried out concluding that the combination of trucks and drones leads to a short makespan. This result suggests that the use of drones in combination with trucks improves the performance of the delivery process in term of completion time.

The TSP-D was studied in [1, 11, 23] providing several insights on the behaviour of this transportation system. In particular, in [11] was proved empirically that the best results are obtained when the speed of the drones is twice that of the trucks. The VRP-D was considered in [24, 28]. The authors addressed simplified version where trucks are not capacitated, and no flight endurance limitation was considered for the drones. They minimized the completion time. From these seminal works, several contributions appeared by considering more realistic scenarios. In particular, in [7] the authors took into account the recharging of the battery of the drones after each drone-delivery. In [8, 25], the minimization of the transportation cost was considered and time window constraints were taken into account in [8]. In addition, [8] introduced the concept of synchronization between truck and drone. In particular, the drone can wait the truck for a limited amount of time after it performed the delivery. This assumption is made for safety and security reasons. The introduction of a limitation on the waiting time has an impact on the behaviour of the transportation system. The speed of the drones with respect to that of the trucks play a crucial role in the definition of deliveries when synchronization issues are taken into account. In particular, the higher the speed of the drone with respect the speed of the truck, the higher the possibility of exceed the maximum allowed waiting time, making several drone-deliveries infeasible [8]. It follows that the insight provided in [11] for the TSP-D is no longer valid.

In this paper we analyze the behavior of a transportation system where trucks and drones are used to perform deliveries. We take into account realistic scenario considering time window and synchronization constraints. Benchmark instances, used by the scientific literature to analyze RPs, are considered for the empirical evaluation. The system is analyzed under both cost and negative externalities efficiency. The resulting VRP-D is compared with the VRP and the RP where only drones are used for delivering parcels, i.e., RPD. The contribution of the paper is to provide a comparative and systematic analysis of the considered transportation systems by highlighting the benefits and the drawbacks of the delivery process in an urban area.

The reminder of the paper is organized as follows. Section 2 formally introduces the addressed problems. Section 3 presents the results of the computational analysis. Section 4 concludes the paper.

2. Transportation systems definition

In this Section we provide a formal description of the considered transportation systems. Firstly, we give the common notations, then we provide the mathematical formulations of the three cases.

Let $V = N \cup \{0, n+1\}$ be the set of nodes composed of the set of n customers N, the depot 0 and its copy $n+1$. Let A be the set that contains all possible connections (i, j) between each pair of nodes $i, j \in V$. In particular, $A = \{(i, j) : i \in N \cup \{0\}, j \in N \cup \{n+1\}\}$. We define the problems over a complete graph $G(V, A)$. A delivery request q_i is associated with each customer $i \in N$. Let $\eta(q_i)$ and $w(q_i)$ be the number of parcels and the weight of request q_i, respectively. A time window $[a_i, b_i]$ is associated with each customer $i \in N$, where a_i is the earliest service time and b_i is the latest service time to customer $i \in N$. This means that customer i have to be served within $[a_i, b_i]$. Let s^t_i and s^d_i be the time needed to serve customer $i \in N$ when the delivery to i is performed by the trucks and he drones, respectively.

A distance is associated with each arc $(i, j) \in A$. We suppose a Manhattan metric for the trucks and the Euclidean metric for the drones. Let d^t_{ij} and d^d_{ij} be the distance travelled by the truck and the drone, respectively, from node $i \in N \cup \{0\}$ to node $j \in N \cup \{n + 1\}$. Let v^t and v^d be the speed of the trucks and the drones, respectively. Thus, the time to traverse an arc $(i, j) \in A$

is given by $t^t_{ij} = d^t_{ij}/v^t$ and $t^d_{ij} = d^d_{ij}/v^d$ for the trucks and the drones, respectively. Costs per distance travelled/flight c^t_{ij} and c^d_{ij} have to be paid along the arc $(i, j) \in A$ by the trucks and the drones, respectively.

We assume a maximum allowed waiting time for the drone defined as T. Thus, a drone can wait at most T instant time for the truck in order to land on.

We assume that each truck and each drone has a capacity W^t and W^d, respectively. In addition, each drone can carry one parcel for each drone-delivery. We assume that energy consumption of the drones is proportional to the distance it flies. Given the battery fully charged at the beginning of each drone-delivery, we retrieve the maximum distance E that each drone can fly for each drone-delivery.

We consider a limited number of trucks and drones. Let K and D be the sets of available trucks and drones, respectively.

2.1. Truck routing problem (VRP)

In this problem we consider only trucks for the delivery process. Let x^k_{ij} be binary variables taking value equal to one if the truck $k \in K$ travel along the arc $(i, j) \in A$, zero otherwise. Let z_{ij} be the weight of the parcels carried by the trucks along the arc $(i, j) \in A$. Let τ^k_i be continuous variables indicating the instant time in which the customer i is served by the truck $k \in K$. The variable τ^k_0 is the starting time of a route performed by the truck $k \in K$. The VRP can be mathematically formulated as follows.

$$min\ C^t(x) = \sum_{i\in V}\sum_{j\in V}\sum_{k\in K} c^t_{ij} d^t_{ij} x^k_{ij} \tag{1}$$

s.t

$$\sum_{j\in N} x^k_{0j} - \sum_{i\in N} x^k_{i,n+1} = 0, \forall k \in K; \tag{2}$$

$$\sum_{i\in V} x^k_{ih} - \sum_{j\in V} x^k_{hj} = 0, \forall h \in N, k \in K; \tag{3}$$

$$\sum_{j\in N} x^k_{0j} \leq 1, \forall k \in K; \tag{4}$$

$$\sum_{i\in N}\sum_{k\in K} x^k_{ij} = 1, \forall j \in N; \tag{5}$$

$$\sum_{j|(j,i)\in A} z_{ji} - \sum_{j|(i,j)\in A} z_{ij} = \begin{cases} \omega(q_i), & \forall i \in N,\\ \sum_{i\in N} -\omega(q_i), & i = 0, \end{cases} \tag{6}$$

$$z_{ij} \leq W^t \sum_{k\in K} x^k_{ij}, \forall (i, j) \in A; \tag{7}$$

$$z_{in+1} = 0, \forall i \in N; \tag{8}$$

$$M_{ij}(x^k_{ij} - 1) + \tau^k_i + s^t_i + t^t_{ij} \leq \tau^k_j, \forall k \in K, i \in V, j \in V; \tag{9}$$

$$a_j \leq \tau^k_j \leq b_j, \forall j \in N, k \in K. \tag{10}$$

Objective function (1) minimizes the travelled cost. Constraints (2) impose that if truck $k \in K$ starts a route, then it must end the route at node $n + 1$. Constraints (3) balance the flow at each customer node $h \in N$. In particular, if the truck k visits customer i, then it must leave the node i after the service. Constraints (4) impose that each truck $k \in K$ can perform at most one route. Constraints (5) impose that each customer $j \in N$ have to be served by exactly one truck. Constraints (6) define the weight of parcels that the trucks carry along the arcs (i, j). Constraints (7) impose that the weight carries along each arc $(i, j) \in A$ must not exceed the capacity of the truck. Constraints (8) impose the trucks to end their route empty. Constraints (9) define the arrival time to each customer $j \in N$. Constraints (10) impose the service to each customer $j \in N$ within its time window. M_{ij} is a sufficiently large number.

2.2. Drone routing problem (RPD)

This problem addresses the case in which only drones perform deliveries. It is assumed that each drone starts/ends its delivery from/at the depot. Among all customers N, only a subset of them can be served by the drones due to both the characteristics of the parcels and the limitation on the flight endurance. In particular, we define the set $N^d = N^d(q) \cup N^d(E)$, where $N^d(q) = \{i \in N : \eta(q_i) = 1, w(q_i) \leq W^d\}$ is the set of customers whose request q_i can be satisfied by the drones and $N^d(E) = \{i \in N^d(q) : d^d_{0i} + d^d_{in+1} \leq E\}$ is the set of customers whose distances from the depot is compatible with the flight endurance of the drones.

Let y^d_{0in+1} be binary variables taking value equal to one if drone $d \in D$ serves customer $i \in N^d$. Let τ^d_i be the instant time in which the customer $i \in N^d$ is served by the drone $d \in D$. The variable τ^d_0 is the starting time of the delivery performed by the drone $d \in K$. We assume that each drone can perform at most one delivery. The mathematical formulation for RPD is given below.

$$min\ C^d(y) = \sum_{i\in N^d}\sum_{d\in D}(c^d_{0i} d^d_{0i} + c^d_{in+1} d^d_{in+1}) y^d_{0in+1} \tag{11}$$

s.t

$$\sum_{d\in D} y^d_{0in+1} = 1, \forall i \in N^d; \tag{12}$$

$$\sum_{i\in N^d} y^d_{0in+1} \leq 1, \forall d \in D; \tag{13}$$

$$M(y^d_{0in+1} - 1) + \tau^d_0 + t^d_{0i} \leq \tau^d_i, \forall d \in D, i \in N^d; \tag{14}$$

$$M(y^d_{0in+1} - 1) + \tau^d_i + s^d_i + t^d_{in+1} \leq \tau^d_{n+1}, \forall d \in D, i \in N^d; \tag{15}$$

$$M(y^d_{0in+1} - 1) + \tau^d_i - t^d_{0i} - \tau^d_0 \leq T, \forall d \in D, i \in N^d; \tag{16}$$

$$a_j \leq \tau^d_j \leq b_j, \forall d \in D, j \in N^d. \tag{17}$$

Objective function (11) minimizes the flight cost. Constraints (5) impose that each customer $i \in N^d$ is served by exactly one drone. Constraints (13) impose that each drone can serve at most one customer $i \in N^d$. Constraints (14) define the arrival time to customer i when it is served by the drone d. Constraints (15) define the arrival time of drone d to the depot. Constraints (16) allow a maximum waiting time T of drone d at customer i before starting the service. Constraints (17) impose the service of drone d to take place within the time window associated with customer i. M is a sufficiently large number. We highlight that the capacity constraint and the maximum allowed flight distance E are included in the definition of set N^d. This means that all drone-deliveries are feasible with respect to the capacity constraint and the flight endurance requirement.

2.3. Truck-Drone routing problem (VRP-D)

We consider the transportation system described in [8]. We briefly describe the characteristics of the delivery process and the assumptions made with respect to the behaviour of the drones, the trucks, and their cooperation. Each truck is equipped with a drone. A subset of customers N^t is served by the trucks, whereas the customers $N^d = N \setminus N^t$ are served by the drones. The trucks perform their route to serve the customers included in N^t. The drones which take in charge the delivery of parcels for the customers in N^d perform the drone-delivery in parallel with the associated truck. This means that the drone-deliveries take place while the trucks perform their routes. We note that the definition of subsets N^t and N^d is a decision. This means that we do not assume a-priori information related to the customers served by the drones and the trucks. A drone-delivery is characterized by the tuple $\langle i, w, j \rangle$; in particular, i is the node associated with the customer where the drone takes off from the truck, w is the customer served by the drone, and j is the node associated with the customer where the drone lands on the truck. The customers i and j belong to the route of the truck whose the drone, performing the drone-delivery $\langle i, w, j \rangle$, is associated. If the drone arrives to customer j with T instant time earlier than the truck, then the drone-delivery $\langle i, w, j \rangle$ is declared infeasible. In other words, the waiting time of the drone for the truck must not exceed T instant time. The mathematical formulation for the VRP-D is a combination of models (1)–(10) and (11)–(17) with further constraints related to the synchronization between each truck and the associated drone. For the mathematical model of the VRP-D, the reader is referred to [8].

2.4. Discussion on CO_2 emission models

In [27] the CO_2 emissions are estimated by considering two elements, i.e., the distance travelled and the weight carried by the truck. In particular, it is computed an emission factor $f(z)$ of CO_2 in terms of kg/km as a function of the load of the truck.

By using the chemical reaction proposed by Lichty [16], the kg of CO_2 per litre of diesel consumed is 2.61. Thus, knowing the consumption of diesel, the emission factor $f(z)$ is determined. In [27] is reported the consumption of diesel for five different load configurations. The emission factors $f(z)$ along with the consumption of diesel for the considered load configurations are reported in Table 1.

Table 1. Estimation of emission factors for a truck with 10-tonne capacity [19].

Load of the vehicle	Weight laden (%)	Consumption (litre/100km)	$f(z)$ (kg CO_2/km)
Empty	0	29.6	0.77
Low loaded	25	34.0	0.83
Half loaded	50	34.4	0.90
High loaded	75	36.7	0.95
Full load	100	39.0	1.01

The emissions of CO_2 in kg is defined by the following function

$$g^t(z, x) = \sum_{k \in K} \sum_{(i,j) \in A} f(z_{ij}) d^t_{ij} x^k_{ij}. \tag{18}$$

Function $g^t(z, x)$ is used to estimate the CO_2 in [19] where the VRP with mixed fleet composed of conventional trucks (diesel) and electric vehicles is considered.

The drone is characterized by zero emissions since it is an electric vehicle. However, the energy consumed by the drone is produced by power generation facilities. The process of power generation produces CO_2 emissions. Thus, we take into account the CO_2 emitted by power generation facilities. In [13] was estimated that 0.3773 kg of CO_2 is emitted for each kWh produced. Let β be the Wh consumed by the drone per km, the CO_2 emission for the drone-deliveries can be estimated by considering the following function

$$g^d(y) = \beta \times 3.773(10^{-4}) \times \sum_{i \in V} \sum_{w \in N^d} \sum_{j \in V} \sum_{d \in D} \left(d^d_{iw} + d^d_{wj}\right) y^d_{iwj} \tag{19}$$

The value of β depends on the characteristics of the drone. In [13] the authors consider $\beta \in [10, 100]$.

3. Computational analysis

In this Section we analyze and compare the results obtained by solving the three models associated with the three transportation systems, i.e., VRP, RPD, and VRP-D. The mathematical formulations are implemented in Java language and solved by using CPLEX 12.5.

The experiments are carried out on an Intel Core i7-4720HQ CPU 2.60 GHz with 8 GB RAM under Microsoft 10 operating system. We consider instances inspired by the scientific literature. The test problems are described in what follows.

3.1. Test problems

The test problems are generated by starting from the well-known Solomon benchmarks for the VRP with time windows [26]. These benchmarks are grouped in three classes: 12 random instances (R2) where the customers are randomly distributed, 8 clustered instances (C2) where subsets of customers are randomly distributed, and 8 random clustered instances (RC2) where some customers are randomly distributed and the remaining ones are clustered. Each instance is characterized of 100 costumers and the depot 0. In order to generate the instances considered in this work, we have adapted the benchmarks R2, C2, and RC2 as described in what follows.

The depot 0 and its copy $n + 1$ are located as in the original instances. We choose $n \in \{5, 10, 15\}$ customers among the original ones randomly, maintaining the information related to the position, the demand, and the time windows.

In order to take into account the limitations related to drone-delivery, we impose that only the 80% of the customers can be served by the drones. In particular, we generate the set of customers $N^d(q) \subset N$ such that $|N^d(q)| = \lceil 0.80n \rceil$. In particular, the $\lceil 0.80n \rceil$ customers with associated a low value of $\omega\{q_i\}$ are included into $N^d(q)$. The service time for the customers served by the trucks, i.e. $s^t_i, \forall i \in N$ is set equal to the original service time, whereas, $s^d_i = 1/2 s^t_i, \forall i \in N^d(q)$. We assume $\eta(q_i) = 1, \forall i \in N$, and we set $E = \max_{(i,j)\in A} d^d_{ij}$, $c^t_{ij} = 25 \times c^d_{ij}$, $v^t = v^d$, $\beta = 10$, and T equal to 10 for classes R2 and RC2 and 90 for class C2. We highlight that the values chosen for the speeds of the trucks and the drones allow to obtain the highest probability of feasible drone-deliveries in presence of synchronization constraints between a truck and the associated drone (see [8]). In addition, the higher transportation cost c^t of the trucks than that of the drone, i.e. c^d, is justified by several reasons, like courier cost and fuel consumption cost among the others (see, e.g. [29]).

3.2. Numerical results

Tables 2–4 summarize the average results for each transportation system and each class of test problems, considering the instances with 5, 10 and 15 customers, respectively. Table 5 reports the numerical results for each transportation system averaged over all instances and classes of test problems.

We impose a time limit for the resolution of each instance of 30 minutes. Thus, if the considered instance is solved within the time limit, the solution obtained is the optimal one. If the resolution process takes more than 30 minutes, the solution returned by CPLEX is a feasible one but not optimal. In the latter case, CPLEX provides the optimality gap that gives an idea on how far is the returned feasible solution from the optimal one.

Tables 2– 5 show the execution time under column time, the optimality gap under column gap, the overall transportation cost, i.e. $C(x, y) = C^t(x) + C^d(y)$, under column $C(x, y)$, and the overall CO_2 emissions, i.e. $g(z, x, y) = g^t(z, x) + g^d(y)$, under column $g(z, x, y)$. The rest of each table is divided into two parts, both of them have four columns. In the first part, named "Truck", we report information related to the trucks, whereas the second one, named "Drones" we report information related to the drones. The empty entries means that no information is available from the resolution process. In particular, for the VRP and the RPD the second and the first parts are empty since no drones and no trucks are considered, respectively. The first and the second parts of the Tables report the transportation costs under columns $C^t(x)$ and $C^d(y)$, the CO_2 emissions under columns $g^t(z, x)$ and $g^d(y)$, the number of trucks and drones used for the deliveries under columns #v and #d, respectively, the number of arcs travelled by the trucks under column arcs, and the potential number of drone-deliveries, i.e., the number of customers for which a feasible drone-delivery exists, under column $|N^d|$. We recall that N^d contains all customers that can be served by a drone. In other words, customers with requests compatible to drone capacity and close enough to the depot such that drone can serve each customer and return back to the depot within the limited flight endurance.

Analysis on transportation cost. Looking at Table 5, we observe that the most expensive transportation system is VRP, followed by VRP-D and RPD. Indeed, the latter shows a transportation cost equal to 334.33. However, due to the technical limitations of the drones, only the 56% of the customers are served, on average (see column #d). This means that, on average, the 44% of the requests cannot be taken in charge. This drawback causes a severe reduction of the quality of service. The transportation system VRP-D takes advantages in term of cost related to the use of drones and overcome the drawback related to the quality of service, thanks to the use of trucks that can perform the deliveries that drones cannot fulfill. Thus, VRP-D shows the best trade-off between quality of service and effectiveness. Indeed, all customers are served and we observe an average reduction of the overall transportation cost $C(x, y)$ of 39% with respect to the cost obtained with VRP.

In what follows, we analyze the average transportation cost per customer served by the trucks and the drones, separately. We refer to $C^t_c(\alpha)$ and $C^d_c(\alpha)$ as the cost per unit of customer served by the trucks and the drones, respectively, considering the transportation system $\alpha \in \{VRP, RPD, VRP - D\}$. On average, $C^t_c(VRP)$ is 797.59 whereas $C^t_c(VRP - D)$ is 1037.59 (see Table 5). The same observation can be done when considering the use of drones. Indeed, $C^d_c(RPD)$ is 50.52 whereas $C^d_c(VRP - D)$ is 52.71. In addition, the number of trucks used in VRP-D is 1.29 lower than the number of trucks used in VRP and the number of drone-deliveries performed in VRP-D is 1.19 times less than that observed for RPD. These results suggest that the use of trucks and drones in both VRP and RPD is more efficient than that observed for VRP-D. However, the combination of trucks and drones leads to a better organization of the delivery process in terms of overall transportation cost (see Table 5, column $C(x, y)$). The observed average trend is the same for each value of $|N|$, as shown in Fig. 1 and Fig. 2, where $C^t_c(\alpha)$ for VRP and VRP-D and $C^d_c(\alpha)$ for RPD and VRP-D are depicted, respectively.

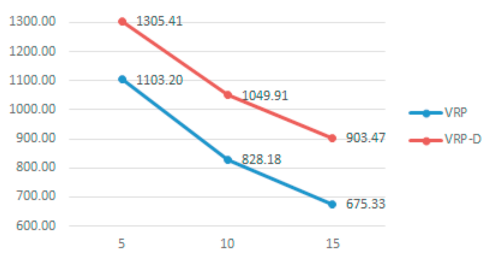

Fig. 1. Average values of $C^t_c(VRP)$ and $C^t_c(VRP - D)$ at varying the number of customers $|N|$.

An interesting trend is observed for $C^t_c(\alpha)$, see Fig. 1. Indeed, the higher the number of customers $|N|$, the lower the cost per customer served by the trucks. An inverted trend is observed

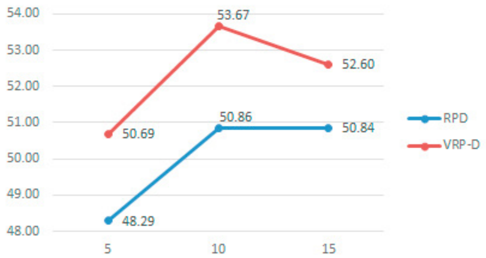

Fig. 2. Average values of $C_c^d(RPD)$ and $C_c^d(VRP-D)$ at varying the number of customers $|N|$.

when the transportation cost per customer served by the drones $C_c^d(\alpha)$ is considered, see Fig. 2.

Despite the lower values of $C_c^t(VRP)$ than the values of $C_c^t(VRP-D)$, the overall transportation cost for VRP-D is lower than that observed for VRP. The trend of $C(x, y)$ for VRP and VRP-D at varying the number of customers is depicted in Fig. 3.

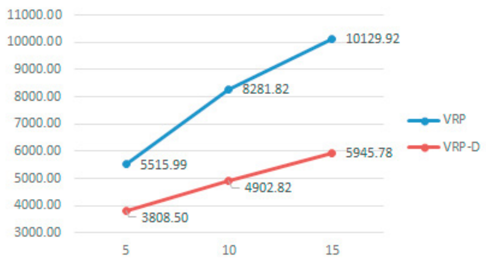

Fig. 3. Average values of $C(x, y)$ for VRP and VRP-D at varying the number of customers $|N|$.

This trend can be justified by considering the number of customers served by the trucks. Whilst for VRP all customers are served by the trucks, for VRP-D only the 57%, 44%, and 40% are served by the trucks, considering $|N|$ equal to 5, 10, and 15, respectively. Thus, the incidence of the transportation cost related to the delivery performed by the trucks reduces for VRP-D with increasing of the number of customers to be served. Indeed, Fig. 3 highlights that the transportation cost for VRP-D is 1.45, 1.59, and 1.60 times lower than the cost paid for VRP, considering $|N|$ equal to 5, 10, and 15, respectively.

Analysis on CO_2 emissions and congestion. As expected, RPD produces on average the lowest amount of emissions (see Tables 2–5). However, we highlight that these emissions are not released in the urban area, but they refers to the emissions of the power generation plants which produce the energy used by the drone during the deliveries. We also highlight that not all customers can be served by the drones for RPD.

In what follows we focus our attention on VRP and VRP-D. Looking at Table 5, we observe that the CO_2 emitted with VRP is 48% higher than the emissions with VRP-D. This is an expected results, since the drones produce a very low CO_2 emissions. In addition, the higher the number of customers to be served the higher the differences between the CO_2 emitted with VRP and VRP-D (see Tables 2–4). In particular, the CO_2 emissions of VRP are 1.64, 2.03, and 2.04 times higher than those emitted with VRP-D, considering $|N|$ equal to 5, 10, and 15, respectively. This trend is depicted in Fig. 4, where the CO_2 emitted for VRP and VRP-D is plotted at varying the number of customers to be served.

Fig. 4. Average values of $g(z, x, y)$ for VRP and VRP-D at varying the number of customers $|N|$.

It is interesting to note that the CO_2 emitted per arcs travelled by the trucks for VRP and VRP-D is the same and equal to about 15. The low value of emissions for VRP-D is justified by the lower arcs travelled than those travelled for VRP. In particular, the number of arcs used for VRP is about twice that for VRP-D, on average, see Table 5. This trend is observed for each value of $|N|$ as shown in Tables 2–4.

The number of arcs travelled gives us a general idea on the congestion generated by the deliveries performed by the trucks. As expected, VRP-D uses a less number of arcs for the delivery process. In particular, #arcs for VRP is 1.65, 2.00, and 2.22 times higher than that observed for VRP-D, considering $|N|$ equal to 5, 10, and 15, respectively (see Tables 2–4, column #arcs). Fig. 5 shows the average number of arcs travelled for VRP and VRP-D at varying the number of customer to be served $|N|$.

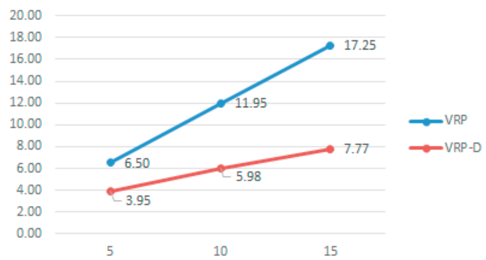

Fig. 5. Average number of arcs travelled considering VRP and VRP-D at varying the number of customers $|N|$.

The increasing difference of #arcs between VRP and VRP-D for increasing values of $|N|$ is justified by the number of customers served by the drones. Indeed, looking at Tables 2–4, the percentage of requests taken in charge by the drones, calculated as $\#d/|N| \times 100$, is 43%, 56%, and 60%, considering $|N|$ equal to 5, 10, and 15, respectively.

As expected, VRP-D uses a less number of trucks. In particular, #v for VRP is 1.29 times higher than that observed for VRP-D, on average. This means that VRP-D gives benefits in terms of congestion since less trucks enter in the urban area.

Final remarks. The computational results highlight the drawback of using only drones for the delivery process. Indeed, for the instances considered in this paper, for the 44% of the customers, on average, the request is not satisfied. However, RPD gives high benefits in terms of transportation cost, CO_2 emissions and congestion. Indeed, the cost per customers served is 50.52 against the 797.59 observed for VRP, on average. The CO_2 emissions is 144.12 times lower than those observed for VRP and the delivery process performed by the drones does not cause congestion. VRP-D takes the advantages of using drones in the delivery process overcoming the drawbacks. Indeed, the request that cannot be satisfied by the drones, are fulfilled by the trucks. VRP-D presents a lower transportation cost than VRP, i.e., a reduction of about 39% is observed. The emissions are drastically reduced thanks to the possibility of using drones. A reduction of about 48% is obtained for VRP-D in comparison with VRP. In addition, a less number of trucks are used for VRP-D and they travel along a less number of arcs with respect to the number of trucks and number of arcs travelled considering VRP. These results highlight the potential of VRP-D of reducing the congestion in the urban area. Overall, VRP-D is the transportation system that provides the better trade-off among transportation cost, CO_2 emissions and congestion.

4. Conclusions

In this paper we analyzed the drawbacks and the benefits of using drones in the delivery process in an urban area. We considered three types of transportation systems, i.e., a delivery process where only trucks are used, referred to as VRP, one where only drones are taken into account, referred to as RPD and a hybrid transportation system where trucks are equipped with drones, in this configuration both typologies of vehicles are used to deliver parcels. The three delivery processes are analyzed in terms of transportation cost, CO_2 emissions and congestion. We provided mathematical formulations used to solve instances inspired by the scientific literature. The computational results highlighted the drawback of RPD that is not able to fulfill all the requests and the benefits in terms of transportation cost, emissions and congestion. VRP is the less efficient transportation system. Indeed, it presents the highest cost, emissions, and congestion among the considered transportation systems. VRP-D is able to serve all customers, overcoming the drawbacks related to RPD taking all the advantages from the drones. Indeed, VRP-D presents a lower cost, emission and congestion than those observed for VRP. Thus, the numerical results suggested that VRP-D has the best trade-off between efficiency and reduction of negative externalities, i.e., CO_2 emissions and congestion. In this work we considered deterministic data. However, some of them, like time to traverse the arcs, service time, fuel consumption of the truck, energy consumption of the drones are uncertain. It should be interesting to analyze the three transportation systems considering such uncertainties within a robust optimization framework [2, 3, 5, 9].

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Table 2. Average numerical results for the instances with 5 customers considering the three transportation systems and the three classes of test problems when minimizing the transportation cost.

							Trucks				Drones			
$\|N\|$	Problem	Class	time	gap	$C(x,y)$	$g(z,x,y)$	$C^t(x)$	$g^t(z,x)$	#v	#arcs	$C^d(y)$	$g^d(y)$	#d	$\|N^d\|$
5	VRP	R2	1.12	0.00%	4636.36	100.04	4636.36	100.04	1.45	6.45				
		C2	0.63	0.00%	5818.75	118.39	5818.75	118.39	1.63	6.63				
		RC2	0.96	0.00%	6092.86	130.73	6092.86	130.73	1.38	6.43				
5	RPD	R2	0.11	0.00%	87.53	0.33					87.53	0.33	2.27	2.27
		C2	0.10	0.00%	90.37	0.34					90.37	0.34	2.00	2.00
		RC2	0.10	0.00%	185.35	0.70					185.35	0.70	3.25	3.25
5	VRP-D	R2	0.82	0.00%	3358.93	64.71	3277.27	64.40	1.09	4.09	81.66	0.31	2.00	2.27
		C2	0.63	0.00%	4350.78	90.15	4275.00	89.86	1.25	4.75	75.78	0.29	1.50	2.00
		RC2	0.39	0.00%	3715.80	57.70	3543.75	57.05	1.00	3.00	172.05	0.65	3.00	3.25
AVG5	VRP		0.90	0.00%	5515.99	116.38	5515.99	116.38	1.48	6.50				
	RPD		0.10	0.00%	121.08	0.46					121.08	0.46	2.51	2.51
	VRP-D		0.62	0.00%	3808.50	70.85	3698.67	70.44	1.11	3.95	109.83	0.41	2.17	2.51

Table 3. Average numerical results for the instances with 10 customers considering the three transportation systems and the three classes of test problems when minimizing the transportation cost.

							Trucks				Drones			
$\|N\|$	Problem	Class	time	gap	$C(x,y)$	$g(z,x,y)$	$C^t(x)$	$g^t(z,x)$	#v	#arcs	$C^d(y)$	$g^d(y)$	#d	$\|N^d\|$
10	VRP	R2	218.34	0.01%	6945.45	166.03	6945.45	166.03	1.73	11.73				
		C2	51.49	0.00%	8300.00	174.56	8300.00	174.56	2.50	12.50				
		RC2	57.89	0.01%	9600.00	226.80	9600.00	226.80	1.63	11.63				
10	RPD	R2	0.95	0.00%	271.86	1.03					271.86	1.03	6.64	6.64
		C2	0.94	0.00%	354.45	1.34					354.45	1.34	6.50	6.50
		RC2	0.88	0.00%	410.47	1.55					410.47	1.55	7.25	7.25
10	VRP-D	R2	74.96	0.01%	4369.22	89.00	4122.73	88.07	1.55	5.82	246.49	0.93	5.73	6.64
		C2	20.44	0.01%	4763.66	86.38	4456.25	85.22	1.75	6.25	307.41	1.16	5.50	6.50
		RC2	43.74	0.01%	5575.58	104.49	5225.00	103.16	1.50	5.88	350.58	1.32	5.63	7.25
AVG10	VRP		109.24	0.01%	8281.82	189.13	8281.82	189.13	1.95	11.95				
	RPD		0.92	0.00%	345.59	1.30					345.59	1.30	6.80	6.80
	VRP-D		46.38	0.01%	4902.82	93.29	4601.33	92.15	1.60	5.98	301.49	1.14	5.62	6.80

Table 4. Average numerical results for the instances with 15 customers considering the three transportation systems and the three classes of test problems when minimizing the transportation cost.

							Trucks				Drones			
$\|N\|$	Problem	Class	time	gap	$C(x,y)$	$g(z,x,y)$	$C^t(x)$	$g^t(z,x)$	#v	#arcs	$C^d(y)$	$g^d(y)$	#d	$\|N^d\|$
15	VRP	R2	1164.93	1.22%	8527.27	209.05	8527.27	209.05	2.00	17.00				
		C2	334.99	0.65%	9818.75	215.77	9818.75	215.77	2.50	17.50				
		RC2	764.19	2.32%	12043.75	294.79	12043.75	294.79	2.25	17.25				
15	RPD	R2	6.03	0.00%	428.75	1.62					428.75	1.62	10.27	10.27
		C2	5.74	0.00%	568.17	2.14					568.17	2.14	10.63	10.63
		RC2	5.71	0.00%	612.05	2.31					612.05	2.31	10.75	10.75
15	VRP-D	R2	1181.05	10.20%	4796.08	97.67	4395.45	96.15	1.64	7.82	400.63	1.51	8.82	10.27
		C2	466.51	0.86%	5794.78	107.61	5312.50	105.79	1.75	7.50	482.28	1.82	9.25	10.63
		RC2	779.39	2.63%	7246.48	148.03	6718.75	146.04	1.75	8.00	527.73	1.99	8.75	10.75
AVG15	VRP		754.70	1.40%	10129.92	239.87	10129.92	239.87	2.25	17.25				
	RPD		5.83	0.00%	536.32	2.02					536.32	2.02	10.55	10.55
	VRP-D		808.98	4.56%	5945.78	117.77	5475.57	115.99	1.71	7.77	470.21	1.77	8.94	10.55

Table 5. Average numerical results over all instances considering the three transportation systems when minimizing the transportation cost.

						Trucks				Drones			
	Problem	time	gap	$C(x,y)$	$g(z,x,y)$	$C^t(x)$	$g^t(z,x)$	#v	#arcs	$C^d(y)$	$g^d(y)$	#d	$\|N^d\|$
AVG	VRP	288.28	0.47%	7975.91	181.79	7975.91	181.79	1.90	11.90				
	RPD	2.29	0.00%	334.33	1.26					334.33	1.26	6.62	6.62
	VRP-D	285.33	1.52%	4885.70	93.97	4591.86	92.86	1.47	5.90	293.84	1.11	5.57	6.62