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A new hybrid distribution paradigm: Integrating drones in medicines delivery

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ABSTRACT

This paper analyses a new hybrid paradigm resulting from the integration of unmanned aerial vehicles (UAV), commonly referred to as drones, in logistics and distribution processes. This work is motivated by a real application, where the company Connect Robotics, the first drone delivery provider in Portugal, made a partnership with a pharmacy located at a rural region to start implementing the delivery of medicines by drone. The pharmacy receives orders throughout the day and has to deliver in the same day with tight lead-times. The resulting problem is modelled as a Dynamic Parallel Drone Scheduling Vehicle Routing Problem with Lead-Time. A solution method is devised to solve it, thus helping the pharmacist to plan the car and drone delivery routes during the day. The results obtained on real instances revealed that the solution method is effective when compared to the optimal solutions of the static version of the problem, since the dynamic solution only differs, on average, about 7% from the static one. Moreover, some managerial insights about the impact of adding drones to the distribution operation are discussed, namely the economic and environmental impacts with cost savings up to 41% and reduction of monthly CO_2 emissions of 310 kg, the use of spare batteries which increase the benefit from 16% to 41%, and same-day versus next-day delivery.

1. Introduction

Unmanned aerial vehicles (UAV), commonly referred to as drones, have been growing rapidly in popularity while also breaking traditionally impenetrable barriers for technological innovation across different industries (Conceição, 2018). Although they are still in an early stage of mass adoption, drones' capability to reach remote areas autonomously with minimum effort, time and energy has been proven useful for various applications, from military to commercial sectors (Joshi, 2018). Consequently, drones were recognized as a disruptive technology (Bamburry, 2015).

One of the most promising applications for drones is the delivery of packages to previously hard-to-access areas, where they can improve lead times, decrease costs, and reduce CO_2 emissions. Additionally, recent technology advancements contribute to the feasibility of drone deliveries with longer flight times, automated navigation systems and improved payloads, which is the maximum amount of weight a drone can carry in addition to its weight (Shavarani et al., 2018). Hence, several delivery and logistics providers have already started to introduce this technology in their operations, such as DHL, SwissPost, Google and Amazon, either by developing their own drone technology or by partnering up with drone manufacturers (Dorling et al., 2017). However, the regulatory issues and the airspace management still represent a concern for the implementation of drone deliveries, which is being surpassed with the drafting of regulations across different countries and the development of Unmanned Traffic Management (UTM) platforms by several companies and associations to manage the increased presence of autonomous vehicles in the air, especially in cities (Mendes, 2017). Therefore, since the existing barriers are fading, there is a new distribution paradigm that must be studied.

Despite these advantages, there are still logistics challenges to be tackled in the implementation of a drone-based distribution operation, such as battery limitations (which limit flight times), low maximum payload, affected by adverse weather conditions. Therefore, a drone-only based distribution operation is not feasible for most companies. The research opportunity that we aim to explore in this work is the

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integration of drones in a medicines delivery system that currently serves remote areas using only cars. This work is motivated by a real application, where the company Connect Robotics, the first drone-delivery provider in Portugal, made a partnership with a pharmacy located in a rural region to start implementing the delivery of medicines by drone. This pharmacy delivers medicines to five nursing homes every day. However, this is a service that causes some problems in the pharmacy's daily operations. First, it requires an available car and an employee (pharmacist) leaving their station for a large portion of the day, meaning that the pharmacy will have one pharmacist less during the deliveries to the nursing homes. Second, rural travels on the mountain are very time-consuming even for small distances and, unfortunately, car accidents are not unprecedented either. Third, the orders are received along the day, each nursing home places multiple orders each day, and some of them are urgent, requiring sometimes multiple car trips per day, with the drawbacks mentioned before. Therefore, drone deliveries appear as a potential answer to these issues, but it requires tackling some logistics challenges brought by the drones' characteristics. The drones used by Connect Robotics can carry packages up to 3 kilos, the maximum flight time is 35 min, the recharge time for the battery is 1 h, it requires a landing site with at least 3 m^2 and the travelling speed is 40 km/h. Given the characteristics of this problem, where a new transportation mean (drone) with specific constraints will be added to the traditional road mean (car), coupled with non-regular requests from the nursing homes received throughout the day that must be fulfilled with tight lead-times, new models and solution approaches are demanded to support the day-by-day car and drone delivery planning. Consequently, the ambition of this work is to develop models that are able to support the day-by-day drone delivery planning and to analyse the impact of using drones as a complementary transportation mean for delivery of medicines. Therefore, our main contributions are as follows:

- First, we introduce a new variant of the vehicle routing problem in which cars and drones are combined to make same-day deliveries, complying with a maximum lead-time, and considering a dynamic/uncertain environment regarding the orders to be received throughout the day. The problem is named as Dynamic Parallel Drone Scheduling Vehicle Routing Problem with Lead-Time (D-PDSVRP-LT);
- Second, a mixed integer linear program (MILP) is proposed to formulate mathematically the static version of the problem (PDSVRP-LT), and it is embedded into a three-step solution approach to solve the dynamic version (D-PDSVRP-LT);
- Third, the solution approach is tested on real data instances, and by comparing the results from different versions of the problem (same-day *versus* next-day, one *versus* two drone batteries, static *versus* dynamic, only-car operation *versus* car + drone operation), useful managerial insights are retrieved to support the decision of delivering medicines by drones.

The paper is structured as follows. In Section 2, the relevant literature is presented. In Section 3, the D-PDSVRP-LT is described, and in Section 4 the solution method proposed to solve it is detailed. Section 5 presents the data and results of a proof-of-concept project to evaluate the potential benefit of integrating drones in the distribution of medicines to nursing homes in a rural area and discusses some managerial implications of adding drones to the traditional delivery operation. Section 6 concludes the paper and identifies some future research directions.

2. Literature review

Nowadays, the transportation industry is changing, and the key drivers of innovation are the new technologies. According to Speranza (2018), six technologies are contributing to innovation in the transportation industry: (a) autonomous vehicles, (b) electric vehicles, (c) connected vehicles, (d) collaborative consumption, (e) efficient multi-modal networks, (f) new materials. Another trend that is driving a shift in the landscape of the transportation and logistics industry is machine learning in delivery routes optimization. Logistics companies rely on route optimisation to make deliveries efficiently. Considering the trend for on-demand deliveries, these companies are now required to generate optimised routes faster to improve their speed and fuel consumption. Therefore, machine learning technologies can enable the aggregation and analysis of not only real-time data, like weather, traffic and construction delays, but also historical data regarding demand for deliveries and pick-ups (Zimberoff, 2018).

Different models are now being introduced to deliver parcels in the last-mile, and one of them is drone deliveries. According to Joerss et al. (2016), drones have two disadvantages. The first is the maximum payload. Even considering a raise in the payload limit to 15 kilos, a drone delivery operator would still require an alternative model to deliver the remaining items. The second is the area required for landing since current drones have significant size. Even small drones are difficult to land in tight urban areas. To diminish these disadvantages, drones should be used for delivering small parcels in rural areas. Moreover, delivering in rural areas within a specific time-window, or even in the same day, with other delivery models can be quite expensive due to the vast distances that have to be covered. Hence, drone delivery might as well be the only cost efficient or even feasible alternative to offer remote recipients high reliability and same-day deliveries. Overall, although the total distance traveled in a drone-only delivery system will likely be longer than in a truck-only delivery system due to the drone's limited payload, drones may be faster than trucks, have a lower cost per mile to operate, and emit less CO2. Thus, they represent a greener alternative to conventional delivery modes (Otto et al., 2018).

The acknowledgement of the potential advantages of employing drones in transportation have already generated considerable research efforts focused on operational planning challenges associated with drones. Most of these studies explore variants of the travelling salesman problem (TSP) and the vehicle routing problem (VRP). Otto et al. (2018) stated that the drone's related planning problems are manifold. The authors divided these problems into (1) drone-only operations (e.g., area coverage, search operations, routing for a set of locations, etc.) and (2) combined operations of drones and other vehicles. The latter is divided into four sub-classes, where the focus of this paper lies on the "Drone and Vehicles Performing Independent Tasks", i.e., without the need of synchronization. In Otto et al. (2018) survey, only six works were identified in this sub-class, and just four are related with delivery systems. In a recent survey, Macrina et al. (2020) identified five more works in the sub-class of problems without synchronization between trucks and drones, to which the work of Nguyen et al. (2021) has been recently added.

The TSP version of the problem was first studied by Murray and Amanda (2015). The authors faced a delivery problem with customers located in close proximity to a warehouse. Drones and a truck pick-up packages at the warehouse to deliver them to customers. Packages may be delivered either by drone, which transports a maximum of one package per sortie, or by truck, which can transport several packages but moves at a slower speed. The problem is named as parallel drone scheduling traveling salesman problem (PDSTSP). The objective is to determine the required number of drones and find tours for the truck and for the drones that minimize makespan. Only very small size-instances were solved through heuristics. Mbiadou Saleu et al. (2018) and Dell'Amico et al. (2020) focused on the same problem, and proposed heuristics and matheuristics that proved to be more efficient and effective than the methods proposed in the seminal work of Murray and Amanda (2015). Li et al. (2018) addressed the same problem, but considered multiple depots, while Schermer et al. (2020) combined the TSP with the location of drone stations.

The VRP version, where a fleet of trucks are available, was studied in the works of Ham et al. (2018), Ulmer and Thomas (2018) and Nguyen et al. (2021). Ham et al. (2018) considered drop and pickup features, and customer time-windows. Also, a multi-depot setting is studied. The authors proposed a constraint programming procedure to solve the problem. Ulmer and Thomas (2018) investigate the same-day delivery setting, in which randomly arriving customer orders should be accepted or declined for same-day delivery by the logistics provider. Deliveries can be performed either by vehicles or by drones. The solution method combines a parametric policy function approximation (PFA) to decide either drone or vehicle, a Markov decision-process model and an insertion heuristic for the routing problem. Nguyen et al. (2021) studied the min-cost Parallel Drone Scheduling Vehicle Routing Problem, where the authors consider multiple trucks, and the objective is to minimize the total transportation cost. A heuristic is proposed and tested in benchmarking instances, where some new best-known solutions are obtained.

A different objective function in a different problem context is presented by Fikar et al. (2016). The authors proposed a decision support system that simulates disasters and plans shipments of relief goods via transfer points to demand points in the affected area. This enables decision-makers to analyze the last-mile distribution of goods by scheduling and routing trucks, off-road, as well as UAVs. A mixed integer linear programming (MILP) formulation is presented, which minimises the average lead-time. The problem is solved through a heuristic procedure.

A multi-objective problem in a cross-docking environment is presented in Tavana et al. (2017). Drones may deliver orders directly from a supplier to a customer, but can carry only a very limited payload. As an alternative, trucks have a much larger carrying capacity, but they have to transport the orders indirectly via an interim warehouse, called cross-dock, where goods are unloaded, re-bundled into vehicle loads based on their destination, and loaded onto new vehicles, which takes much time because of the reloading of the goods and the limited capacity of the cross-dock. Two objective functions are considered: cost minimization and delivery time minimization. The Epsilon-Constraint method is applied to solve the multi-objective problem. A very small instance is solved with 3 suppliers and 3 customers.

Although the problem without synchronization is getting more attention from the academy in the recent years, it is receiving less interest when compared with the problem with synchronization (e.g., Salama and Srinivas (2020), Murray and Raj (2020), Dayarian et al. (2020), Thomas et al. (2022)). This imbalance can be observed from the surveys of Otto et al. (2018) and Macrina et al. (2020). It is worth to mention the work of Jackson and Srinivas (2021), where the delivery of medicines by drone is explored by discrete event simulation over three delivery-mode scenarios: truck-only, drone-only, and truck-drone tandem. Here, drones and trucks work independently but not in parallel. Since the focus of this paper is on the problem without synchronization, where vehicles and drones work in parallel, we will not further discuss the problems with synchronization.

Following the classification made in the survey of Macrina et al. (2020), Table 1 summarizes the works where vehicles and drones work independently (without synchronization). It can be observed that customer time window, customer lead-time and drop and pickup operations are very seldom studied. Moreover, capacity constraints (for truck or drone) are not considered by a large part of the works, and only one work considers a dynamic framework. In addition, the great majority of the papers tested the models and solution methods proposed only in literature instances, where real instances are only considered in one work. Our work contributes to fill some of these gaps by considering some real features like customer lead-time, capacity constraints, and tackles a dynamic environment. Moreover, a real application triggered this work, where real data was used to test the solution methodology proposed and to get managerial insights regarding this new distribution paradigm, where medicines can be delivered by drones.

3. Problem description

The Dynamic Parallel Drone Scheduling Vehicle Routing Problem with Lead-Time is an extension of the PDSTSP introduced by Murray and Amanda (2015). In the PDSTSP, given a set of requests $i \in R$, three decisions must be taken: i) which transportation mean should serve each order (car or drone), ii) which is the visit sequence (for the car route), and iii) when each order must be served. In the Dynamic PDSVRP with Lead-Time (D-PDSVRP-LT), a dynamic environment is addressed, where orders are received throughout the day from multiple customers (and even the same customer sends multiple orders throughout the day) and must be delivered on that same day with tight lead-times. Therefore, a decision must be made each time an order is received: should we wait for receiving more orders and deliver later, or should we fulfil the order right now using either car or drone? Moreover, in the D-PDSVRP-LT,

Table 1

Summary of the main features of contributions where vehicles and drones work independently (without synchronization).

Reference	# Drones	# Trucks	# Depots	Objective Function	T-W	Lead-Time	Drop-Pick up	Drone Capacity	Trucks Capacity	Dynamic	Instances
Murray and Amanda (2015)	n	1	1	Makespan	No	No	No	No	No	No	Literature (up to 10 cust.)
Fikar et al. (2016)	n	n	n	Average Lead-Time	No	Yes	No	No	No	Yes	Real (up to 58 requests)
Tavana et al. (2017)	n	n	n	Multi-Objective (Completion Time and Operations Costs)	No	No	No	No	Yes	No	7 instances (with 3 customers)
Ulmer and Thomas (2018)	n	n	1	Expected number of customers served	No	No	No	No	No	Yes	Literature (up to 800 requests)
Mbiadou Saleu et al. (2018)	n	1	1	Completion Time	No	No	No	No	No	No	Literature (up to 229 cust.)
Li et al. (2018)	1	1	n	Operations Costs	No	No	No	No	No	No	Literature (up to 20 customers)
Ham (2018)	n	n	n	Makespan	Yes	No	Yes	No	No	No	Literature (up to 100 customers)
Schermer et al. (2020)	n	1	n	Makespan	No	No	No	No	No	No	Literature (up to 50 customers)
Dell'Amico et al. (2020)	n	1	1	Completion Time	No	No	No	No	No	No	Literature (up to 229 customers)
Nguyen et al. (2021)	n	n	1	Operations costs	No	No	No	Yes	Yes	No	Literature (up to 400 customers)
This Paper	**n**	**n**	**1**	**Operations Costs**	**No**	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**Real (up to 30 requests)**

multiple car and drone trips are allowed, meaning that for the drone case, the battery recharge time must be taken into consideration for scheduling purposes.

The same-day delivery assumes that all requests received at day t must be satisfied within the same day, with a maximum lead-time. This means that vehicle allocation (either car or drone) and routes must be scheduled by taking into account a maximum waiting period for the customer between ordering and receiving the medicines. For example, given a lead-time of 3 h, if a request is received by the pharmacy at 10 a.m., it must be delivered before 1 p.m. Since the demand is uncertain, with no pattern, this means that making the decision on when to send a car or a drone to serve a certain customer becomes more difficult, because the pharmacy does not know if more orders from the same customer will arrive or if a nearby customer will also send additional orders throughout the day. For example, if by 11 a.m. an exit from the pharmacy is scheduled to make a delivery to customer 1 (who had placed an order of 3 units by then), and if by 1 p.m. an order for 6 additional units has arrived from the same customer, then if the delivery was scheduled to start after 1 p.m. a trip would have been spared.

The problem can be stated as follows. A single car with capacity QC and a single drone with capacity QD are available at the depot location (the pharmacy). Both means of transportation can do multiple trips per day to deliver medicines to a set of customers $c \in H$ (nursing homes) to fulfil a set of requests R (recipes) that are ordered throughout the day. The car workday is made up of a set of car trips $C = \{1, \cdots, w\}$ and the drone workday is made up of a set of drone trips $D = \{1, \cdots, g\}$. We assume that both car and drone trips are performed in the order $1, 2, \ldots, w$ and $1,2, \ldots, g$, respectively. The drone battery recharge time is given by B and the number of available spare batteries is given by Ω. These parameters will dictate the time elapsed between two consecutive drone trips. Each request $i \in R$ is characterized by a release time s_i, that indicates the time in which a request is received by the pharmacy, a quantity demanded q_i, that indicates the number of units ordered, a service time p_i, that accounts for the time spent at the nursing home to deliver the medicines, and a maximum lead-time l_i, that represents the maximum time to fulfil each request. If a request is urgent, then it must be delivered in a short period of time, i.e., within a short lead-time. The sub-set $R_c \subseteq R$ represents the requests by customer c. The goal is to determine the car trips and drone trips and schedule them to meet the maximum lead-time of each order in order to minimize the transportation cost. The transportation cost corresponds to the fuel cost for the car trips plus the energy cost for the drones' trips.

4. Solution approach for the dynamic parallel drone scheduling vehicle routing problem with lead-time

The solution approach devised to tackle the Dynamic PDSVRP with Lead-Time is made up by three main modules (see Fig. 1): 1) Decision-Moments, where it is identified which are the moments when the Deliver or Wait decision must be made, e.g., every time an order arrives, on an hourly basis, three times per day, etc.; 2) Decision-Making, where for each decision moment, and for each order received until that moment, the Deliver or Wait decision is made; and 3) Routing & Scheduling, where the orders whose decision was Deliver are assigned to a transportation mean, and the visit sequence is defined and scheduled.

4.1. Module 1: Decision-moments

Decision moments are time instants during the day when the pharmacy needs to decide if the orders received until then should either be delivered now or wait for the next decision moment. The time interval between decision moments is called shift. The number of decision moments could vary from each time an order is received (i.e., the maximum number of decision moments is equal to the number of orders received in a day) to the ratio between the workday duration and the lead-time (i.e., if the workday duration is equal to 10 h, and the lead-time is equal to 5 h, the minimum number of decision moments is equal to two). In between, another event should be taken into account to decide the number of decision moments: a drone is available to start a trip. Each time a drone trip is available also influence the number of decision moments (and when they occur). To this end, the battery duration, the recharge time, and the number of spare batteries must be considered. Note that a decision-moment implies that the decision maker runs the algorithm (Modules 2 and 3, see Fig. 1), then the car and/or drone are loaded, and the deliveries are performed. Therefore, too many decision-moments would imply a too large effort from the decision-maker, and too many interruptions on his/her normal activity at the pharmacy. Hence, the number of decision moments should be tested starting from the minimum number, and gradually increasing that number according to drone availability until an appropriate value from an operational point of view is reached.

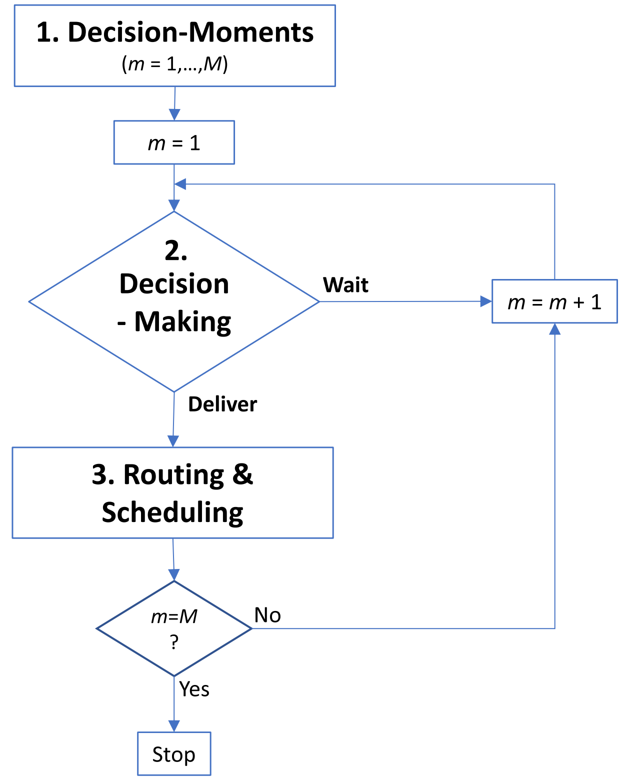

Fig. 1. Overview of the solution approach.

To schedule the potential decision moments (where φ_m stands for schedule time of decision moment m) we start from defining when the last moment should occur (φ_M), in order to be able to deliver the requests before the end of the day (T). To this end, the maximum duration between the longest car drive, i.e., the shortest car route that visits all customers, and the longest drone trip, i.e., the drone trip to the farthest customer, is determined. Therefore, the last moment is defined as T − max {longest car drive + loading time + service time × |H|; longest drone trip + loading time + service time}. All other moments are scheduled starting from the last one accordingly with drone availability.

For each shift, the general objective is to maximize the number of drone trips. Thus, we backtrack from the last moment, considering the battery recharge time, the longest drone trip (including loading and service time) as the battery duration (to be conservative), and the number of spare batteries available. After all the possible decision moments are defined, different options regarding the number of decision moments can be considered, and for each number different schedules can be defined (this is illustrated in Fig. 2).

In Fig. 2 is given an illustrative example where the workday duration is 10 h (600 min), from 9 am until 7 pm, and the lead-time is 4 h (240′).

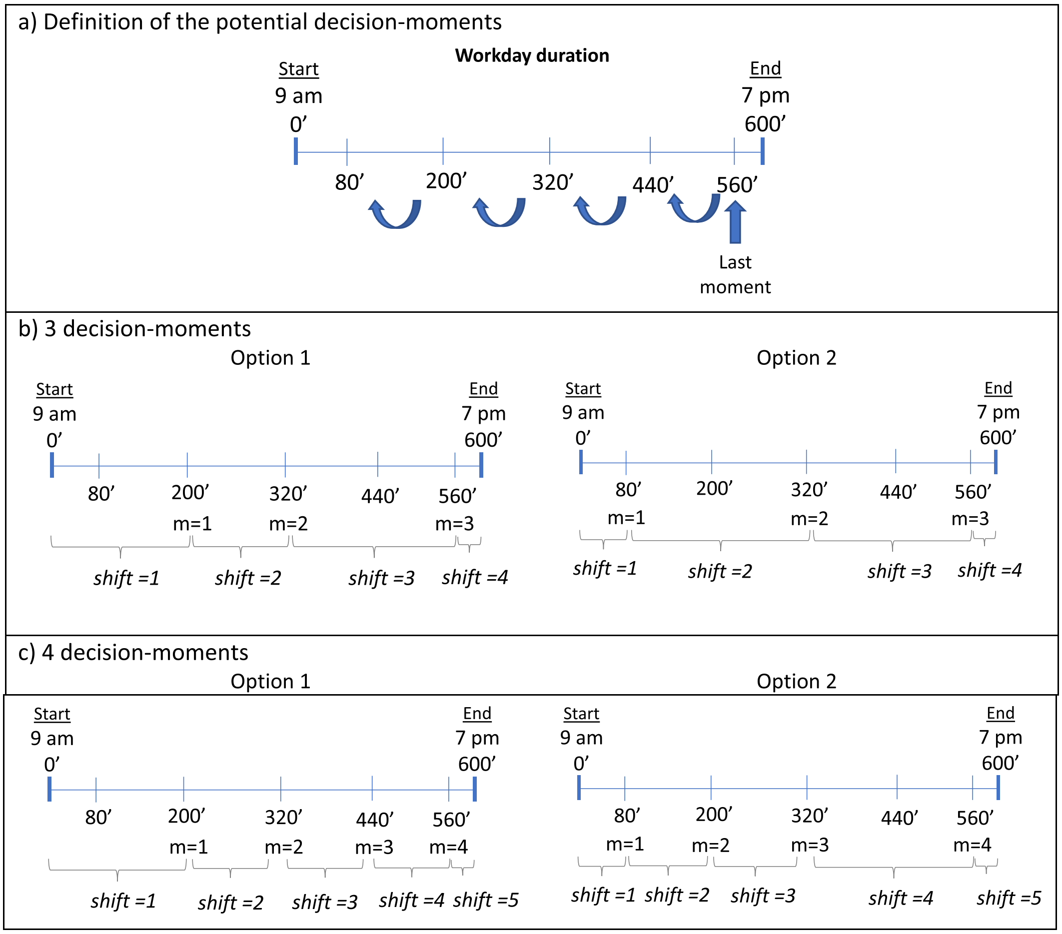

Fig. 2. Illustrative example of the definition of the decision-moments.

In Fig. 2a) the potential decision-moments are defined considering the last moment and going backward by considering a battery recharge time plus the longest drone trip of 120 min (no spare batteries are available in this example). Given the minimum number of decision moments equal to 3 ($600/240 = 2.5$), Fig. 2b) shows two possible options to schedule the 3 decision moments ($Option1 : \varphi_1 = 200^{'}, \varphi_2 = 320^{'}, \varphi_3 = 560^{'}$, $Option2 : \varphi_1 = 80^{'}, \varphi_2 = 320^{'}, \varphi_3 = 560^{'}$). Fig. 2c) shows two possible solutions when considering 4 decision-moments.

All orders received until each decision-moment are subject to the decision-making module (Module 2).

4.2. Module 2: Decision-making

At each decision moment, a decision must be made: either to deliver now all the orders received so far or deliver partially, or wait for more orders to arrive and deliver at the next moments. Since the drone trips have a much lower cost than the car, the goal is to send the maximum possible number of requests by drone. An algorithm was devised to solve Module 2 (see Fig. 3).

Each order i from customer c ($i \in R_c$) can be categorized into four types: i) mandatory car order, ii) mandatory drone order, iii) optional car order, iv) optional drone order. If they break the lead-time constraint $(\varphi_{m+1} + t_{ij} + U - s_i \geq l_i)$, then they are mandatory, otherwise they are optional; if they fit the drone capacity ($q_i \leq QD$), then they are drone orders, otherwise they are car orders. Note that although the former are here defined as drone orders, the transportation mean for those orders is decided within Module 3. Mandatory orders always have to be delivered in the current decision-moment. However, if a customer has a mandatory car order, then, to save trips, all this customer's current orders are delivered too.

If a customer has an optional car order, then the decision is to wait, because this means that a trip by car to that customer will be made, so it can encompass more orders that will possibly appear in the future. If a customer has an optional drone order, it is put on a list of optional drone orders (Conditional Delivery). Conditional Delivery means that after checking all customer's orders, if the mandatory drone orders are less than the drone trips available for that shift, some or all optional drone orders can be delivered now. If the optional drone orders are less than or equal to the remaining drone trips available, all optional drone orders are delivered. Otherwise, we have to choose which optional drone orders should be delivered sorting the customers by a priority coefficient. This procedure uses past data to determine which customer usually makes more car orders. To this end, past data is aggregated by customer and by shift. All the customer's orders in a shift that have $q_i > QD$ are added, and then divided by the number of days this customer makes orders. Then they are sorted by increasing values of this coefficient. Meaning that the first customer usually makes less of car orders, and so forth. This is to give drone usage priority to the customers that are more likely to be able to receive all their orders by drone, therefore saving a car trip. While preserving this order, first, it is checked if the customer has a current total number of optional drone orders smaller than or equal to the current drone trips available. In other words, if all current orders of this customer can be delivered by drone, then the decision is to deliver them and to subtract the number of drone trips from the current available ones. Otherwise, we move on to the next customer until either the customers are all served, or all drone trips are used. If this process ends and there are still drone trips available, then use them all to send the orders belonging to the customer with highest priority. All other orders

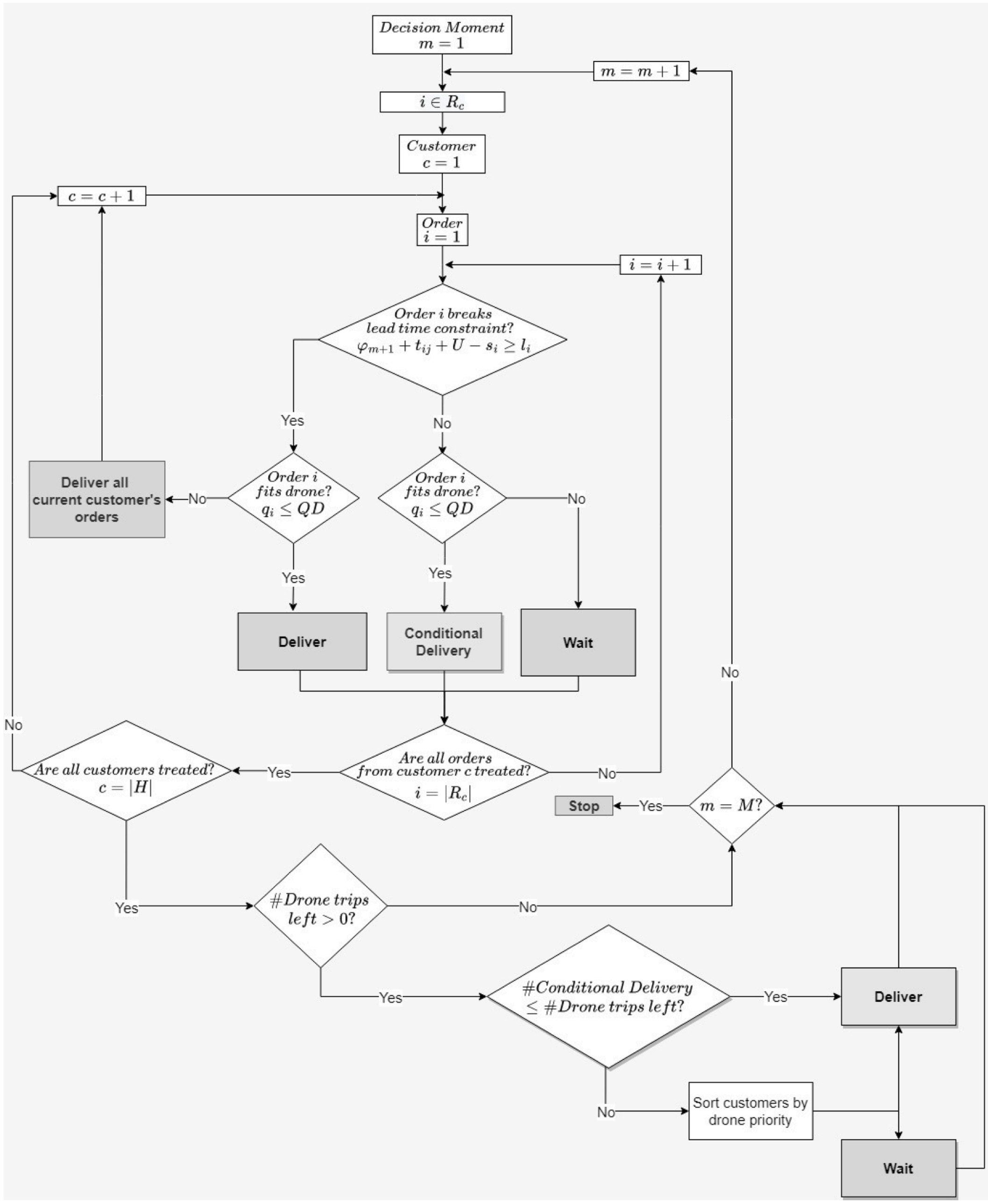

Fig. 3. Flowchart of Module 2.

are delayed.

4.3. Module 3: Routing & scheduling

When the decision is to Deliver, the delivery routes must be planned and performed. In this module, the PDSVRP with maximum lead-time is solved, considering the set of requests whose decision is "Deliver" from the previous module. Note that this set of requests is given as an input, and it is the model that decides the transportation mean, route sequence and scheduling that minimizes the transportation cost. Even if in the analysis of the previous module an order could be delivered by drone ($q_i \leq QD$), the decision taken by this module could be to deliver it by car, since here also other orders from a nearby customer are considered.

The problem is defined on a complete directed graph $G = (V, A)$ with arcs $(i, j) \in A$ and vertices $V = \{1, \cdots, n+2w\}$. Although a single physical depot location exists, we assign it to two unique sets of depots: the departure depots and the arrival depots, where each car trip starts at a unique departure depot and ends at a unique arrival depot. Therefore, the single physical depot location is replicated as many car trips exists, i.e., w. Thus, $V = V_d \cup R \cup V_f$, where $V_d = \{1, \cdots, w\}$ are the set of departure depots, $R = \{w+1, \cdots, w+n\}$ are the set of requests and $V_f = \{w+n+1, \cdots, n+2w\}$ are the set of arrival depots. A car travel time t_{ij} is associated with every arc $(i, j) \in A$.

The mathematical formulation for the PDSVRP with maximum lead-time is given below.

Sets

- Set of nodes $V = \{1, 2, \ldots, w, w+1, \ldots, w+n, w+n+1, \ldots, n+2w\}$
  - o Sub-set of departure depots $V_d \subseteq V$, $V_d = \{1, 2, \ldots, w\}$
  - o Sub-set of requests nodes $R \subseteq V$, $R = \{w+1, w+2, \ldots, w+n\}$
  - o Sub-set of arrival depots $V_f \subseteq V$, $V_f = \{n+w+1, n+w+2, \ldots, n+2w\}$
- Set of car trips $C = \{1, 2, \ldots, w\}$

- Set of drone trips D = {1, 2, …, g}
- Set of departure depots plus requests $V^{+} = V_d \cup R$
- Set of requests plus arrival depots $V^{0} = V_f \cup R$

Parameters

- q_i quantity demanded by request $i \in R$ (in units)
- s_i release time of request $i \in R$ (in minutes)
- l_i maximum lead-time of request $i \in R$ (in minutes)
- p_i service time of request $i \in R$ (in minutes)
- t_{ij} travel time by car from node $i \in V^{+}$ to node $j \in V^{-}$ (in minutes)
- d_i travel time by drone to request $i \in R$ (in minutes)
- $m_{ik} = 1$ if car trip $k \in C$ corresponds to depot $i \in V_d \cup V_f$
- QC car capacity (in units)
- QD drone capacity (in units)
- U loading/unloading time (in minutes)
- B Battery recharge time (in minutes)
- T duration of a working day (in minutes)
- α car travel cost per minute (in euros)
- β drone travel cost per minute (in euros)
- M Big enough number

Variables

x_{ijk} binary variable that is equal to 1 if node j is visited after node i by car trip k ($i \in V^{+}, j \in V^{0},\ k \in C$)

y_{ij} flow variable ($i,j \in V$)

b_{ik} binary variable that is equal to 1 if request i is visited by car trip k ($i \in R$, $k \in C$)

e_i fulfilment time of request i served by car ($i \in R$)

e_j start time of car trip k ($j \in V_d$, $m_{jk} = 1$)

$e_{j'}$ end time of car trip k ($j' \in V_f$, $m_{j'k} = 1$)

δ_{ih} binary variable that is equal to 1 if order i is visited by drone trip h ($i \in R$, $h \in D$)

τ_{ih} fulfilment time of request i by drone trip h ($i \in R$, $h \in D$)

γ_k binary variable that is equal to 1 if car trip k is used ($k \in C$)

Model

$$\min \mathbb{C} = \alpha \sum_{i \in V^{+}} \sum_{j \in V^{0}} \sum_{k \in C} x_{ijk} t_{ij} + \beta \sum_{i \in R} \sum_{h \in D} 2 d_i \delta_{ih} \tag{1}$$

s.t.

$$\sum_{k \in C} b_{ik} + \sum_{h \in D} \delta_{ih} = 1,\ i \in R \tag{2}$$

$$\sum_{\substack{j \in V \\ j \neq i}} (y_{ji} - y_{ij}) = q_i \sum_{k \in C} b_{ik},\ i \in R \tag{3}$$

$$\sum_{i \in V_d} \sum_{j \in R} y_{ij} = \sum_{j \in R} q_j \sum_{k \in C} b_{jk} \tag{4}$$

$$\sum_{j \in R} \sum_{i \in V_d} y_{ji} \leq wQC - \sum_{j \in R} q_j \sum_{k \in C} b_{jk} \tag{5}$$

$$\sum_{i \in V_f} \sum_{j \in R} y_{ij} \leq wQC \tag{6}$$

$$\sum_{\substack{j \in V \\ i \neq j}} x_{ijk} + \sum_{\substack{j \in V \\ i \neq j}} x_{jik} = 2 b_{ik},\ i \in R,\ k \in C \tag{7}$$

$$y_{ij} \leq QC \sum_{k \in C} x_{ijk},\ i,j \in V,\ i \neq j \tag{8}$$

$$b_{ik} = \sum_{j \in V} x_{ijk},\ i \in V, k \in C \tag{9}$$

$$\sum_{i \in V_d} \sum_{j \in R} x_{ijk} \leq 1,\ k \in C \tag{10}$$

$$\sum_{j \in V} x_{ijk} = 0,\ i \in V_d,\ k \in C:\ m_{ik} = 0 \tag{11}$$

$$\sum_{i \in V} x_{ijk} = 0,\ j \in V_f,\ k \in C:\ m_{jk} = 0 \tag{12}$$

$$\sum_{j \in V} x_{ijk} \leq 1,\ i \in V_d,\ k \in C:\ m_{ik} = 1 \tag{13}$$

$$\sum_{i \in V} x_{ijk} \leq 1,\ j \in V_f,\ k \in C:\ m_{jk} = 1 \tag{14}$$

$$\sum_{j \in R} \sum_{k \in C} x_{ijk} \leq 1,\ i \in V_d \tag{15}$$

$$\sum_{j \in R} \sum_{k \in C} x_{jik} \leq 1,\ i \in V_f \tag{16}$$

$$\sum_{i \in R} b_{ik} \leq n\gamma_k,\ k \in \mathrm{C} \tag{17}$$

$$\gamma_k \leq \sum_{i \in R} b_{ik},\ k \in \mathrm{C} \tag{18}$$

$$\gamma_k \geq \gamma_{k+1},\ k = 1, \cdots, w-1 \tag{19}$$

$$e_i + p_i + t_{ij} - M\left(1 - \sum_{k \in C} x_{ijk}\right) \leq e_j,\ \ i \in V^{+}, j \in V^{0}, i \neq j \tag{20}$$

$$e_j \geq (s_i + U) b_{ik},\ j \in V_d,\ i \in R,\ k \in C: m_{jk} = 1 \tag{21}$$

$$e_i \leq e_{i-n-w+1},\ i = n+w+1, \cdots, n+2w-1 \tag{22}$$

$$e_i \leq (s_i + l_i) \sum_{k \in C} b_{ik},\ i \in R \tag{23}$$

$$e_i \leq T,\ i \in V_f \tag{24}$$

$$\sum_{i \in R} \delta_{ih} q_i \leq QD,\ h \in D \tag{25}$$

$$\sum_{i \in R} \delta_{ih} \leq 1,\ h \in D \tag{26}$$

$$\sum_{i \in R} \delta_{ih} \geq \sum_{i \in R} \delta_{ih+1},\ h = 1, \cdots, g-1 \tag{27}$$

$$\tau_{ih} + p_i + B + d_i \delta_{ih} + U + d_j \delta_{jh+1} \leq \tau_{jh+1} + M\left(1 - \delta_{jh+1}\right),\ i,j \in R, h \in D \tag{28a}$$

$$\tau_{ih} + p_i + d_i \delta_{ih} + U + d_j \delta_{jh+1} \leq \tau_{jh+1} + M\left(1 - \delta_{jh+1}\right),\ i,j \in R, h \in D \tag{28b}$$

$$\tau_{ih} + p_i + B + d_i \delta_{ih} + U + d_j \delta_{jh+2} \leq \tau_{jh+2} + M\left(1 - \delta_{jh+2}\right),\ i,j \in R, h \in D \tag{28c}$$

$$\tau_{ih} \geq (s_i + U) \delta_{ih} + d_i \delta_{ih},\ i \in R, h \in D \tag{29}$$

$$M \delta_{ih} \geq \tau_{ih},\ i \in R, h \in D \tag{30}$$

$$\tau_{ih} \leq s_i + l_i,\ i \in R, h \in D \tag{31}$$

$$\tau_{ih} \leq T - d_i,\ i \in R,\ h \in D \tag{32}$$

$$x_{ijk} \in \{0,1\},\ i,j \in V, k \in C \tag{33}$$

$$b_{ik} \in \{0,1\},\ i \in V, k \in C \tag{34}$$

$$y_{ij} \geq 0, \ i,j \in V \tag{35}$$

$$\delta_{ih} \in \{0,1\}, \ i \in R, \ h \in D \tag{36}$$

$$e_i \geq 0, \ i \in V \tag{37}$$

$$\tau_{ih} \geq 0, \ i \in R, \ h \in D \tag{38}$$

$$\gamma_k \in \{0,1\}, \ k \in C \tag{39}$$

The objective function (1) is to minimize transportation cost. The first part corresponds to fuel cost when requests are served by car trips. The second part corresponds to energy cost when requests are served by drone trips. Equations (2) ensure that each request must be served either by car or by drone. Constraints (3) to (24) are related with car trips, while constraints (25) to (32) are related with drone trips.

Constraints (3) ensure that if request *i* is served by car trip *k*, then the inflow minus the outflow of request *i* is equal to its demand. Constraints (4) to (6) model the flows from/to the departure/arrival depots. Constraints (4) ensure that the total outflow from the departure depot is equal to the total demand that is served by car trips. Constraints (5) impose that the total inflow to the departure depot must be less or equal than the residual capacity of the car trips. Constraints (6) ensure that the total outflow from the arrival depot must be less or equal than the total capacity of the car trips. Constraints (7) impose that if request *i* is served by car trip *k*, there must be an arc entering and an arc leaving request *i*. Constraints (8) state that the flow of arc (i,j) must be lower than or equal to the car capacity if that arc is transversed. If node i is visited by car trip k, then the variable b_{ik} takes the value 1 (Constraints (9)). Constraints (10) ensure that each car trip can departure at most once from the departure depot. Constraints (11) to (14) link the car trip *k* to the corresponding departure and arrival depot. Constraints (15) and (16) ensure that each departure and arrival depot are used at most once. Constraints (17) to (19) impose that the car trips must be in order. Constraints (20) to (24) model the time constraints. Constraints (20) guarantee the arrival time of request *i* plus the service time plus the traveling time from *i* to *j* is equal to the arrival time of request *j*. Constraints (21) ensure that the start time of car trip *k* must be higher than or equal to the release time of the requests belonging to that car trip. Constraints (22) guarantee that the start time of the next car trip must be higher than the end time of the previous car trip. The maximum lead-time of each request is ensured by constraints (23) and the total duration of a workday by constraints (24).

Drone capacity is ensured by constraints (25). Constraints (26) guarantee that each drone trip serves at most one request. Constraints (27) imply that drone trips must be in order. Constraints (28) set the start time of the drone trips taken into account the number of batteries available. If only one battery is available (28a), the arrival time of request *j* by drone trip $h + 1$ is equal to the arrival time of request *i* by drone trip *h* plus the service time plus the traveling time to the depot plus the battery recharge time plus the loading time plus the travelling time to request *j*. If a spare battery is available (i.e., two batteries are available in total), then drone trip $h + 1$ can start after drone trip *h* has finished (constraint 28 b), but trip $h + 2$ must lag the battery recharge time from trip *h* (constraint 28 c). Constraints (29) ensure that the arrival time to request *i* by drone trip *h* must be equal or greater than the release time plus the loading time plus the travelling time. Constraints (30) imply that the arrival time variable only takes values if request *i* is served by drone trip *h*. The maximum lead-time of each request is ensured by constraints (31) and the total duration of a workday by constraints (32). Finally, constraints (33) to (39) specify the decision variable domains.

5. Proof-of-Concept

In this section we present the results of a proof-of-concept project to evaluate the potential benefit of integrating drones in the distribution of medicines to nursing homes in a rural area.

5.1. General description

Farmácia da Lajeosa, a pharmacy located in the district of Viseu, serves the population of the parish of Lajeosa do Dão but also some nearby populations. Nowadays, the pharmacy is testing drones to deliver medicines in the region, to offer a better response to the needs of the most isolated populations.

In addition to over-the-counter sales, the pharmacy offers two types of services to the nursing homes: punctual delivery of medicines and weekly deliveries. Punctual deliveries of medicines, which are the focus of this study, are made on the same day they are ordered and includes medication that users have started taking due to changes in medication or detection of new diseases, and it may be urgent or not. If urgent, it may be necessary to carry out the delivery immediately. The punctual orders are communicated to the pharmacy either by phone or by email, where the name of the nursing home, as well as the user, the medicine and the respective dosage are transmitted. Subsequently, the pharmacist registers the order in the database and proceeds to prepare it. Currently, punctual visits take place around 4 pm, therefore all orders placed up to that time are answered on the same day, unless there is no medicine in stock. As a rule, requests that arrive after that time are only fulfilled on the next day, except rare situations of high urgency (Sismeiro, 2021). Moreover, the pharmacy intends to deliver all orders within 5 h, which is currently impossible given that only one deliver per day (around 4p.m.) is performed.

The pharmacy supplies five nursing homes, which are scattered throughout the Lajeosa do Dão region (see Fig. 4) from Monday to Saturday.

The current service is performed by car using the personnel of the pharmacy. Due to the relatively long distances, the irregularity of the demand and the conflict on the use of personnel from the pharmacy to perform the delivery duties, in many cases delays and postponement to the next day of the deliveries are observed. Therefore, the pharmacy started using drones to perform occasional delivery tasks. The aim of this proof-of-concept is to evaluate the potential of drone deliveries when the service is planned by using structured routing and scheduling techniques.

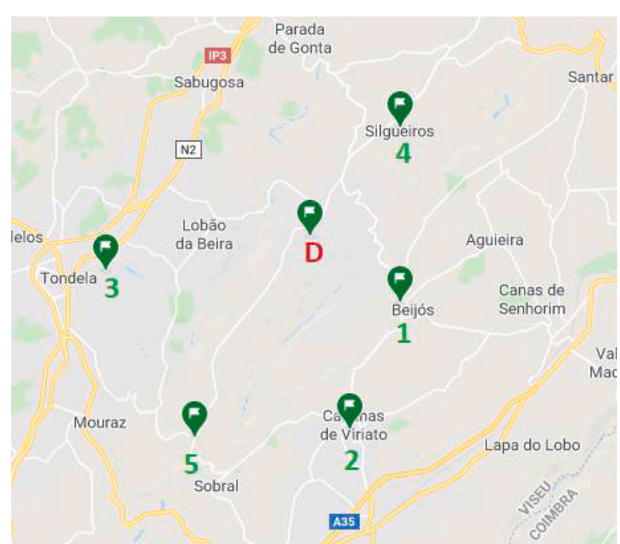

Fig. 4. Location of the nursing homes (numbered from #1 to #5) and Farmácia da Lajeosa (signed with a D). Retrieved from Google Maps (2020).

5.2. Data

The pharmacy provided data of the requests received from nursing homes #1 to #5 from January 2018 until June 2018 (151 days), where a total of 14 527 recipes were received, corresponding to 15 891 units ordered. The distribution of the order quantity for the 5 nursing homes is given in Fig. 5. Nursing home #2 is the one which orders the larger quantity of medicines, while nursing home #1 orders less.

To test our approach and be able to discuss some managerial insights regarding this new distribution paradigm, the data provided was divided into two subsets: a learning set that will be use to “learn” how orders behave and calculate the priority coefficient (Module 2); and a testing set, where the whole solution approach is going to be applied and the results compared with the current solution (where the deliveries are made only by car). The learning period consists of the first 120 days of data (it represents approximately 80% of the whole data set), and the testing period consists of the remaining 31 days (from day 121 to day 151).

The parameter’s values considered are shown in Table 2.

The car travel cost per minute (α) considers an average car’s consumption of 6 L per 100 km and the average cost of fuel in Portugal of 1.65€ per litre and an average speed of 60 km per hour. Note that only the fuel cost is being pondered, thus representing a conservative approach, since the car travel cost should also account for the labour cost regarding the pharmacist that drives the car to make the deliveries. Moreover, the fuel consumption and the average speed considered are optimistic taken into account the type of roads involved, again leading to a very conservative approach.

The drone travel cost per minute (β) considers that a regular drone battery usually has a voltage of 11.1 V and an approximate capacity to store energy of 5200 mAh, which allows for a maximum flight time of 35 min. Conversely, this battery requires a power of 57.72 Wh to recharge fully. According to official statistics, the cost of electricity in Portugal is around 0.20€ per kWh. Consequently, the battery costs 0.0115 € in Portugal to be recharged to its maximum capacity (PORDATA, 2018). Since the battery duration is 35 min, the energy cost per minute is 0.0003286 €.

The drone routes require ANAC approval, so for the approved routes, the distances from the nursing homes to the pharmacy are shown in Table 3. Considering a speed of 40 km/h, the expected flight time is determined.

The travel time by car (t_{ij}) was retrieved from Google Maps (see Table 4).

5.3. Settings

- Number of drone batteries

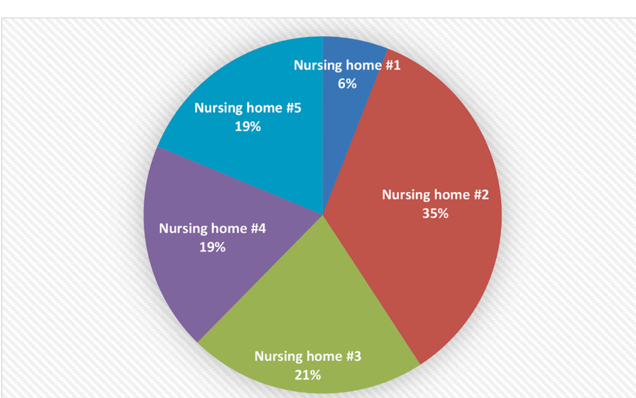

Fig. 5. Distribution of the order quantity by nursing home in 151 days.

Table 2
Parameter’s values for the testing set.

Parameters	Value
QC Car capacity	90 units
QD Drone Capacity	7 units
U Loading time	5 min
B Battery recharge time	60 min
T Working day length	660 min (from 9 am to 8 pm)
l_i *Lead-Time (equal to all requests i)*	300 min (5 h)
p_i *Service time (equal to all requests i)*	2 min
α *car travel cost per minute*	0.1 €/minute
β *drone travel cost per minute*	0.0003286€/minute

Table 3
Distance and travel time for drone trips to visit each nursing home.

Nursing Homes	#1	#2	#3	#4	#5
Distance to Pharmacy (km)	3.77	5.98	6.28	4.22	7.63
Travel time by drone (m)	6	9	10	7	12

Table 4
Travel time by car.

	#1	#2	#3	#4	#5
Pharmacy	14	20	19	6	12
#1	–	6	29	12	15
#2		–	28	18	10
#3			–	23	19
#4				–	19

The number of batteries available will dictate the number of potential drone trips. A battery has a capacity of 35 min. The shortest drone route is to nursing home #2, with 12 min (round-trip), plus the service time of 2 min. The longest drone route is to nursing home #5, with 24 min, plus the service time of 2 min. From a conservative perspective, the pharmacy intends that after a drone trip, the battery should be recharged. The recharge time is 60 min. If a spare battery is available, after the first drone trip, a second one can be made right after, by replacing the used battery by a fully recharge one. Therefore, it will be tested the existence of 1 spare battery (meaning that 2 batteries are available), and the no existence of a spare battery (meaning that only 1 battery is available).

- Decision-moments

The minimum number of decision-moments is three since the workday has 660 min, and the maximum lead time is 300 min. To define all possible decision-moments taken into account the drone’s trip availability, we apply the procedure mentioned at Section 3.2, considering that one or zero spare battery are available.

We start by defining when the last decision-moment must be scheduled, in order to be able to deliver the orders before the end of the day (8:00 p.m., 660 min). Considering that the longest car drive is 72 min, passing through all 5 customers, plus 2 min of service time per customer and 5 min to load the car, the total time of delivery is 87 min. So, 660 min–87 min = 573 min (6:33 p.m.). This means that 6:33 p.m. is the last decision-moment. All other decision-moments are backtracked from the last one, considering the battery recharge time plus the longest drone trip, to be conservative. The battery recharge time is 60 min, and the longest drone trip is 24 min of travel time, 5 of loading time and 2 of service time which equals a total of 31 min. When only 1 battery is available (zero spare batteries), the possible decision-moments are identified at Fig. 6a). When 2 batteries are available (one spare battery), the possible decision-moments are identified at Fig. 6b).

Since only 11% of the orders are received in the first two hours (from 9 a.m. to 11 a.m., see Fig. 7), we decide that the first decision moment

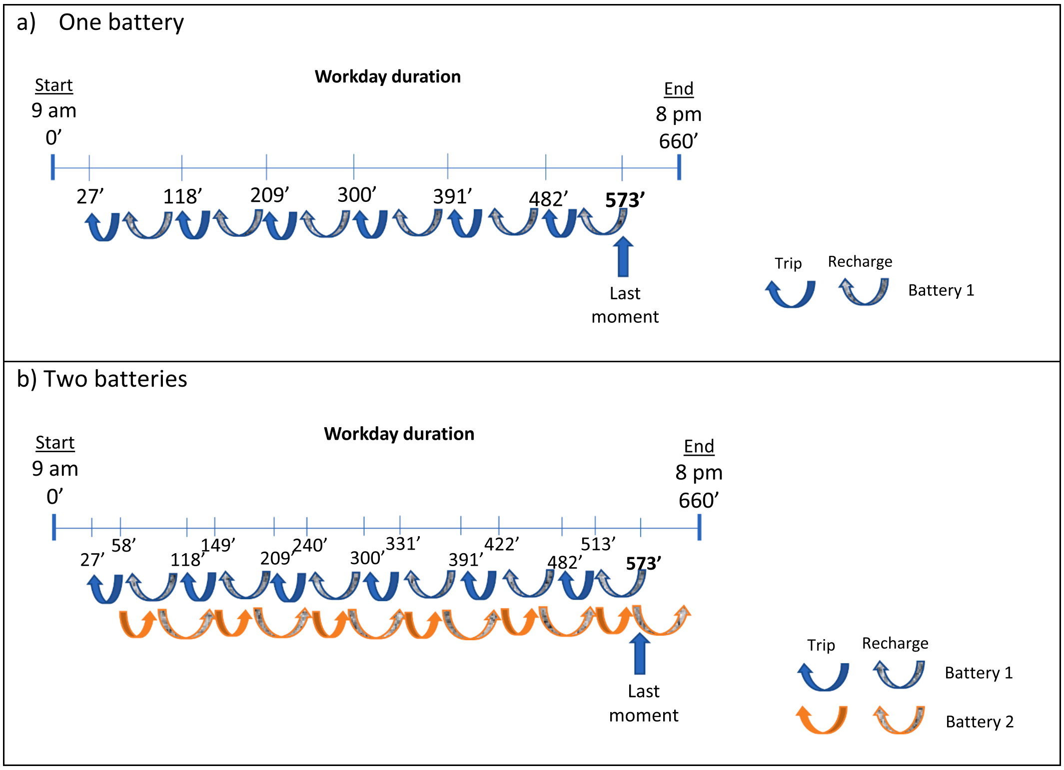

Fig. 6. Definition of the potential decision-moments, considering a) one battery, and b) two batteries.

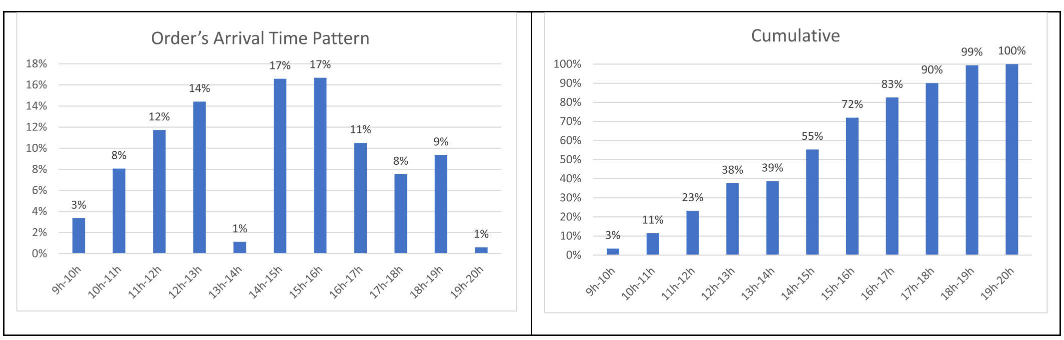

Fig. 7. Percentage of orders received by hour.

can be at minute 118 (or later), and the last decision moment has to be at minute 573. With this time interval in mind, several combinations will be tested, varying the decision-moment times (accordingly with the possible decision-moments shown in Fig. 6) to find the best combination and the best number of decision-moments. From three to six decision-moments will be tested. More than six decision-moments is, from an operational point of view, difficult to implement since the pharmacists also have to serve the public.

5.4. Results

The proposed solution approach was coded in Python, using CPLEX version 12.10 to solve the mathematical model, and all the experiments were run in a computer Intel i9-10850K 3.60 GHZ, 64 GB RAM. As previously mentioned, the results presented in this section are simulations of what would happen if the methodology proposed would be implemented by the pharmacy to decide which orders should be delivered by car or by drone, and when.

Fig. 8 shows the total cost (considering the 31-day testing period) by varying the number of decision-moments (DM) and selecting the best

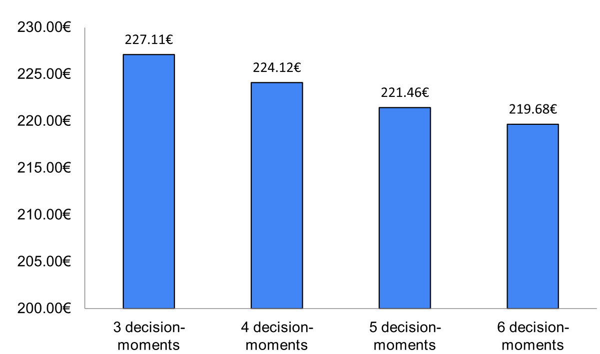

Fig. 8. Best Total Cost by Number of Decision-Moments.

combination for decision-moments times (the results for all combinations tested are shown in Appendix A). We can observe that the difference in the total cost is not significant among the four options studied

[219.68–227.11€]. Nonetheless, three and four decision-moments had worse results than five and six decision-moments solutions. The best result for three DM is 227.11 € with the combination {209′, 422′, 573′} and 224.12 € for four DM with the combination {118′, 240′, 422′, 573′}. With five and six DM, there are slight improvements. The best result for five DM is 221.46 € with combination {209′, 391′, 422′, 482′, 573′} and 219.68€ for six DM with combination {209′, 331′, 391′, 422′, 482′, 573′}. One of the advantages of having more DM is related to the lead-time constraint of the orders. More DM mean higher flexibility in relation to what shift an order has to go in. Let's take the three DM example. Because there is such a big gap between 209 and 422, all orders that were made roughly before minute 122 (11:02 h), cannot go in the next shift due to the lead-time constraint (less than 300 min). Fig. 9 shows that with 3 and 4 DMs only a reduce percentage of orders is postponed (at shift 1, around 15% of the orders are postponed, and at shift 2, around 30% of the orders are postponed), while with 6 DM the percentage of orders postponed are always (every shift) higher that 45%.

Given the best combination found, the number of drone trips available are shown in Table 5. The number of drone trips and car trips actually performed is given in Fig. 10, where we can see that the trend is to perform more drone trips in the firsts shifts and more car trips in the lasts shifts. Comparing the number of available drone trips with the actual number, we find a utilization rate of 6.28/10 for 3 DM, and 6.84/10 for 6 DM. Thus, regardless of the number of decision-moments, the average number of drone trips per day do not differ significantly. The same conclusion is obtained for the average number of car trips: 2.24 car trips per day with 3 and 4 DM and 2.36 with 5 and 6 DM.

5.5. Discussion

- **Effectiveness of the proposed solution method**

To assess the effectiveness of the proposed method to solve the Dynamic PDSVRP-LT, the results are now compared with the optimal ones if the demand were known in advance (static version of the problem). If at the beginning of the day we had perfect information about the number of units that each nursing home will order during the day, and which will be the release time of each order, what would be the optimal planning (routing and scheduling) to fulfil those orders? To answer this question, the mathematical model for the PDSVRP presented in Section 4 is solved for each day, considering the information about all daily orders. The model was executed for the 31-day period and the results are presented in Table 6. Table 6 shows the total number of requests received per day, the objective function value (OFV) when solving the MILP model with information of all orders in advance, the CPLEX lower-bound gap, the computational time (every run was limited to 3600 s), and the number of car and drone trips obtained for each day. Note that the time limit of 3600 s was only imposed for the static version (just to

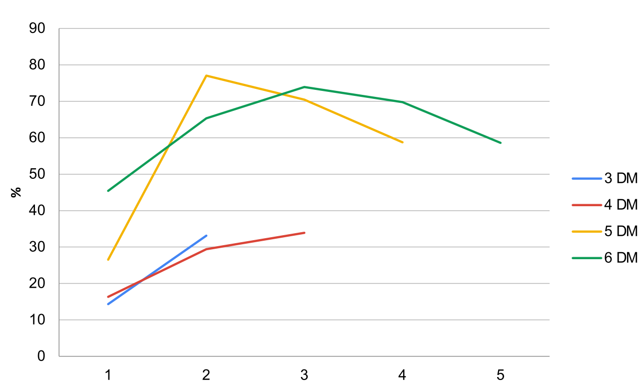

Fig. 9. Percentage of postponed orders in each shift for different number of decision-moments.

test the effectiveness of the algorithm, not for practical purpose since in real-life we do not have information about all orders at the beginning of the day to plan ahead). For the dynamic version, a time limit of 2 min was imposed for every run, and never reached.

The (quasi) optimal transportation cost for the 31-day sample, using car and drone trips to fulfil the orders, is 205.41€, with a total of 53 car trips and 175 drone trips. We need to use the term quasi optimal since for some runs the optimality has not been proven within the computational time limit. The results are compared with the proposed solution method for the Dynamic PDSVRP-LT in the last five columns of Table 6. Considering the best solution found (with 6 decision-moments), a total deviation of 7% from the (quasi) optimal solution is obtained, where for 8 days the optimal solution was reached, and in 12 days the deviation was less than 9%. Note that in days 128 and 135, the dynamic approach found a solution better that the static one, which was not solved to optimality. These results demonstrate that the proposed method is effective, along with the short computational time needed to provide a solution (in less than two seconds optimality was proved for every decision-moment). On the other hand, in 9 days the deviation is higher than 11% where the dynamic solution has almost always one car trip more than the static one. In two days, the deviation was higher that 65% (days 125 and 142). We examined in detail these two days to find out the reasons behind this difference. Fig. 11 shows both solutions for day 125. Request #9 was released at 173′ with a demand of 12 units ($s_9 = 173'$ and $q_9 = 12$), meaning that it must be delivered by car ($q_9 > QD$). At the static optimal solution (on the left of Fig. 11), request #9 is delivered by car in a route that starts at 461′ and arrives at nursing home #4 at 473′, exactly 300 min after the release time, complying with the maximum lead-time. In the same route, requests #15, #17, and #19 are delivered as well (all of them belong to nursing home #4). Note that request #19 was released at 456′ and the delivery route had started right before that (5 min after given the loading time). At the dynamic solution (on the right of Fig. 11), at DM1 (209′) it was decided to postpone the delivery of request #9. Also, at DM2 (331′) and DM3 (391′) the decision was the same. However, at DM4 (422′) it was no longer possible to postpone the delivery for the next DM since DM5 is at 482′, meaning that the lead time for request #9 would not be met ($482' + 5' + 7' - 173' > 300'$). Therefore, a car trip needs to be performed at DM4, and includes all the requests received so far from nursing home #4 and not delivered yet (i.e., requests #9 and #15). Since we are at 422′, and requests #17 and #19 will only be released at 432′ and 456′, respectively, this car trip only delivers #9 and #15. Therefore, at the dynamic solution another car trip to nursing home #4 needs to be performed at DM6 (573′), since request #19 has a demand of 8 units ($q_{19} > QD$).

A similar situation happened at day 142, where in the static optimal solution one car trip is performed starting at 533′, including requests that were released between 240′ and 528′. The request released at 240′ had arrived at 539′, meeting the lead-time constraint. At the dynamic solution, that request was delivered at DM5 (482′) since at DM6 (573′) was not possible to meet the lead-time. Moreover, at shift 6 three requests were received, and only 2 drone trips are available, so one of the requests needed to go by car. Therefore, two car trips are done in the dynamic solution, increasing the cost of the solution comparing with the static one, where all information regarding the release times were knew beforehand.

- **Economic and environmental impact of adding drones to the traditional operation**

Currently, all deliveries are made by car. As a rule, the pharmacy makes one delivery per day, around 4p.m. Nonetheless, sometimes two deliveries per day are made, one in the early afternoon and the other at the end of the day. To have a fair comparison between the operation with only car with the operation with drones, we assume two deliveries per day, since in that way the lead-time of 300 min (5 h) can be met. With only one delivery per day around 4p.m., besides not meeting the

Table 5
Number of drone trips available in each shift for different number of decision-moments.

	3 Decision-Moments {209′,422′,573′}	4 Decision-Moments {118′,240′,422′,573′}	5 Decision-Moments {209′,391′,422′,482′,573′}	6 Decision-Moments {209′,331′,391′,422′,482′,573′}
Shift 2	5	3	4	3
Shift 3	3	4	1	1
Shift 4	2	3	1	1
Shift 5		2	2	1
Shift 6			2	2
Shift 7				2
Total	**10**	**12**	**10**	**10**

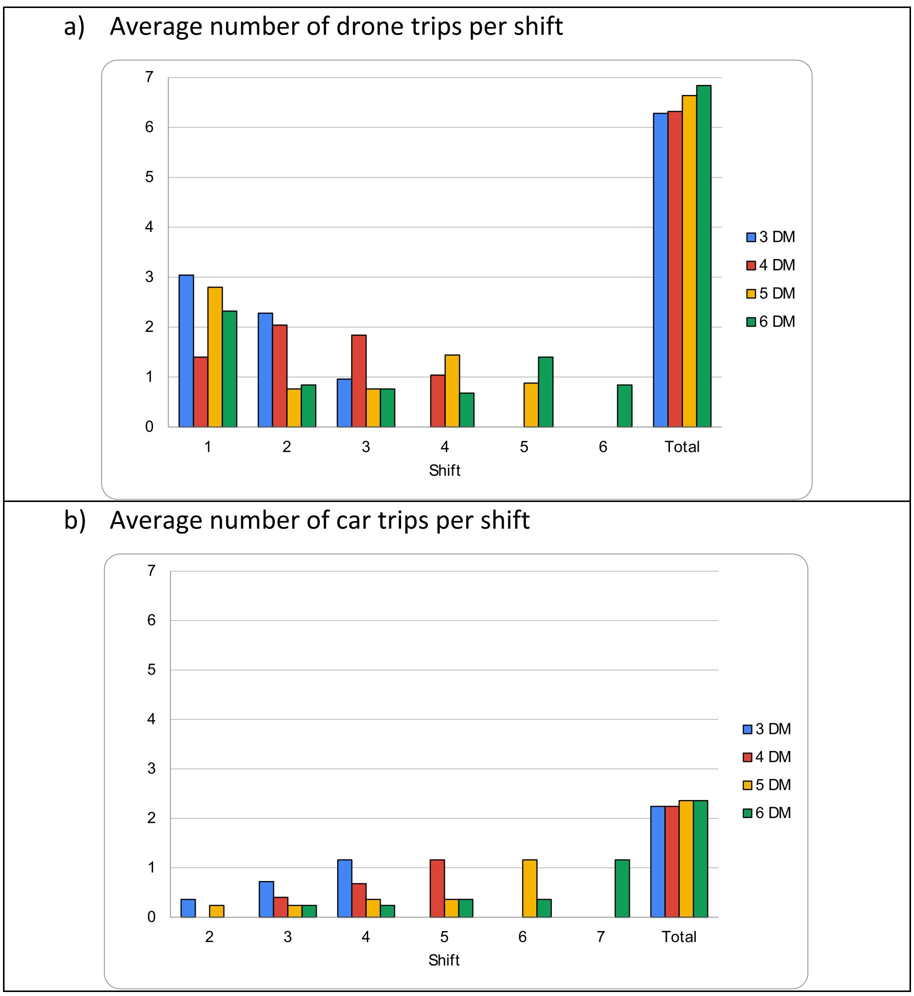

Fig. 10. Average number of (a) drone and (b) car trips performed in each shift for different number of decision-moments.

lead-time, around 30% of the orders would not be delivered in the same day. To simulate two car deliveries per day, two decision-moments were considered: the first at 2p.m. (300′) and the second at 6:33p.m. (573′). The PDSVRP model with only a set of car trips available was run for each moment, where all orders received until that moment must be delivered. The results are presented in Table 7.

The total cost is 369€, where there is always one to two car trips in the early afternoon and one to three at the end of the day. Adding a drone to perform the delivery operations, brings savings of 41%, which represents a saving cost of around 150€ per month. Note that only a conservative fuel cost was considered for the car trips (the fuel consumption rate was assumed to be 6 l/100 km, what is a low value for the type of road network in the studied region). If the car travel cost per minute doubles (i.e., if a higher fuel consumption rate or a higher cost per litre of fuel are considered), the saving cost reaches 300€ per month. If the pharmacist cost were included, the cost savings would be even higher. A brief sensitive analysis was conducted on the car travel cost per minute (α) and on drone travel cost per minute (β), increasing the values from +10% until +100%, but the solutions did not change (the number of drone and car trips remains the same, given the large cost difference

Table 6
Comparison of the results obtained for the Static PDSVRP-LT and Dynamic PDSVRP-LT (with 6 DM) for the 31-day testing period.

		Static PDSVRP-LT					Dynamic PDSVRP-LT				Deviation
Days	# Req. Total	OFV (€)	GAP (%)	CPU (s)	# car trips	# drone trips	Cost	CPU (s)	# car trips	# drone trips	%
121	9	6.026	0%	1.7	1	5	6.031	0.51	1	6	0.1%
122	3	4.005	0%	1.1	1	1	4.005	0.40	1	1	0.0%
123	17	6.845	0%	3258	1	8	8.041	0.71	2	8	17.5%
124	10	9.205	0%	232	2	1	9.216	0.57	2	3	0.1%
125	16	3.648	0%	352	2	8	6.040	0.82	3	7	65.6%
126	21	12.409	39%	3600	3	2	12.422	0.73	3	4	0.1%
127	7	4.015	0%	1.4	1	3	4.019	0.50	1	4	0.1%
128	24	12.856	40%	3600	2	11	12.835	0.98	3	8	-0.2%
129	15	7.850	0%	92	2	7	8.044	0.58	2	7	2.5%
130	21	7.268	22%	3600	2	10	8.456	0.83	2	8	16.3%
131	12	3.858	0%	2.3	1	10	3.858	0.54	1	10	0.0%
132	16	8.800	38%	3600	2	0	11.016	0.53	3	4	25.2%
133	5	0.027	0%	1	0	5	0.027	0.39	0	5	0.0%
134	15	5.264	0%	458	2	11	6.459	0.74	3	10	22.7%
135	19	11.614	33%	3600	4	3	10.431	0.77	3	6	-10.2%
136	16	1.265	0%	12	1	10	1.265	0.53	1	10	0.0%
137	14	8.213	0%	33	2	2	10.429	0.53	3	5	27.0%
138	10	6.826	0%	38	2	4	7.622	0.44	3	4	11.7%
139	6	0.035	0%	1.2	0	6	0.035	0.47	0	6	0.0%
140	14	10.632	39%	3600	2	6	10.632	0.73	2	6	0.0%
141	20	8.038	0%	3600	2	7	8.051	0.76	2	9	0.2%
142	14	1.261	0%	1.7	1	10	2.461	0.55	2	10	95.2%
143	17	10.806	28%	3600	3	1	10.818	0.62	3	4	0.1%
144	10	9.018	0%	758	2	3	9.132	0.44	2	5	1.3%
145	4	0.024	0%	1.1	0	4	0.024	0.50	0	4	0.0%
146	20	15.944	42%	3600	4	8	17.338	1.91	4	7	8.7%
147	14	9.028	11%	3600	2	6	9.235	0.58	3	7	2.3%
148	18	4.458	72%	3600	2	9	5.455	0.58	2	10	22.4%
149	13	9.620	11%	3600	2	4	9.634	0.54	2	6	0.2%
150	16	6.542	37%	3600	2	8	6.638	0.87	2	7	1.5%
151	2	0.012	0%	1.1	0	2	0.012	0.40	0	2	0.0%
Total	**418**	**205.41**			**53**	**175**	**219.68**		**61**	**193**	6.9%

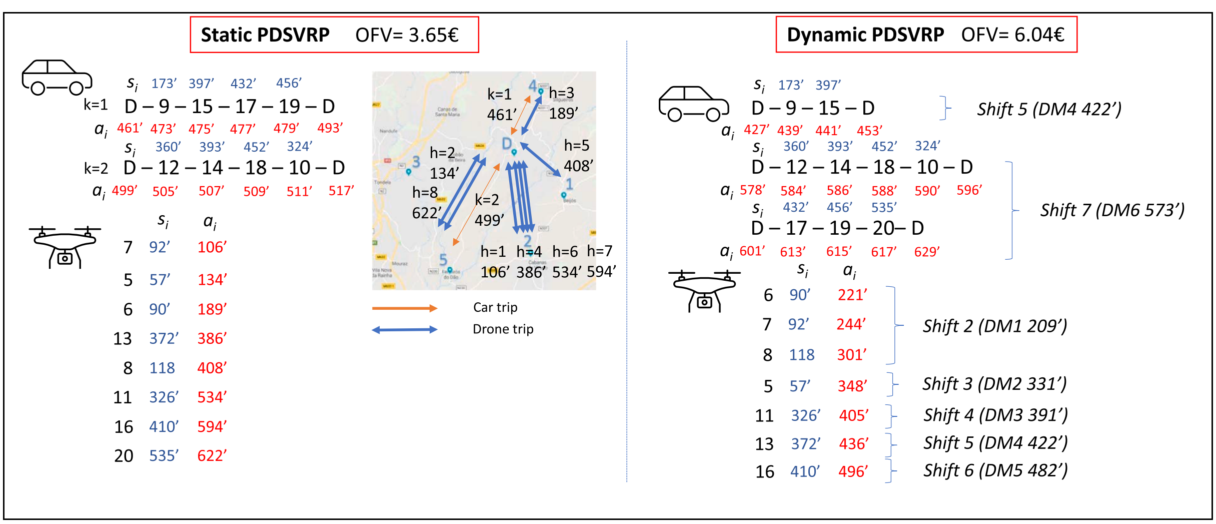

Fig. 11. Representation of the solutions obtained for day 125 when solving the Static PDSVRP-LT (on the left) and the Dynamic PDSVRP-LT (on the right).

between them).

Besides the positive economic impact of adding drones to the current operation, the environmental impact is also noteworthy. The impact in terms of CO_2 emissions is here assessed through a simple method. The number of kilometres travelled by car are assessed in both situation (only car vs. car + drone). Those kilometers are then translated into fuel consumed and then converted into CO_2 emissions through the conversion factor of 2.64 kg of CO_2 per liter of diesel fuel (EEA Grants, 2021). In the only car solution, 2406 km are travelled. According to Demir et al. (2014), on a slope, wheel horsepower demand increases significantly with vehicle weight because of road slope force. In some regions, road gradient plays an important role and can result higher CO_2 emissions, which is the case of the region studied (mountains). The study of Demir et al. (2011) shows that fuel consumption of a medium-duty vehicle on a 1% road slope may increase by up to six liters on a 100 km road segment. Given that the roads on the mountains have a slope higher than 1%, but on the other hand we are dealing with a light-duty vehicle and not a medium-duty vehicle, we will use the increase of six liters. Thus, 12 l/100 km is the fuel consumption rate considered for this application, meaning that 289 L are consumed. Applying the conversion factor of 2.64 kg of CO_2 per liter of fuel, 762 kg of CO_2 are emitted per month for the only car operation. For the car + drone operation, the number of

Table 7
Results for the only car operation with two delivery-moments per day.

	Total		1st Delivery Moment			2nd Delivery Moment		
Days	Cost (€)	# car trips	OFV (€)	GAP (%)	CPU (s)	OFV (€)	GAP (%)	CPU (s)
121	11.60	2	4.4	0	0.01	7.2	0	0.07
122	5.20	2	1.2	0	0	4	0	0.07
123	11.80	2	7.2	0	0.6	4.6	0	0.94
124	10.20	2	6	0	0.09	4.2	0	0.1
125	10.00	3	4.6	0	0.04	5.4	0	3.59
126	15.60	3	8.4	0	5.84	7.2	0	0.04
127	8.40	2	4	0	0.01	4.4	0	0.02
128	13.90	2	6.7	0	0.22	7.2	0	2.72
129	13.50	2	6.7	0	0.08	6.8	0	0.12
130	15.20	3	7.2	0	0.09	8	0	0.52
131	11.80	2	4.6	0	0.05	7.2	0	0.04
132	9.20	2	4.6	0	0.18	4.6	0	0.65
133	11.10	2	7.1	0	0.01	4	0	0.01
134	11.70	2	7.1	0	0.06	4.6	0	0.13
135	15.10	3	7.1	0	0.12	8	0	0.54
136	11.80	2	4.6	0	0.09	7.2	0	0.68
137	17.40	3	6.7	0	0.06	10.7	0	3.95
138	11.80	2	4.6	0	0.05	7.2	0	0.02
139	8.60	2	4.6	0	0.02	4	0	0.01
140	13.90	2	7.1	0	0.06	6.8	0	0.16
141	13.90	2	6.7	0	0.1	7.2	0	1.86
142	9.20	2	4.6	0	0.1	4.6	0	0.64
143	12.60	3	4.6	0	0.1	8	0	0.36
144	11.00	2	4.2	0	0.02	6.8	0	0.05
145	8.60	2	4.6	0	0.01	4	0	0
146	18.40	4	7.2	0	0.08	11.2	0	18.09
147	14.30	2	7.1	0	0.08	7.2	0	0.21
148	11.80	2	4.6	0	0.1	7.2	0	0.21
149	14.40	2	7.2	0	0.04	7.2	0	0.2
150	9.20	2	4.6	0	0.05	4.6	0	0.61
151	8.00	2	4	0	0	4	0	0
Total	**369.20**	**70**	**173.9**	**0**	**8.36**	**195.3**	**0**	**36.61**

Table 8
Comparison of the results obtained with one or two drone batteries available.

	2 Batteries			1 Battery			Deviation		
Days	Cost (€)	# car trips	# drone trips	Cost (€)	# car trips	# drone trips	Cost (%)	# car trips	# drone trips
121	6.03	1	6	6.03	1	5	0%	0	−1
122	4.00	1	1	4.00	1	1	0%	0	0
123	8.04	2	8	14.83	4	5	84%	2	−3
124	9.22	2	3	9.22	2	3	0%	0	0
125	6.04	3	7	10.23	4	5	69%	1	−2
126	12.42	3	4	14.81	4	3	19%	1	−1
127	4.02	1	4	5.21	2	2	30%	1	−2
128	12.83	3	8	14.91	3	3	16%	0	−5
129	8.04	2	7	10.42	3	3	29%	1	−4
130	8.46	2	8	13.53	3	5	60%	1	−3
131	3.86	1	10	10.43	2	5	170%	1	−5
132	11.02	3	4	11.01	3	3	0%	0	−1
133	0.03	0	5	0.03	0	5	0%	0	0
134	6.46	3	10	14.33	3	5	122%	0	−5
135	10.43	3	6	10.42	3	5	0%	0	−1
136	1.27	1	10	11.03	3	5	772%	2	−5
137	10.43	3	5	14.42	4	3	38%	1	−2
138	7.62	3	4	7.62	3	4	0%	0	0
139	0.03	0	6	4.02	1	4	11450%	1	−2
140	10.63	2	6	14.61	3	3	37%	1	−3
141	8.05	2	9	15.62	3	5	94%	1	−4
142	2.46	2	10	13.43	4	5	446%	2	−5
143	10.82	3	4	10.81	3	3	0%	0	−1
144	9.13	2	5	9.13	2	5	0%	0	0
145	0.02	0	4	0.02	0	4	0%	0	0
146	17.34	4	7	22.12	5	3	28%	1	−4
147	9.24	3	7	10.81	4	3	17%	1	−4
148	5.45	2	10	8.23	4	5	51%	2	−5
149	9.63	2	6	10.82	3	4	12%	1	−2
150	6.64	2	7	8.22	3	3	24%	1	−4
151	0.01	0	2	0.01	0	2	0%	0	0
Total	**219.68**	**61**	**193**	**310.35**	**83**	**119**	**41%**	**22**	**−74**

kilometers is 1427 km, meaning 171 L of fuel are consumed, and 452 kg of CO_2 are emitted per month. Therefore, 310 kg of CO_2 less are emitted per month when adding drones to the traditional operation, representing an annual environmental impact benefit of 3720 kg of CO_2.

- **Impact of spare batteries available**

The results presented before assumed that the pharmacy has one spare battery at its disposal (i.e., a total of 2 batteries). However, the existence of one spare battery has an associated cost. Therefore, the hypothesis of having only one battery was studied, and the Dynamic PDSVRP-LT was solved considering that after a drone trip is performed, a recharging time of 1 h must be complied.

Table 8 contains the comparison between the possible operations with one and two batteries available, considering 6 decision-moments. Having only one battery increases the cost in 41% (310€ vs. 220€), what is somehow significant. It is also worth noticing that the number of car trips does not increase much with only 1 battery (83 vs. 61), meaning that more customers are visited in the same car trip. The number of drone trips reduces by a third (193 vs. 119). This is explained by the fact that the utilization rate when two batteries are available is 62% while when one battery is available is 77%. Moreover, in 11 out of 31 days, it doesn't make any difference having two batteries instead of one. If the cost of a spare battery is 90€ or less per month, it worth to have a spare one; otherwise, no. Nonetheless, having only one battery implies a small reduction comparing with the only car operation (310€ vs. 369€, representing a cost saving of 16%).

- **Impact of Same Day delivery versus Next Day delivery**

The solution approach proposed permits the pharmacy to do the deliveries at the same day when orders are made. In this sub-section we intend to investigate what is the cost increment of delivering on the same day, instead of delivering on the next day. To obtain a solution for the next day delivery, the PDSVRP model can be used, since it gives a solution considering that all the demand is known and can be aggregated by nursing home. Moreover, the scheduling constraints are inactive since there is no need to comply with any lead-time since orders are delivered on the next day. The results with and without drones are described in Table 9.

In the Next Day Delivery scenarios, as the route planning is done for the next day, it allows the number of trips for the same customer to be kept to a minimum, since all orders can be aggregated and delivered at the same time. For this reason, these scenarios have the lowest costs (195€ for an only-car operation, and 157€ for a car + drone operation). Considering the traditional operation, with only car trips, the same day delivery becomes very expensive comparing with the next-day delivery (the cost increases 89%). However, when an operation with drones is available, that cost difference reduces to 38%. We can also state that the cost of a same-day operation with drones (220€) is somehow similar with a next-day operation with only car (195€). Meaning that adding drones to the operation is able to increase the service level to the customers (providing a same-day delivery, with a tight lead-time), with a slight increase in cost.

Table 9
Comparison of the results for the next and same day delivery, with and without drones.

	Next Day Delivery (Only Car)	Same Day Delivery (Only Car)	Next Day Delivery (Car + Drones)	Same Day Delivery (Car + Drones)
Cost (€)	195.3€	369.2€	157.05€	219.68€
# car trips	44	70	36	61
# drone trips	0	0	26	193
Cost Deviation (Same *versus* Next Day)		+89%		+38%

We also tested a hybrid scenario, where Same Day Delivery is made, but only for orders received until a particular hour. This means that orders received until that time are delivered on the same day, and the remaining orders are delivered next day. For that, we apply our methodology, but changed the last decision-moment to 4:00 p.m. (420′), and 5:00 p.m. (480′). We notice that the cost is slightly higher than our proposal (with the last decision-moment equal to 573′), but the service level is significantly worse since 119 requests (28% of the total requests, that represents, on average, 3.8 requests per day) and 60 requests (14% of the total requests, that represents, on average, 1.9 requests per day) are delivered next day when the last decision-moment is 4:00p.m. and 5 p.m., respectively (see Appendix B). One could expect that the cost would be lower and offset the decrease in service level, but what happens is that the requests not served within the same day need to be delivered on the next day and become somehow "urgent". In fact, their release time is now equal to 0' (i.e., 9:00 a.m.) and their lead-time of 300' must be still met. This implies extra trips done in the morning that do not happen in our baseline scenario.

- **Testing scalability**

To test the scalability of the proposed algorithm and given the characteristics of this type of problem/application – rural areas, delivering of medicines to nursing homes, where we are not serving individual customers – we opted to double the number of nursing homes to be served by the pharmacy. The locations for the new potential nursing homes are represented in Fig. 12. The orders of each new nursing home for the 31-day testing period were randomly generated, following the orders' pattern of the original nursing homes (see Fig. 13). In the original data we had a total of 418 orders and now we generate 414 more, totalizing 832 orders.

All parameters' values were maintained except for the car capacity, where we consider QC = 135 (50% more than the original capacity), and the travel times matrices (car and drone) were updated. To apply the proposed algorithm, we need to recalculate the last decision moment and then check the number of drones trips that can be made in each shift. Now the shortest car route to visit all 10 nursing homes is 101 min. The last decision moment is now 534′ ($660' - 101' - 2' \times 10 - 5'$), and then we backtracked the other decision moments following the same pattern that the best one from the base case: {170′, 292′, 352′, 383′, 443′, 534′}. Since now the last decision moment is sooner, this will have two implications. On one hand, it is possible to do three drone trips in the last shift (instead of two, totalizing 11 possible drone trips per day). On the other hand, since the pharmacy receives orders until 6:30 p.m., all orders received after 5:54 p.m. will not be attended at the same day. We identify how many orders fall in this situation. In addition, we have performed a second simulation where all those orders were considered to be received before 5:54 p.m. to assess the impact. In practical terms, the pharmacy needs to inform all nursery homes about the last hour. The results of both simulations are in Table 10.

From Table 10 we conclude that the proposed algorithm can scale and is able to solve larger instances, with more nursing homes and more requests. In the first simulation, where requests received after 534′ are not considered (74 requests out of 832), a solution is obtained in few seconds (on average 1.81 s, with a maximum of 9 s). For the second simulation, where all requests were considered to be received before 534′, the average computational time needed increases (on average 8.18 s, 6 s more that in the first simulation) but still in a very reasonable time for this type of application (the CPU time is the total considering the six DM). In the second simulation there is one day (day 128) where the 2-minute limit was reached for one decision-moment.

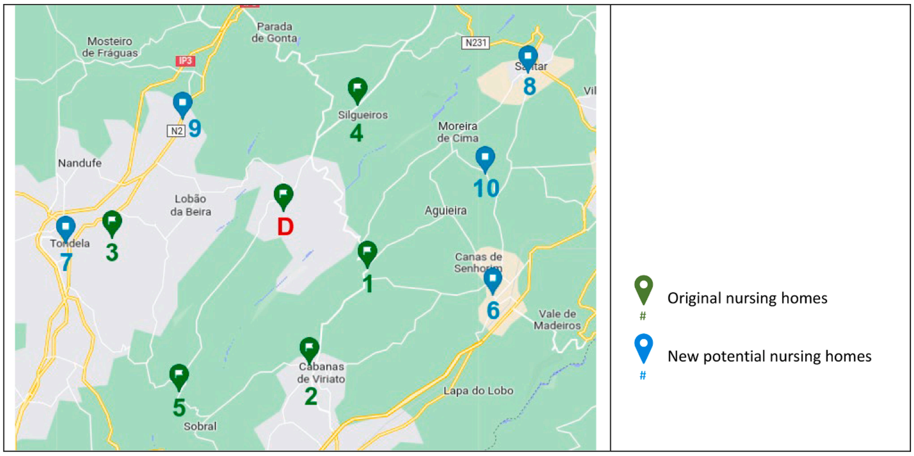

Fig. 12. Location of the original (in green) and potential new (in blue) nursing homes.

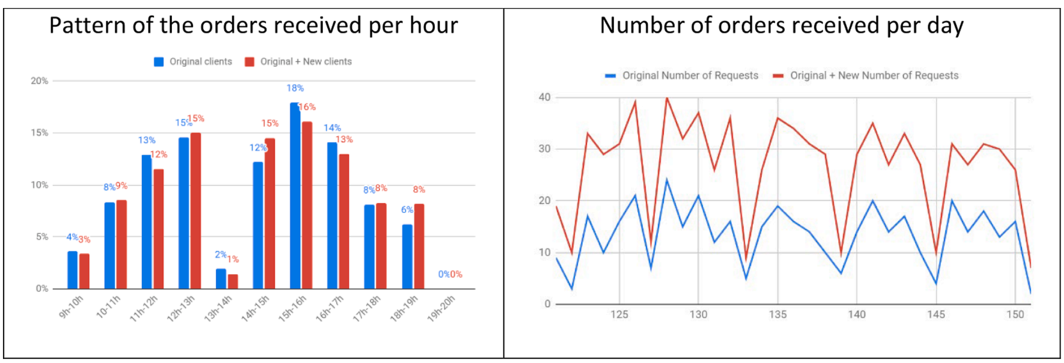

Fig. 13. Pattern and number of the original orders (in blue) and original + new orders (in red).

6. Conclusions

This work tackles a new hybrid distribution paradigm where medicines can be delivered either by car or drone in rural areas. The potential of drones is greater in rural areas, since there are fewer obstacles to their use, as there are in urban areas. Furthermore, in rural areas there are isolated regions of difficult access, considering the road conditions and/or large distances separating them from cities, making it expensive for a vehicle to travel to these places to meet demand. Thus, Farmácia da Lajeosa saw in this technology a way to improve their service to its customers (nursing homes), while reducing operation costs. Despite being a recent technology, there are already countless studies about deliveries by drones, and some where restrictions, such as battery and payload are already considered. However, for most studies done, route planning is done knowing the demand in advance. There are few studies, where demand uncertainty is taken into account. Hence, we developed a solution approach to solve the Dynamic PDSVRP with Lead-Time, since the pharmacy does not know what orders will be placed during the day, having to make decisions about when to deliver and by which transportation mean (car or drone), to comply with a same-day delivery with a certain lead-time. The solution approach involves three steps, where at the last step a new mathematical model was developed to solve the PDSVRP considering multiple car trips and drone trips, car and drone capacity, lead-time, and battery charging constraints.

The solution approach was applied to 31 days considering the real orders received by the pharmacy in those days. Testing several combinations for the schedule of 3 to 6 decision-moments, the best solution was found for 6 DM, not evenly spread through the day {209′, 331′, 391′, 422′, 482′, 573′}. The effectiveness of the solution method was assessed by comparing the results to the static version of problem and a total deviation of 7% was observed, meaning that dealing with the uncertainty regarding the orders that will be received throughout the day by the methodology devised only deviates 7% in cost from knowing in advance all information about the orders.

Adding drones to the current operation for the pharmacy reduces costs by 41% and increases service level since all orders can be delivered within the same-day and respecting a tight lead-time. This result could be enhanced if urgent orders are considered. Moreover, the impact in cost reduction would be even higher since a conservative approach regarding the cost involved was followed in this work. Moreover, the reduction in CO_2 emissions is something that is also worth to be pointed out. Another important conclusion is that using drones allows a same-day delivery operation to have almost the same cost as a next-day operation with only car. Also, the impact of having a spare battery was assessed as somehow significant.

Given that companies are increasingly considering drones to make their deliveries, models and algorithms that could be incorporated into decision support tools to help them allocating orders among different transportation means, orders' scheduling and routing are needed. Some future research directions should be pursued, such as, split deliveries to cope with the drone capacity constraint, modelling more accurately energy consumption and recharge (a conservative approach was followed in this work, meaning that results could be improved if the battery consumption was incorporated rather than assuming that after a drone trip, a recharge must happen). Also, stochastic models could be explored to tackle the dynamic feature.

CRediT authorship contribution statement

Tânia Rodrigues Pereira Ramos: Conceptualization, Methodology,

Table 10
Results for larger instances.

		1st Simulation							2nd Simulation				
Days	# Req. Total	Cost	CPU (s)	Gap	# car trips	# drone trips	# Req. after Last DM	Requests Delivered	Cost	CPU (s)	Gap	# car trips	# drone trips
121	19	18.834	0.17	0.00%	3	6	2	17	18.850	0.58	0.00%	2	8
122	10	4.062	0.10	0.00%	1	8	0	10	4.062	0.71	0.00%	1	8
123	33	18.478	3.02	0.00%	4	11	4	29	19.278	22.68	0.00%	4	11
124	29	18.568	1.62	0.00%	4	8	1	28	18.772	2.24	0.00%	4	9
125	31	13.170	2.22	0.00%	3	10	2	29	13.170	2.37	0.00%	3	10
126	39	22.155	0.56	0.00%	5	8	4	35	22.162	0.62	0.00%	5	9
127	12	9.243	0.10	0.00%	2	7	0	12	9.243	0.10	0.00%	2	7
128	40	15.186	3.70	0.00%	3	11	6	34	16.981	120.26	6.19%	3	11
129	32	16.783	7.87	0.00%	3	11	1	31	16.783	12.21	0.00%	3	11
130	37	23.185	1.29	0.00%	5	11	1	36	23.185	1.45	0.00%	5	11
131	26	11.372	1.05	0.00%	2	11	2	24	11.872	7.07	0.00%	2	11
132	36	24.237	0.70	0.00%	4	7	2	34	24.251	0.96	0.00%	4	9
133	9	0.058	0.09	0.00%	0	9	0	9	0.058	0.07	0.00%	0	9
134	26	14.076	0.21	0.00%	3	11	4	22	16.374	0.74	0.00%	3	11
135	36	17.580	0.93	0.00%	4	10	6	30	18.482	38.73	0.00%	4	10
136	34	20.961	2.09	0.00%	4	9	4	30	21.272	5.78	0.00%	4	10
137	31	17.063	0.51	0.00%	4	9	4	27	19.473	2.79	0.00%	5	10
138	29	12.981	2.34	0.00%	2	11	1	28	13.169	3.72	0.00%	2	10
139	10	6.153	0.37	0.00%	1	8	0	10	6.153	0.17	0.00%	1	8
140	29	18.460	0.40	0.00%	4	8	9	20	19.963	3.16	0.00%	4	8
141	35	21.187	1.24	0.00%	4	11	3	32	21.187	3.90	0.00%	4	11
142	27	13.470	9.40	0.00%	3	10	0	27	13.470	9.71	0.00%	3	10
143	33	17.280	2.18	0.00%	3	10	2	31	17.883	2.23	0.00%	3	10
144	27	18.173	1.68	0.00%	3	10	4	23	18.677	3.44	0.00%	3	10
145	10	10.543	0.20	0.00%	2	6	0	10	10.543	0.18	0.00%	2	6
146	31	16.674	0.79	0.00%	4	10	3	28	18.568	3.28	0.00%	4	9
147	27	15.660	0.93	0.00%	2	9	3	24	15.952	4.04	0.00%	2	8
148	31	11.972	1.43	0.00%	2	11	1	30	11.972	1.88	0.00%	2	11
149	30	19.868	0.79	0.00%	4	10	3	27	21.068	12.10	0.00%	5	10
150	26	9.966	1.94	0.00%	2	10	2	24	9.966	4.84	0.00%	2	10
151	7	6.437	0.13	0.00%	2	5	0	7	6.437	0.15	0.00%	2	5
Total	**832**	**463.84**			**92**	**286**	**74**	**758**	**479.28**			**93**	**291**

* 1st Simulation: Orders received after the last moment are not delivered.
** 2nd Simulation: All orders are received until the last moment, so all orders received are delivered.

Software, Validation, Formal analysis, Investigation, Writing – original draft, Visualization. **Daniele Vigo:** Conceptualization, Methodology, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

3 Decision-Moments	Total Cost
[118, 300, 573]	242.35 €
[118, 331, 573]	238.29 €
[209, 300, 573]	241.37 €
[209, 331, 573]	237.31 €
[209, 391, 573]	235.33 €
[209, 422, 573]	**227.11** €
[209, 482, 573]	243.01 €
[209, 513, 573]	252.08 €

4 Decision-Moments	Total Cost
[118, 209, 331, 573]	237.33€
[118, 209, 391, 573]	235.35€
[118, 209, 422, 573]	227.12€
[118, 240, 331, 573]	237.31€
[118, 240, 391, 573]	234.99€
[118, 240, 422, 573]	**224.12€**
[118, 240, 482, 573]	238.39€
[118, 300, 331, 573]	237.31€
[118, 300, 391, 573]	234.98€
[118, 300, 422, 573]	224.81€
[118, 300, 482, 573]	233.52€
[118, 300, 513, 573]	241.46€
[118, 331, 391, 573]	235.29€
[118, 331, 422, 573]	229.77€
[118, 331, 482, 573]	235.11€
[118, 331, 513, 573]	238.79€
[209, 240, 331, 573]	237.29€
[209, 240, 391, 573]	234.92€
[209, 240, 422, 573]	224.73€
[209, 240, 482, 573]	238.36€
[209, 300, 331, 573]	236.33€
[209, 300, 391, 573]	234.93€
[209, 300, 422, 573]	224.45€
[209, 300, 482, 573]	233.50€
[209, 300, 513, 573]	240.46€
[209, 331, 391, 573]	234.13€
[209, 331, 422, 573]	225.05€
[209, 331, 482, 573]	232.61€
[209, 331, 513, 573]	236.61€
[178, 209, 360, 573]	236.82€
[178, 209, 391, 573]	235.26€
[178, 209, 451, 573]	231.45€
[178, 269, 360, 573]	236.82€
[178, 269, 391, 573]	234.94€
[178, 269, 451, 573]	227.16€
[178, 269, 482, 573]	233.49€
[178, 300, 360, 573]	236.83€
[178, 300, 391, 573]	234.95€
[178, 300, 451, 573]	227.18€
[178, 300, 482, 573]	233.51€
[178, 300, 542, 573]	239.59€
[178, 360, 391, 573]	234.14€
[178, 360, 451, 573]	226.38€
[178, 360, 482, 573]	231.22€
[178, 360, 542, 573]	234.52€
[178, 391, 451, 573]	233.72€
[178, 391, 482, 573]	233.93€
[178, 391, 542, 573]	239.07€

5 Decision-Moments	Total Cost
[118, 149, 209, 331, 573]	237.34€
[118, 149, 209, 391, 573]	235.36€
[118, 149, 209, 422, 573]	227.13€
[118, 149, 209, 482, 573]	243.05€
[118, 149, 240, 331, 573]	237.32€
[118, 149, 240, 391, 573]	234.92€
[118, 149, 240, 422, 573]	224.14€
[118, 149, 240, 482, 573]	237.33€
[118, 149, 300, 331, 573]	236.26€
[118, 149, 300, 391, 573]	234.93€
[118, 149, 300, 422, 573]	224.84€
[118, 149, 300, 482, 573]	233.54€
[118, 209, 240, 331, 573]	237.32€
[118, 209, 240, 391, 573]	234.93€
[118, 209, 240, 422, 573]	224.15€
[118, 209, 240, 482, 573]	237.41€
[118, 209, 300, 331, 573]	236.25€
[118, 209, 300, 391, 573]	234.93€
[118, 209, 300, 422, 573]	223.85€
[118, 209, 300, 482, 573]	233.51€
[118, 209, 331, 391, 573]	234.14€
[118, 209, 331, 422, 573]	224.06€
[118, 209, 331, 482, 573]	232.62€
[118, 209, 331, 513, 573]	236.62€

(*continued on next page*)

(*continued*)

5 Decision-Moments	Total Cost
[118, 209, 391, 422, 573]	222.74€
[118, 209, 391, 482, 573]	225.78€
[118, 209, 391, 513, 573]	233.21€
[118, 240, 300, 331, 573]	236.34€
[118, 240, 300, 391, 573]	234.91€
[118, 240, 300, 422, 573]	223.82€
[118, 240, 300, 482, 573]	233.52€
[118, 240, 331, 391, 573]	234.11€
[118, 240, 331, 422, 573]	223.84€
[118, 240, 331, 482, 573]	232.64€
[118, 240, 331, 513, 573]	236.62€
[118, 240, 391, 422, 573]	222.31€
[118, 240, 391, 482, 573]	225.10€
[118, 240, 391, 513, 573]	232.77€
[209, 240, 300, 331, 573]	236.62€
[209, 240, 300, 391, 573]	235.00€
[209, 240, 300, 422, 573]	223.83€
[209, 240, 300, 482, 573]	233.49€
[209, 240, 300, 513, 573]	240.45€
[209, 240, 331, 391, 573]	238.10€
[209, 240, 331, 422, 573]	226.64€
[209, 240, 331, 482, 573]	232.62€
[209, 240, 331, 513, 573]	236.60€
[209, 240, 391, 422, 573]	222.32€
[209, 240, 391, 482, 573]	225.19€
[209, 240, 391, 513, 573]	232.68€
[209, 240, 422, 482, 573]	227.91€
[209, 240, 422, 513, 573]	222.94€
[209, 240, 482, 513, 573]	242.15€
[209, 300, 331, 391, 573]	238.12€
[209, 300, 331, 422, 573]	226.66€
[209, 300, 331, 482, 573]	232.62€
[209, 300, 331, 513, 573]	236.61€
[209, 300, 391, 422, 573]	222.14€
[209, 300, 391, 482, 573]	225.48€
[209, 300, 391, 513, 573]	232.69€
[209, 300, 422, 482, 573]	227.84€
[209, 300, 422, 513, 573]	222.36€
[209, 300, 482, 513, 573]	234.60€
[209, 331, 391, 422, 573]	223.34€
[209, 331, 391, 482, 573]	222.99€
[209, 331, 391, 513, 573]	231.80€
[209, 331, 422, 482, 573]	222.27€
[209, 331, 422, 513, 573]	222.20€
[209, 331, 482, 513, 573]	234.31€
[209, 391, 422, 482, 573]	**221.46€**
[209, 391, 422, 513, 573]	223.98€
[209, 391, 482, 513, 573]	229.95€
[209, 422, 482, 513, 573]	229.02€
[178, 209, 269, 360, 573]	236.81€
[178, 209, 269, 391, 573]	235.02€
[178, 209, 269, 451, 573]	227.16€
[178, 209, 269, 482, 573]	233.48€
[178, 209, 269, 542, 573]	238.88€
[178, 209, 300, 360, 573]	236.81€
[178, 209, 300, 391, 573]	235.03€
[178, 209, 300, 451, 573]	227.18€
[178, 209, 300, 482, 573]	233.50€
[178, 209, 300, 542, 573]	239.57€
[178, 209, 360, 391, 573]	234.13€
[178, 209, 360, 451, 573]	226.37€
[178, 209, 360, 482, 573]	230.12€
[178, 209, 360, 542, 573]	234.42€
[178, 209, 391, 451, 573]	225.87€
[178, 209, 391, 482, 573]	225.69€
[178, 209, 391, 542, 573]	231.81€
[178, 209, 451, 482, 573]	230.66€
[178, 209, 451, 542, 573]	230.25€
[178, 209, 482, 542, 573]	246.09€
[178, 269, 300, 360, 573]	236.82€
[178, 269, 300, 391, 573]	235.03€
[178, 269, 300, 451, 573]	227.17€
[178, 269, 300, 482, 573]	233.50€
[178, 269, 300, 542, 573]	239.58€
[178, 269, 360, 391, 573]	234.14€
[178, 269, 360, 451, 573]	226.36€

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(*continued*)

5 Decision-Moments	Total Cost
[178, 269, 360, 482, 573]	230.13€
[178, 269, 360, 542, 573]	234.42€
[178, 269, 391, 451, 573]	225.38€
[178, 269, 391, 482, 573]	225.11€
[178, 269, 391, 542, 573]	231.72€
[178, 269, 451, 482, 573]	226.57€
[178, 269, 451, 542, 573]	226.27€
[178, 269, 482, 542, 573]	233.98€
[178, 300, 360, 391, 573]	234.14€
[178, 300, 360, 451, 573]	226.36€
[178, 300, 360, 482, 573]	230.14€
[178, 300, 360, 542, 573]	234.43€
[178, 300, 391, 451, 573]	225.38€
[178, 300, 391, 482, 573]	225.50€
[178, 300, 391, 542, 573]	231.72€
[178, 300, 451, 482, 573]	226.59€
[178, 300, 451, 542, 573]	226.29€
[178, 300, 482, 542, 573]	234.00€
[178, 360, 391, 451, 573]	223.49€
[178, 360, 391, 482, 573]	223.01€
[178, 360, 391, 542, 573]	230.99€
[178, 360, 451, 482, 573]	226.68€
[178, 360, 451, 542, 573]	225.59€
[178, 360, 482, 542, 573]	231.31€
[178, 391, 451, 482, 573]	232.94€
[178, 391, 451, 542, 573]	238.12€
[178, 391, 482, 542, 573]	235.73€

6 Decision-Moments	Total Cost
[118, 149, 209, 240, 331, 573]	237.33€
[118, 149, 209, 240, 391, 573]	234.94€
[118, 149, 209, 240, 422, 573]	224.15€
[118, 149, 209, 240, 482, 573]	237.32€
[118, 149, 209, 300, 331, 573]	236.26€
[118, 149, 209, 300, 391, 573]	234.93€
[118, 149, 209, 300, 422, 573]	223.85€
[118, 149, 209, 300, 482, 573]	233.52€
[118, 149, 209, 300, 513, 573]	240.49€
[118, 149, 209, 331, 391, 573]	234.14€
[118, 149, 209, 331, 422, 573]	224.06€
[118, 149, 209, 331, 482, 573]	232.64€
[118, 149, 209, 331, 513, 573]	236.64€
[118, 149, 209, 391, 422, 573]	222.66€
[118, 149, 209, 391, 482, 573]	225.79€
[118, 149, 209, 391, 513, 573]	233.23€
[118, 149, 209, 422, 482, 573]	224.66€
[118, 149, 209, 422, 513, 573]	224.37€
[118, 149, 240, 300, 331, 573]	236.25€
[118, 149, 240, 300, 391, 573]	234.92€
[118, 149, 240, 300, 422, 573]	223.83€
[118, 149, 240, 300, 482, 573]	233.52€
[118, 149, 240, 300, 513, 573]	240.47€
[118, 149, 240, 331, 391, 573]	234.12€
[118, 149, 240, 331, 422, 573]	223.85€
[118, 149, 240, 331, 482, 573]	232.65€
[118, 149, 240, 331, 513, 573]	236.62€
[118, 149, 240, 391, 422, 573]	222.33€
[118, 149, 240, 391, 482, 573]	225.21€
[118, 149, 240, 391, 513, 573]	232.70€
[118, 149, 240, 422, 482, 573]	225.94€
[118, 149, 240, 422, 513, 573]	221.57€
[118, 149, 240, 482, 513, 573]	241.12€
[118, 149, 300, 331, 391, 573]	234.13€
[118, 149, 300, 331, 422, 573]	224.85€
[118, 149, 300, 331, 482, 573]	232.66€
[118, 149, 300, 331, 513, 573]	236.64€
[118, 149, 300, 391, 422, 573]	225.93€
[118, 149, 300, 391, 482, 573]	229.47€
[118, 149, 300, 391, 513, 573]	232.69€
[118, 149, 300, 422, 482, 573]	227.04€
[118, 149, 300, 422, 513, 573]	222.17€
[118, 149, 300, 482, 513, 573]	234.64€
[118, 149, 331, 391, 422, 573]	225.71€
[118, 149, 331, 391, 482, 573]	230.99€

(*continued on next page*)

(*continued*)

6 Decision-Moments	Total Cost
[118, 149, 331, 391, 513, 573]	232.58€
[118, 149, 331, 422, 482, 573]	228.33€
[118, 149, 331, 422, 513, 573]	223.87€
[118, 149, 331, 482, 513, 573]	234.44€
[118, 149, 391, 422, 482, 573]	248.47€
[118, 149, 391, 422, 513, 573]	243.86€
[118, 149, 391, 482, 513, 573]	255.95€
[118, 209, 240, 300, 331, 573]	236.25€
[118, 209, 240, 300, 391, 573]	235.01€
[118, 209, 240, 300, 422, 573]	223.84€
[118, 209, 240, 300, 482, 573]	233.50€
[118, 209, 240, 300, 513, 573]	240.47€
[118, 209, 240, 331, 391, 573]	234.13€
[118, 209, 240, 331, 422, 573]	223.86€
[118, 209, 240, 331, 482, 573]	232.63€
[118, 209, 240, 331, 513, 573]	236.62€
[118, 209, 240, 391, 422, 573]	222.33€
[118, 209, 240, 391, 482, 573]	225.20€
[118, 209, 240, 391, 513, 573]	232.70€
[118, 209, 240, 422, 482, 573]	225.94€
[118, 209, 240, 422, 513, 573]	221.57€
[118, 209, 240, 482, 513, 573]	241.20€
[118, 209, 300, 331, 391, 573]	234.13€
[118, 209, 300, 331, 422, 573]	223.86€
[118, 209, 300, 331, 482, 573]	232.63€
[118, 209, 300, 331, 513, 573]	236.62€
[118, 209, 300, 391, 422, 573]	222.16€
[118, 209, 300, 391, 482, 573]	225.10€
[118, 209, 300, 391, 513, 573]	232.70€
[118, 209, 300, 422, 482, 573]	225.85€
[118, 209, 300, 422, 513, 573]	220.99€
[118, 209, 300, 482, 513, 573]	234.61€
[118, 209, 331, 391, 422, 573]	222.16€
[118, 209, 331, 391, 482, 573]	223.00€
[118, 209, 331, 391, 513, 573]	231.81€
[118, 209, 331, 422, 482, 573]	221.08€
[118, 209, 331, 422, 513, 573]	221.01€
[118, 209, 331, 482, 513, 573]	234.32€
[118, 209, 391, 422, 482, 573]	220.28€
[118, 209, 391, 422, 513, 573]	221.60€
[118, 209, 391, 482, 513, 573]	228.56€
[118, 240, 300, 331, 391, 573]	234.12€
[118, 240, 300, 331, 422, 573]	223.84€
[118, 240, 300, 331, 482, 573]	232.66€
[118, 240, 300, 331, 513, 573]	236.62€
[118, 240, 300, 391, 422, 573]	222.13€
[118, 240, 300, 391, 482, 573]	224.90€
[118, 240, 300, 391, 513, 573]	232.68€
[118, 240, 300, 422, 482, 573]	225.86€
[118, 240, 300, 422, 513, 573]	220.97€
[118, 240, 300, 422, 513, 573]	220.97€
[118, 240, 300, 482, 513, 573]	234.62€
[118, 240, 331, 391, 422, 573]	222.14€
[118, 240, 331, 391, 482, 573]	222.33€
[118, 240, 331, 391, 513, 573]	231.80€
[118, 240, 331, 422, 482, 573]	224.88€
[118, 240, 331, 422, 513, 573]	220.99€
[118, 240, 331, 482, 513, 573]	234.34€
[118, 240, 391, 422, 482, 573]	223.97€
[118, 240, 391, 422, 513, 573]	220.88€
[118, 240, 391, 482, 513, 573]	227.99€
[118, 300, 331, 391, 422, 573]	228.72€
[118, 300, 331, 391, 482, 573]	228.49€
[118, 300, 331, 391, 513, 573]	234.17€
[118, 300, 331, 422, 482, 573]	228.86€
[118, 300, 331, 422, 513, 573]	227.76€
[118, 300, 331, 482, 513, 573]	237.14€
[118, 300, 391, 422, 482, 573]	228.96€
[118, 300, 391, 422, 513, 573]	227.64€
[118, 300, 391, 482, 513, 573]	235.03€
[118, 331, 391, 422, 482, 573]	234.60€
[118, 331, 391, 422, 513, 573]	234.41€
[118, 331, 391, 482, 513, 573]	239.74€
[209, 240, 300, 331, 391, 573]	234.12€
[209, 240, 300, 331, 422, 573]	223.66€
[209, 240, 300, 331, 482, 573]	232.63€

(*continued on next page*)

(*continued*)

6 Decision-Moments	Total Cost
[209, 240, 300, 331, 513, 573]	236.60€
[209, 240, 300, 391, 422, 573]	222.14€
[209, 240, 300, 391, 482, 573]	225.00€
[209, 240, 300, 391, 513, 573]	232.78€
[209, 240, 300, 422, 482, 573]	227.05€
[209, 240, 300, 422, 513, 573]	222.17€
[209, 240, 300, 482, 513, 573]	234.60€
[209, 240, 331, 391, 422, 573]	226.14€
[209, 240, 331, 391, 482, 573]	228.20€
[209, 240, 331, 391, 513, 573]	235.78€
[209, 240, 331, 422, 482, 573]	227.68€
[209, 240, 331, 422, 513, 573]	223.80€
[209, 240, 331, 482, 513, 573]	234.32€
[209, 240, 391, 422, 482, 573]	225.36€
[209, 240, 391, 422, 513, 573]	223.28€
[209, 240, 391, 482, 513, 573]	231.88€
[209, 300, 331, 391, 422, 573]	226.15€
[209, 300, 331, 391, 482, 573]	228.60€
[209, 300, 331, 391, 513, 573]	235.79€
[209, 300, 331, 422, 482, 573]	227.68€
[209, 300, 331, 422, 513, 573]	223.81€
[209, 300, 331, 482, 513, 573]	234.32€
[209, 300, 391, 422, 482, 573]	225.17€
[209, 300, 391, 422, 513, 573]	223.30€
[209, 300, 391, 482, 513, 573]	232.17€
[209, 331, 391, 422, 482, 573]	**219.68€**
[209, 331, 391, 422, 513, 573]	223.39€
[209, 331, 391, 482, 513, 573]	229.28€
[209, 391, 422, 482, 513, 573]	226.26€
[178, 209, 269, 300, 360, 573]	236.81€
[178, 209, 269, 300, 391, 573]	234.93€
[178, 209, 269, 300, 451, 573]	227.17€
[178, 209, 269, 300, 482, 573]	233.49€
[178, 209, 269, 300, 542, 573]	239.57€
[178, 209, 269, 360, 391, 573]	235.32€
[178, 209, 269, 360, 451, 573]	226.36€
[178, 209, 269, 360, 482, 573]	231.12€
[178, 209, 269, 360, 542, 573]	233.71€
[178, 209, 269, 391, 451, 573]	226.45€
[178, 209, 269, 391, 482, 573]	225.00€
[178, 209, 269, 391, 542, 573]	231.80€
[178, 209, 269, 451, 482, 573]	226.57€
[178, 209, 269, 451, 542, 573]	226.27€
[178, 209, 269, 482, 542, 573]	233.98€
[178, 209, 300, 360, 391, 573]	235.33€
[178, 209, 300, 360, 451, 573]	226.36€
[178, 209, 300, 360, 482, 573]	231.12€
[178, 209, 300, 360, 542, 573]	233.72€
[178, 209, 300, 391, 451, 573]	226.46€
[178, 209, 300, 391, 482, 573]	225.38€
[178, 209, 300, 391, 542, 573]	231.81€
[178, 209, 300, 451, 482, 573]	226.59€
[178, 209, 300, 451, 542, 573]	226.29€
[178, 209, 300, 482, 542, 573]	233.99€
[178, 209, 360, 391, 451, 573]	223.48€
[178, 209, 360, 391, 482, 573]	223.98€
[178, 209, 360, 391, 542, 573]	230.89€
[178, 209, 360, 451, 482, 573]	224.97€
[178, 209, 360, 451, 542, 573]	224.50€
[178, 209, 360, 482, 542, 573]	230.21€
[178, 209, 391, 451, 482, 573]	224.98€
[178, 209, 391, 451, 542, 573]	227.96€
[178, 209, 391, 482, 542, 573]	228.38€
[178, 209, 451, 482, 542, 573]	230.23€
[178, 269, 300, 360, 391, 573]	234.14€
[178, 269, 300, 360, 451, 573]	226.37€
[178, 269, 300, 360, 482, 573]	231.13€
[178, 269, 300, 360, 542, 573]	234.42€
[178, 269, 300, 391, 451, 573]	224.28€
[178, 269, 300, 391, 482, 573]	224.81€
[178, 269, 300, 391, 542, 573]	231.81€
[178, 269, 300, 451, 482, 573]	226.59€
[178, 269, 300, 451, 542, 573]	226.47€
[178, 269, 300, 482, 542, 573]	234.00€
[178, 269, 360, 391, 451, 573]	222.29€
[178, 269, 360, 391, 482, 573]	223.71€

(*continued on next page*)

(*continued*)

6 Decision-Moments	Total Cost
[178, 269, 360, 391, 542, 573]	230.81€
[178, 269, 360, 451, 482, 573]	224.88€
[178, 269, 360, 451, 542, 573]	224.68€
[178, 269, 360, 482, 542, 573]	230.23€
[178, 269, 391, 451, 482, 573]	224.80€
[178, 269, 391, 451, 542, 573]	227.78€
[178, 269, 391, 482, 542, 573]	227.21€
[178, 269, 451, 482, 542, 573]	224.98€
[178, 300, 360, 391, 451, 573]	223.49€
[178, 300, 360, 391, 482, 573]	223.72€
[178, 300, 360, 391, 542, 573]	230.81€
[178, 300, 360, 451, 482, 573]	224.69€
[178, 300, 360, 451, 542, 573]	224.49€
[178, 300, 360, 482, 542, 573]	230.23€
[178, 300, 391, 451, 482, 573]	224.80€
[178, 300, 391, 451, 542, 573]	227.78€
[178, 300, 391, 482, 542, 573]	227.20€
[178, 300, 451, 482, 542, 573]	225.00€
[178, 360, 391, 451, 482, 573]	221.92€
[178, 360, 391, 451, 542, 573]	224.90€
[178, 360, 391, 482, 542, 573]	224.80€
[178, 360, 451, 482, 542, 573]	225.09€
[178, 391, 451, 482, 542, 573]	240.44€

Appendix B

When the last decision moment is set to 4:00 p.m. (420'), and 5:00 p.m. (480'), 119 requests and 60 requests, respectively, are delivered next day. The cost is slightly higher as in the baseline scenario (with the last decision-moment equal to 573'), and the service level is significantly worse. On the other hand, when testing a later time (e.g., 7:13 p.m., considering T= 8:00 p.m.; shortest car drive to the farthest customer (back and forth) = 40'; service time: 2'; loading time: 5'), no request is received after that time, but the cost is higher due to a higher number of car trips (69 *vs.* 61), and overtime is needed since in some days, the remaining 47 minutes (8:00 p.m. – 7:13 p.m.) are not enough to perform the car trips at the last shift.

Last Decision-Moment (DM)	**Cost**	**#car trips**	**# drone trips**	**# Req. after Last DM [%]**	**Overtime**
420' (4:00 p.m.)	222.11€	60	194	119 [28%]	–
480' (5:00 p.m.)	222.51€	60	196	60 [14%]	–
573' (6:33 p.m.)	219.68€	61	193	0	–
613' (7:13 p.m.)	242.45€	69	185	0	145'

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