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1 **USING DRONES IN THE LAST-MILE LOGISTICS PROCESSES OF MEDICAL**  
2 **PRODUCT DELIVERY: A FEASIBILITY CASE STUDY IN ROTTERDAM**

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**1 ABSTRACT**

2 The term last-mile delivery refers to the final leg of a business-to-customer service, in which prod-  
3 ucts are shipped from a depot to a destination point by means of land transportation, such as vans  
4 and small trucks. Although these vehicles provide a common and easy way to consign products,  
5 companies are striving for new transport technologies to reduce congestion, infrastructure limita-  
6 tions and air pollution. An alternative to road-bounded vehicles that has recently gained attention is  
7 the adoption of drones in parcel delivery. Drone applications range from military training, surveil-  
8 lance, path recognition and shipment of perishable products in emergency situations. Research on  
9 drones as delivery vehicles is still in its early stages, with some practical trials carried out by leader  
10 companies such as Google and Amazon. However, the application of drones in the pharmaceutical  
11 sector for home deliveries of medical products, has not been investigated yet. To gain new insights  
12 into the feasibility of introducing drones in the delivery fleet, drone applications were studied for  
13 the delivery operations of the pharmacy BENU 't Slag, in Rotterdam. Two scenario alternatives  
14 were tested using the Vehicle Routing Problem formulation. A Large-scale Neighborhood Search  
15 algorithm was implemented to solve the problem and derive the performance indicators associ-  
16 ated with each scenario. Performances were then analyzed through a comparative analysis. When  
17 drones were introduced in the delivery fleet, indicators showed improvements in environmental  
18 aspects, service time and delivery costs, with a reduction of 9% in CO2 emissions, 12% in service  
19 time and 5.6% in cost per item.

20

21 *Keywords:* Drones, Large-scale Neighborhood Search, last-mile delivery, medical products, net-  
22 work optimization, pharmaceutical sector, Vehicle Routing Problem

## 1 INTRODUCTION

2 The term last-mile delivery refers to the final leg of a business-to-customer service, in which a  
3 product is shipped from a depot to a destination point (1). Last-mile logistics are generally oper-  
4 ated by road transportation means, such as vans and small trucks. The growing demand of home  
5 deliveries is increasing the number of vans on roads, leading to traffic congestion and air pollution  
6 (2). Together with congestion and environmental impact cutbacks, cost reduction is a big challenge  
7 faced by the last-mile sector. Studies have shown that the last-mile leg is the most expensive part  
8 of the delivery process, accounting up to 75% of the total cost of the logistic chain (3).

9 To provide a faster and more cost-efficient home delivery service, companies are now striving  
10 for new technologies. With specific attention to urban areas and densely populated neighborhoods,  
11 the aim of recent studies was to find feasible alternatives to vans, so that less or smaller vehicles  
12 are introduced in the daily traffic, to reduce congestion, speed up the delivery process and save on  
13 operational costs. According to Gruber et al. (4), a valid alternative is represented by electric cargo  
14 bikes, which can deliver packages to the end user in a fast and reliable way, avoiding traffic con-  
15 gestion and increasing accessibility. Another option introduced by Agatz et al. (5) is the adoption  
16 of drones in the delivery fleet, to reduce congestion and pollution and overcome the problem of  
17 infrastructure limitation.

18 Although several studies have been conducted regarding drone's utilization, especially in  
19 aerial photography, surveillance and path recognition, their application in the pharmaceutical sec-  
20 tor, and specifically for home deliveries of medical products, has not been investigated yet. Starting  
21 from the initial hypothesis that drones provide a feasible fleet addition for the last-mile logistics of  
22 medical product, the following research question is raised:

23 *How can the pharmaceutical sector benefit from the introduction of drones for the last-mile*  
24 *logistic process, in combination with the current means of transport?*

25 To gain new insights into the feasibility of introducing drones in the delivery fleet composi-  
26 tion, this research utilizes a Vehicle Routing Problem (VRP) optimization technique to analyze and  
27 compare two different network alternatives. The first alternative refers to the current situation, in  
28 which medical products are delivered using three vans with three corresponding drivers, each of  
29 them loading the products at the pharmacy and visiting a pre-defined set of customers. The second  
30 alternative envisions a future scenario, in which drones are introduced in the heterogeneous fleet  
31 composition cooperating with vans. Drones are piloted remotely from the pharmacy and work in  
32 a non-synchronized way with vans, meaning that each vehicle has its own set of customers and its  
33 own delivery route. A Large-scale Neighborhood Search (LNS) algorithm is used to implement the  
34 VRP and examines the performance indicators associated with the two design alternatives. Conclu-  
35 sively, several indicators show improvement by the introduction of drones in the fleet composition,  
36 especially in terms of service time and CO2 emission.

## 37 BACKGROUND ANALYSIS

### 38 The last-mile delivery sector

39 Last-mile delivery refers to the final process of a business-to-customer (B2C) service and concerns  
40 the logistic operations of from a depot to the end user. According to Gevaers et al. (6), important  
41 logistic decisions must be taken upon consignments, being the identification of the starting point  
42 and delivery destinations, the means through which customers can collect the products and the  
43 delivery agreements on time of shipment and return policies.

1 The main problems that hamper the effectiveness and efficiency of the last-mile delivery sector  
2 are high costs of operations, traffic congestion and environmental damage. Studies have shown that  
3 the last-mile leg is the most expensive part of the delivery process, counting up to 75% of the total  
4 cost of the logistic process (3). Moreover, vans and small trucks are the most used vehicles for  
5 last-mile delivery, which cause not only traffic congestion, especially in densely urbanized areas,  
6 but also air pollution. In light of these challenges, companies are striving for new technologies, in  
7 order to provide a faster, more cost efficient and greener delivery service (5).

8 In the context of urban areas, electric cargo bikes proved to be an efficient alternative to trucks,  
9 addressing the problem of congestion and limited-access areas (4, 7). Cargo bikes can use a much  
10 denser road network, being able to run in both directions even on one-way roads, and can deliver  
11 packages in limited- or no-access zones, such as pedestrian zones. Moreover, the fact that less  
12 parking space is required, it becomes easier to deliver in areas with narrow streets, without causing  
13 congestion or excessive roadblock (8). A very recent alternative that has been proposed to solve  
14 traffic congestion, pollution and infrastructure limitation, is the use of Unmanned Aerial Vehicles  
15 (UAVs), mostly referred as drones (5). Drones are fast and can operate without a human driver,  
16 saving time on congested road and cost per kilometer. On the other hand, there is an upper limit to  
17 the size of the package to be delivered and the flight range. Nonetheless, the Aerospace Industries  
18 Association (AIA) forecasts that within 20 years, a large amount of cargo drones will be introduced  
19 in the market. Investments in research and development will rise from a few hundred million USD  
20 to 4 billion USD by 2028 and 30 billion USD by 2036 (9).

## 21 **Drone applications**

22 Drone applications started in the nineteenth century, when the Austrian army used an unmanned  
23 aerial vehicle as a balloon carrier to launch 200 incendiary balloons at the city of Venice (10).  
24 Later, during World War 1, UAVs were used for training personnel (11). The Vietnam war in 1955  
25 (12), the Lebanon war in 1982 and the Gulf war in 1991 (13), saw the use of drones for surveillance  
26 purposes and as armament carriers.

27 Nowadays, drones are mainly used for photography, surveillance, path recognition and ad-  
28 vertisement purposes (14). Studies have also been conducted on the applicability of drones in  
29 emergency situations. Being not bounded to a physical transport infrastructure, having a relatively  
30 high speed and the capability of fly in a straight line between two points, drones have been proved  
31 to be useful when it comes to save lives. Truhlář et al. (15) proposed the use of drones to monitor  
32 beach environments, to increase the survival rate of drowning victims. Their research was followed  
33 by a study from Claesson et al. (16) on how to use drones to provide cardiopulmonary resuscita-  
34 tion and automated external defibrillator in those drowning emergency situations. According to  
35 Haidari et al. (17), other potential applications of drones for medical purposes concern the trans-  
36 port of vaccines in low- and middle-income countries. Modelling the vaccine supply chain for  
37 the Gaza province, in Mozambique, they found that implementing a drone system could increase  
38 vaccine availability and decrease costs, once the high capital investments are overcome.

39 The state of research on drone delivery is still on its early stages. Practical trials were carried  
40 out by leader companies in the delivery sector, such as Amazon, Alibaba and Google (5). In  
41 2014, the American company AMP Electric Vehicles together with the University of Cincinnati  
42 Department of Aerospace Engineering, developed a combined mode of truck and drone for last-  
43 mile delivery (18): while the delivery truck visits a set of locations, a drone simultaneously visits  
44 another set of locations, returning to the truck after each delivery, to pick up another package. In

1 this way, the benefits of trucks (long range, high payload capacity) are combined with the benefits  
2 of drones (high speed and high accessibility), to provide an efficient and cost-effective delivery  
3 service.

#### 4 **Transport network assessment**

5 Last-mile delivery is a transport network problem in which products are shipped from a depot to  
6 a set of customers, using a fleet of vehicles. The logistics of these deliveries should be such that  
7 the cheapest option is selected, providing thus an optimal tour that starts and ends at the depot and  
8 visits all the scheduled customers. Given a set of locations, the most common model formulations  
9 in operation research are the Travelling Salesman Problem (TSP) and the Vehicle Routing Problem  
10 (VRP). The TSP formulated by Dantzig (19), aims to find the shortest path that connects a set of  
11 nodes, for which the order of visit is not important. The VRP, firstly formulated by Fisher and  
12 Jaikumar (20), is a generalization of the TSP. The goal is to define the optimal tour given a set of  
13 nodes and a vehicle fleet composition, such that each node is visited once and only once and total  
14 costs of operations are minimized. The main differences between the TSP and the VRP are in the  
15 vehicle fleet composition and the vehicle capacity restriction, with the latter being able to account  
16 for a heterogeneous fleet composition, with each vehicle having a different capacity (21).

17 Adaptations of the TSP that include drones in the vehicle fleet are found in Murray and Chu  
18 (22). The Flying Sidekick TSP (FSTSP) considers a set of nodes that must be served at least once  
19 and only once by either a truck or a drone. In this configuration, drone and truck depart together  
20 from the depot and can either travel in tandem or independently, carrying out their deliveries si-  
21 multaneously. This configuration is particularly useful when the average distance between the  
22 depot and the nodes to be served is higher than the drone's range. In the case that the depot is in a  
23 convenient position with respect to the nodes to be served (i.e. within the flight range of the fleet  
24 of drones), the TSP can be modified into the Parallel Drone Scheduling TSP (PDSTSP). In this  
25 adaptation, trucks and drones depart and return independently, with the truck serving customers  
26 along a TSP route and the drones serving customers directly from the depot. Being part of two  
27 different networks, no synchronization is needed between van and truck. According to the results,  
28 the gain in travel time is much more consistent in the PDSTSP compared to the FSTSP (22).

#### 29 **METHODOLOGY AND DATA DESCRIPTION**

30 The objective of this study was to determine how can the pharmaceutical sector benefit from the  
31 introduction of drones in the last-mile logistic process. To do so, a comparative analysis was  
32 carried out between two different scenarios, one referring to the current situation and one to the  
33 future plan for home delivery logistics. In the current situation, deliveries are operated with three  
34 delivery vans and three corresponding drivers, that pick up the products from the pharmacy, carry  
35 out their scheduled consignments and conclude their tour back to the pharmacy. In the future  
36 scenario, a heterogeneous vehicle fleet is operated, composed by vans and drones which carry out  
37 home deliveries in a parallel way, each vehicle visiting its own set of customers, starting and ending  
38 at the pharmacy. The choice to adopt a parallel utilization of vans and drones in a non-synchronized  
39 way was supported by the study of Murray and Chu (22), which proved the PDSTSP to be more  
40 efficient than the FSTSP. Moreover, the area covered by the delivery service was not such as to  
41 justify synchronized operations.

42 Data on the current situation, such as vehicle fleet composition, delivery service characteristics  
43 and demand distribution, were obtained from the pharmacy BENU 't Slag, part of BENU Apotheek

1 franchising, located in Rotterdam. For what concerns drone specifications, values referred to the  
 2 x8 long range cargo drone (23). Products are stored in a box attached to the lower part of the  
 3 drone, from which customers can collect their products using a personal pin code. A prototype  
 4 of this box (Figure 1) was developed by a team of students from the faculty of Mathematics and  
 5 Applied Science of Leiden.

6



**FIGURE 1:** Box prototype for drone delivery

7 Input parameters are divided into vehicle characteristics, fleet characteristics, labor restriction,  
 8 delivery agreements and product demand. More specifically, parameters that are inserted in the  
 9 model are as follows (sensitive data omitted):

10 Vehicle characteristics

- 11 • Average van speed = 35 km/h
- 12 • Average drone speed = 70 km/h
- 13 • Fixed and distance costs of van = [-]
- 14 • Fixed and distance costs of drone = [-]
- 15 • Distance limitation for vans = 560 km
- 16 • Distance limitation for drones = 3.2 km
- 17 • Flight time limitation for drones = 1 hour
- 18 • Van capacity = 50 products
- 19 • Drone capacity = 7 products

20 Fleet characteristics

- 21 • Number of vans current situation = 3
- 22 • Number of vans future scenario = 2
- 23 • Number of drones future scenario = 1

24 Labor restriction

- 25 • Working time limit for van drivers = 6 hours

26 Delivery service characteristics

- 27 • Number of depots = 1
- 28 • Number of customers = [-]
- 29 • Service time for products drop off = [-]
- 30 • Distance between customers = [-]

1 Demand

- 2 • Product demand for each customer = [-]

3

4 Drones have strict limitations on distance range and time of flight, which depend on the energy  
5 consumption rate and the charge power (e.g. how many kilometers can be flown with one charge).  
6 For this reason, the classical formulation of the VRP was adapted to include the range and time  
7 constraints for the drone fleet, but also to account for the heterogeneity of the fleet in the objective  
8 function, adding the subscript  $k$  to the cost component  $c_{ijk}$ , so that costs can be differentiated per  
9 vehicle type. The VRP problem was formulated as follows:

**TABLE 1:** Model formulation of VRP

$$\begin{array}{ll}
 \text{OF:} & \min \sum_{i=1}^n \sum_{j=1}^n \sum_{k=1}^m c_{ijk} * x_{ijk} \\
 \\
 \text{ST:} & 1) \sum_{k=1}^m y_{ik} = 1, \quad 1 \leq i \leq n \\
 & 2) \sum_{k=1}^m y_{ik} = m, \quad i = 0 \\
 & 3) \sum_{i=1}^n q_i * y_{ik} \leq Q_k, \quad 1 \leq k \leq m \\
 & 4) \sum_{j=0}^n x_{ijk} = y_{ik}, \quad 0 \leq i \leq n, 1 \leq k \leq m \\
 & 5) \sum_{i=0}^n x_{ijk} = y_{jk}, \quad 0 \leq j \leq n, 1 \leq k \leq m \\
 & 6) \sum_{i \in S} \sum_{j \in S} x_{ijk} \leq |S| - 1, \quad S \subseteq 1, \dots, n, 1 \leq k \leq m \\
 & 7) \sum_{i=0}^n \sum_{j=0}^n t_{ijk} \leq T_k, \quad 1 \leq k \leq m \\
 & 8) \sum_{i=0}^n \sum_{j=0}^n x_{ijk} * d_{ij} \leq R_k, \quad 1 \leq k \leq m
 \end{array}$$

10 The objective is to minimize the cost of the tour, by providing the cheapest possible sequence  
11 of nodes to be visited. For what concerns the cost function  $c_{ijk}$ , fixed and variable components were  
12 calculated developing two cost models, one for each scenario alternative. The decision variable  $x_{ijk}$   
13 assumes the value of 1 if customer  $j$  is visited immediately after customer  $i$  by vehicle  $k$ , and 0  
14 otherwise. The variable  $y_{ik}$  defines whether customer  $i$  is visited with vehicle  $k$ . Constraint 1 sets  
15 that each customer  $i$  must be visited at least once, and only once by just one vehicle  $k$ . Vehicle are  
16 bounded to return to the depot by constraint 2, 4 and 5. The capacity of the vehicles is limited by  
17 constraint 3, in which  $q_i$  indicates the demand at each node visited by vehicle  $k$  and  $Q_k$  the capacity  
18 of vehicle  $k$ . Constraint 6 guarantees that not sub tours are generated. Constraint 7 refers to the  
19 flight time constraint, indicating that the total time from  $i$  to  $j$  using vehicle  $k$  must not exceed the  
20 maximum utilization  $T_k$ . Constraint 8 concerns the distance limitation, imposing that the distance  
21 covered by a vehicle must not exceed the maximum range  $R_k$ .

22 Model output were fleet allocation, customer sequence and vehicle allocation. Results were  
23 displayed in terms of a binary  $n * n * k$  matrix with customer visit sequence and vehicle allocation,  
24 from which vehicle allocation characteristics could be retrieved per single vehicle: distance trav-  
25 elled  $d_k$  [km], driving time  $t_k$  [hour], working time  $wt_k$  [hour], number of stops per vehicle  $n_{stops}$   
26 [-], initial loading  $Q_{used,k}$  [products], and cost of operations  $c_k$  [euro].

27 After having implemented the model, output parameters were used as inputs to calculate the  
28 Key Performance Indicators for the current situation and the future scenario. Alternatives were



1 assessed based on the delivery cost per item (DC), the service time (ST), the fuel consumption  
 2 (FC), the CO<sub>2</sub> emissions, the energy consumption (EC), the cost of power supply (PS) and the  
 3 payload capacity (PC). Based on the type of van used, CO<sub>2</sub> emission rate for the van fleet was  
 4 assumed to be 115 g/km, whereas the fuel consumption was averaged to 5 liters/100km (24). For  
 5 the fuel price, the average amount for the year 2018 was considered, equal to 1.33 euro/liter (25).  
 6 Based on the drone characteristics, energy consumption was fixed to 0.26kW/h (23) and the energy  
 7 price was set to 0.1024 euro/kW (26).

$$8 \quad DC = \sum_k c_k / n_{del} \quad [euro/item] \quad (1)$$

$$9 \quad ST = \sum_k t_k \quad [hours] \quad (2)$$

$$10 \quad FC = \sum_k d_k * 5 / 100 \quad \text{with } k \in \text{van fleet} \quad [liters] \quad (3)$$

$$11 \quad CO_2 = \sum_k d_k * 115 \quad \text{with } k \in \text{van fleet} \quad [g] \quad (4)$$

$$12 \quad EC = \sum_k t_k * 0.26 \quad \text{with } k \in \text{drone fleet} \quad [kW] \quad (5)$$

$$13 \quad PS = 1.33 * FC + 0.1024 * EC \quad [euro] \quad (6)$$

$$14 \quad PC = \left( \sum_k Q_{used,k} / Q_{available,k} \right) / n_{vehicles} \quad [%] \quad (7)$$

## 16 SOLUTION APPROACH

17 Many solution approaches are available for solving the Vehicle Routing Problem. For this case  
 18 study it was decided to use an open source spreadsheet solver specific for VRP, developed by Er-  
 19 dođan (27). Alternatives were tested using a Large-scale Neighbourhood Search (LNS) algorithm,  
 20 to find quasi-optimal solutions by means of iterations (28). Based on all the input inserted, the  
 21 model provided the optimal number of vehicles to be used, the sequence of visits, the cost as-  
 22 sociated with each vehicle, the distance and the time travelled by each vehicle and the total cost  
 23 of operation. Furthermore, locations and routes could be visually inspected in the visualization  
 24 worksheet, where the tour for each vehicle was placed upon the map from the GIS web service.

25 Two important modifications were operated. For what concerns the variable costs, the Ex-  
 26 cel Spreadsheet Solver did not account for time related costs, but only distance related costs. To  
 27 overcome this drawback and still include the human labor cost and the energy cost (expressed in  
 28 euro/hour), these two costs were converted into distance costs (expressed in euro/km) using the  
 29 average vehicle speed. Calculating how many hours are needed to travel 1 kilometer, and multi-  
 30 plying this value by the hourly cost, it was indeed possible to obtain the time related components  
 31 expressed in euro/km. The second modification concerned the distance computation method and  
 32 the average vehicle speed used in the implementations. Vans and drones are inherently different,  
 33 especially in terms of average speed and path followed for going from origin A to destination B.  
 34 The assumptions made on vehicle speed assigned an average speed of 35 km/h for the van fleet  
 35 and 70 km/h for the drone fleet. The distance computation method for vans was the Bing Map  
 36 real distance, which calculates the real distance between two points, following the real existing  
 37 infrastructure and the road regulations that are applied. For the drone, the Birdflight distance com-  
 38 putation was used, that calculates the shortest straight line that a plane would cover between two

1 points. The Spreadsheet Solver allowed for only one distance computation per implementation,  
2 and just one vehicle speed could be inserted. Running the model first with the Bing Maps compu-  
3 tation and vehicle speed of 35 km/h and then with the Birdflight computation and vehicle speed of  
4 70 km/h, results for distance and time travelled were on average respectively 37% and 65% higher  
5 in the first run. Therefore, the inability of the solver to use two different distance computations  
6 in the same implementation might have brought biased results, assigning less customers to the  
7 drone route. For this reason, for the future scenario assessment, two implementations were run,  
8 one with distance and speed characteristics of vans and one with distance and speed characteristics  
9 of drones. Results were then assembled together so that the route is still feasible, and capacity and  
10 node constraints are still respected.

11 To quantify the credibility of the model, verification and validation tests were performed. A  
12 code verification and a calculation verification were performed, to ensure that the computer model  
13 accurately implemented the mathematical formulation. Moreover, an extreme condition validation  
14 test was also executed, to compare the simulation outcome and the experimental outcome on a  
15 quantitative level and define the extent to which the model accurately represents the real world.

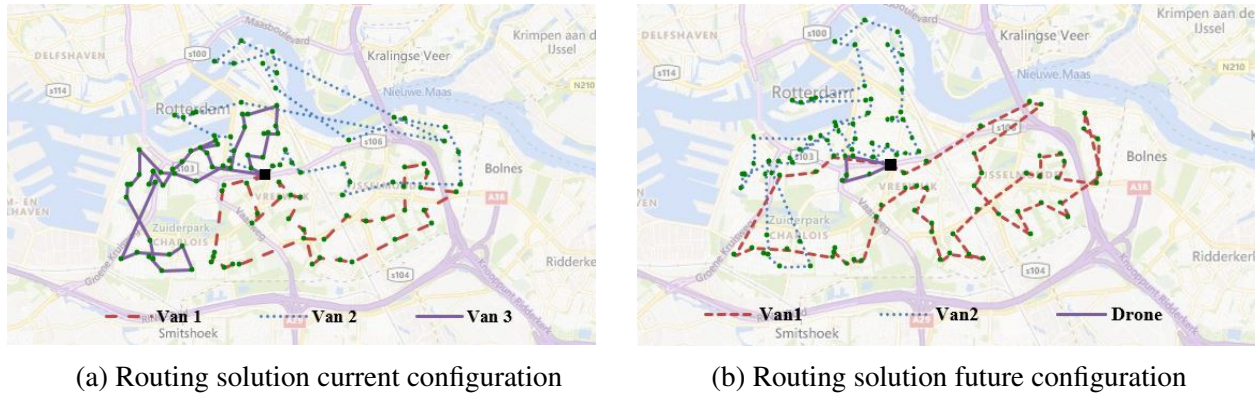
16 To test the solution algorithm, a known problem was run with the VRP Excel Solver and the  
17 solutions obtained were compared with the best know solutions. The benchmark data set used in  
18 his research was the one provided in Christofides et al. (29), containing data about Capacitated  
19 VRP and Distance Constrained VRP. The best-known solution values are then compared to the so-  
20 lutions obtained with the VRP Excel spreadsheet solver. Furthermore, an example of a real world  
21 situation was run with pickups and deliveries with 1 depot and 10 customer locations spread in the  
22 United Kingdom, made available by Erdoğan (27). The calculation verification test was performed  
23 considering a sub-problem of the initial one, with just 5 customers and one van. Numerical results  
24 obtained with the VRP Excel Spreadsheet Solver were compared to analytical results using the  
25 Farthest Insertion Heuristic algorithm, to find the numerical error induced by the computer model.  
26 Lastly, the extreme condition test was carried out by setting all the input parameters to their ex-  
27 treme values. Two situations were run: one with parameters set to zero and one with parameters  
28 approaching infinity.

29 Verification results showed that the code was properly written, with a 0.6% average gap on  
30 best known VRP solutions, and the model was correctly formulated, with a 0.15% gap on model  
31 development. The numerical error introduced by the computer model proved to be very small,  
32 with a gap of 0.016% between numerical solutions and analytical calculations. Moreover, extreme  
33 condition tests provided expected results both in a qualitative and quantitative way.

## 34 RESULTS

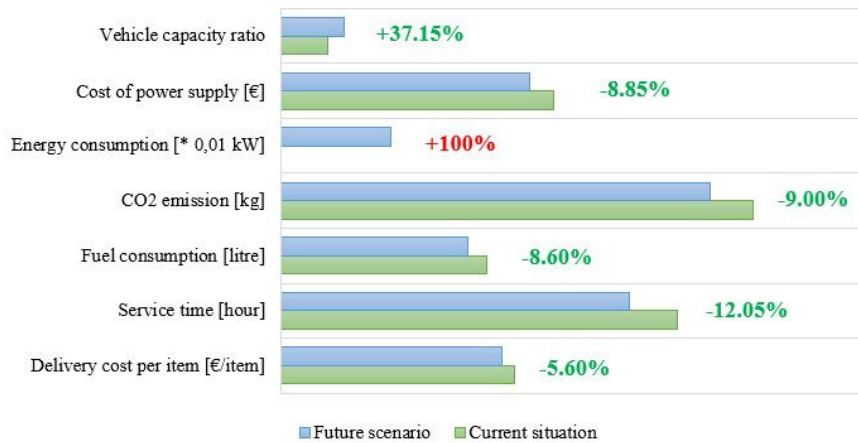
35 Results were reported in terms of routing solutions, in which customer sequence for each vehi-  
36 cle was visualized on top of the map of Rotterdam. Tables containing the routing sequence, total  
37 number of stops, distance travelled, service time, vehicle loading and cost of operations for each  
38 vehicle resulted from the model implementation. With these model outputs, a KPI comparison was  
39 conducted and results were provided using bar charts. Performance values were expressed in terms  
40 of day of operation, except for the delivery cost per item, which is specific for each item delivered.  
41 In this way, the comparative analysis could be carried out under an economic perspective, but also  
42 under environmental, time savings and payload utilization perspectives.

43



**FIGURE 2:** Comparison of routing solutions for current situation and future configuration

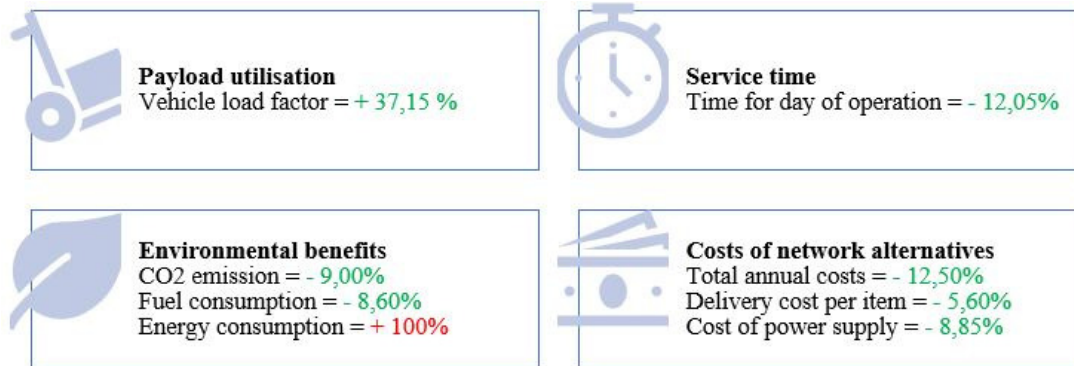
1 Referring to Figure 2, vehicle utilization is higher in the future configuration. With the elim-  
 2 ination of one van and the introduction of one drone, the total available capacity is reduced from  
 3 150 products to 107. Consequently, each van visits more customers compared to the previous  
 4 situation, since the drone can only visit a limited number of customers, mostly due to capacity  
 5 restrictions. Figure 3 shows a comparison of performance indicators between the two alternative  
 6 situations. Sensitive data have been omitted, providing just the percentages of variations.  
 7



**FIGURE 3:** Comparison of Key Performance Indicators

8 For the comparison of costs associated with network alternatives, two different analysis were  
 9 made. The first one compared the costs associated with one day of operation in the current situation  
 10 with the costs of the same operation in the future scenario. A second analysis considered the  
 11 business model of adopting the future scenario alternative, characterized by the purchase of one  
 12 drone and the sale of one van and all the implications that followed, evaluating the monetary  
 13 benefit in terms of total annual cost. It was found that with the adoption of drones, the pharmacy  
 14 could potentially save 12.5% of the total annual expenses, based on a 5-year depreciation period.  
 15 Based on the demand distribution, the cost per item is reduced by 5.60% per package delivered.  
 16 Routes were found to be faster, decreasing the total service time by 12.05%, suggesting that more

1 customers could potentially be served and the geographical area expanded. The introduction of  
 2 flying vehicles and the consequent reduction of road vehicles brought indisputable improvements  
 3 under an environment perspective: CO2 emissions were reduced by 9.00% for a daily operation,  
 4 and less vehicles were driving in the urban area, decreasing the amount of traffic congestion.



**FIGURE 4:** Benefits of introducing drones in the delivery fleet

## 5 Sensitivity analysis

6 To evaluate the extent to which changes in model inputs affect the model outputs, thus the perfor-  
 7 mance indicators, a sensitivity analysis was carried out. Several implementations were run, and in  
 8 each run only one parameter was changed.

### 9 *Changes in vehicle speed*

10 In the model formulation, time related costs were embedded in distance cost, by transforming  
 11 the time in the network into distance travelled using the average speed. Therefore, changing the  
 12 vehicle speed entailed a change in operational cost, given the fact that less or more kilometer can be  
 13 travelled. The performance indicator that was mostly affected by vehicle speed variations was the  
 14 cost per item, which considerably decreased by increasing vehicle speed. Service times and fuel  
 15 consumption were slightly affected by vehicle speed variations, showing a small increase in the  
 16 first one and decrease in the second one. Vehicle capacity ratio remained unaffected by variations  
 17 of vehicle speed.

### 18 *Changes in vehicle capacity*

19 All KPIs were somehow affected by these changes: the cost per item decreased after a first increase  
 20 in vehicle capacity, to remain constant higher values. As expected, capacity ratio values fluctuate  
 21 depending on the number of vehicle used for deliveries: increase the capacity brought a decrease  
 22 in vehicle utilization, to increase again once it is enough to eliminate one vehicle from the fleet.

### 23 *Changes in distance limitation*

24 Variations in distance limits did not cause significant changes performance indicator values. With  
 25 very restrictive values (from the minimum allowable value of 19 km to 25 km), a small decrease in  
 26 cost per item, fuel consumption and service time was noticed, to settle to a constant value for bigger  
 27 distances. Vehicle capacity ratio remained constant for all the distance limitations considered.

1 *Changes in time limitation*

2 Variations in working time limits did not cause any change in cost per item, service time fuel  
3 consumption and vehicle capacity ratio. The reason behind these results is that the time limit  
4 constraint for the van fleet was not as restrictive as other constraints, for example the capacity  
5 constraint. Therefore, provided that a minimum distance range is guaranteed, increasing this pa-  
6 rameter did not bring any changes in the performance indicators.

7

8 In addition, three other potential future situations were assessed and compared with the future  
9 scenario envisioned in this research. One situation referred to a fleet entirely composed by electric  
10 vehicles (EVs), i.e. electric vans and drones. One other situation concerned a fleet composed by  
11 only drones. In this way, the influence of the power supply mode and the vehicle fleet composition  
12 on Key Performance Indicators was assessed. Lastly, a scenario with multiple depots was briefly  
13 analyzed, to assess the influence of depot location.

14 *Test scenario with only EVs*

15 In this test scenario, only EVs were considered for the delivery fleet, composed by 2 e-vans and  
16 1 drone. A new cost model was developed considering the cost related to the e-van fleet, which  
17 results showed an increase of 13.9% in annual costs. Vehicle capacity of e-vans was assumed to  
18 remain the same as non-electric ones, hence the vehicle capacity ratio did not change between the  
19 two compared scenarios. For the energy consumption it was assumed that the consumption of e-  
20 vans is equal to 0.11 kW/h (30). The total energy consumed for a day of operation was almost 30  
21 times higher than the scenario with non EVs. CO<sub>2</sub> emissions and fuel consumption were reduced  
22 to a null value, since no gasoline was needed to operate vehicles. Therefore, the total cost of power  
23 supply referred only to the energy cost, and it was dropped by 98.72% per day of operation. Cost  
24 per item changed substantially, with an increase of 53.6%. Lastly, service time changes marginally,  
25 being only 2.35% higher in the test scenario with EVs only.

26 *Test scenario with only drones*

27 The aim of this test was to define how many vehicles would be needed in case of a fleet composed  
28 entirely by drones. Demand was kept equal to the initial values and fixed and variable costs referred  
29 to the one found in the cost model for the future scenario. After performing a first LNS iteration,  
30 the model found a non-feasible solution due to range limitation: with a maximum range of 4 km,  
31 some customers could not be reached and had to be excluded from the home delivery service. To  
32 avoid this loss, the drone range was increased up to 32 km at the expenses of payload capacity (23).  
33 With a range of 32 km and a drone capacity of 3 products, a new implementation was run. Time  
34 constraint remained unchanged. Results of this implementation showed that the minimum number  
35 of drones needed to complete a daily operation was 35. With this information, a new cost model  
36 was developed, which results showed that annual costs increase of 243.8%. Indicators showed  
37 an overall improvement. Vehicle capacity improved by 10 percentage points. Environmentally  
38 speaking, the test scenario brought considerable benefits, dropping to 0 the CO<sub>2</sub> emissions and  
39 the fuel consumption. Cost of power supply dropped by 98.42%, since the energy cost is lower  
40 than the fuel cost and the consumption rate is less in electric vehicles. Service time also improved,  
41 with a reduction of 27.4%. As expected, the energy consumption largely increased, due to the  
42 introduction of a big number of electric vehicles. The delivery cost per item also experienced a

1 steep increase, which was related to the higher annual cost associated with this test scenario.

## 2 *Test scenario with 5 depots*

3 Starting and ending locations were increased up to 5 depot locations (including the pharmacy).  
4 The cost model was the same as the one for the test scenario with drones only, hence with an in-  
5 crease in annual costs of 243.8%. Vehicle characteristics were also kept unchanged from that test  
6 scenario. Some indicators did not change when the number of depots was incremented. Vehicle  
7 capacity ratio remained the same, since the same demand and the same vehicle capacity was con-  
8 sidered for the two scenarios. Same line of reasoning for the CO<sub>2</sub> emission and fuel consumption:  
9 characterized by a fully electric drones fleet, both alternatives had zero emissions and zero fuel  
10 consumption. When multiple depots were introduced, vehicles could carry out their deliveries in  
11 a faster way, travelling a shorter distance. Therefore, a decrease in service time and cost of oper-  
12 ations was noticed: adding four more depots reduced the service time by 11.8% and the cost of  
13 power supply by 33.3%.

## 14 **DISCUSSION OF RESULTS**

15 The existing literature presented a promising overview on drone's utilization, with several studies  
16 concerning shipment of medicines and blood samples in emergency situations. With this research,  
17 the initial hypothesis is validated, being drones a feasible fleet addition for the last-mile logistics  
18 of medical products, and the research question is answered providing a quantitative analysis of  
19 the improvements in cost per item, service time, environmental impact and payload utilization.  
20 Implementing a Vehicle Routing Problem, the optimal customer sequence and vehicle allocation  
21 are found for both scenarios with and without drones, and network efficiency is assessed and com-  
22 pared using Key Performance Indicators. Although results showed a clear predisposition towards  
23 the adoption of drones in the home delivery fleet, some aspects are worth to mention.

24 First of all, results and performance indicators refer to the case study of BENU 't Slag in  
25 Rotterdam. Cost components highly depend on the average number of deliveries per day and  
26 on the distance between nodes. Input data are either assumed or obtained from the pharmacy.  
27 Nonetheless, it is believed that results can be extended for similar case studies, for which research  
28 could potentially produce similar or better results.

29 Speaking of data availability, it is important to mention that a lot of assumptions were made,  
30 especially on cost components and demand distribution. Real data pertaining the case study were  
31 used for the total demand and for the area in which BENU 't Slag operates the home delivery  
32 service. The exact number of costumers and their precise location was not made available by the  
33 pharmacy; therefore, node distribution was made randomly within the postcodes, trying to cover as  
34 much area as possible. Changes in the demand allocation produce a different routing solution and  
35 a different associated cost. Although noticeable, these variations were not substantial and similar  
36 results were obtained.

37 For what concerns the solution approach, two important modifications were operated. The  
38 first modification concerned the variable cost component of the objective function: time-related  
39 costs were converted into distance-related costs, using the average vehicle speed. The second  
40 modification referred to the implementation of the future configuration alternative. Two different  
41 implementations were run within the future scenario, and results were assembled together in a  
42 feasible way, to account for the different vehicle speed and distance computation for the van fleet  
43 and for the drone fleet.

1 To evaluate the cost savings brought by the introduction of drones in the vehicle fleet for  
2 home delivery of medical products, comparing the cost model of the current situation and the  
3 future configuration was not sufficient. For this reason, two different analysis were made. A first  
4 analysis considered the business model of adopting the future scenario alternative, characterized  
5 by the purchase of one drone and the sale of one van and all the implications that follow, evaluating  
6 the monetary benefit in terms of total annual cost. Results showed that with the adoption of the  
7 future fleet configuration, the pharmacy could save 12.5% of the total annual expenses. The second  
8 analysis compared the costs associated with one day of operation in the current situation with the  
9 costs of the same operation in the future configuration.

## 10 CONCLUSIONS

11 Throughout the research, several problems of the current last-mile transportation means have been  
12 addressed. The main challenges that were defined consisted in cost reduction and congestion and  
13 pollution diminution. Two design alternatives were elaborated and tested to understand to which  
14 extent the pharmaceutical sector can benefit from the adoption of a heterogeneous fleet composed  
15 by vans and drones. Benefits were calculated in terms of cost, environment, service time and  
16 payload utilization.

17 Performance indicators showed that with the introduction of drones in the vehicle fleet, deliv-  
18 ery cost per item is reduced by 5.60%, and total annual costs were reduced by 12.5%.

19 Environmental benefits were compared evaluating the CO<sub>2</sub> emission, the fuel consumption  
20 and the energy consumption in each network configuration. With the removal of one van from  
21 the vehicle fleet and the introduction of one electric vehicle, the total distance travelled by road  
22 vehicles decreases, leading to a consequent decrease in CO<sub>2</sub> emission and fuel consumption, but  
23 an increase in energy consumption. As expected, CO<sub>2</sub> emissions decreased on average by 9% per  
24 day of operation and fuel consumption was reduced by 8.6% a day.

25 Service time is defined as the time that each vehicle spends to complete its tour, summed  
26 over all vehicles. It indicates the total time spent in the system, to conclude the daily deliveries.  
27 Drones are faster than vans, and most importantly are not bounded by the physical infrastructure.  
28 As expected, the adoption of the future scenario alternative reduced the total service time by 12%.

29 Payload utilization was calculated as the ratio between the used capacity and the available  
30 capacity. Total demand was kept unchanged between the two network alternatives. For what  
31 concerns the total vehicle capacity, van capacity was assumed to be 50 units whereas drone capacity  
32 only 7 units, meaning that scenario 1 had a maximum available capacity of 150 products while  
33 scenario 2 only 107 products. As expected then, payload utilization increased drastically in the  
34 future scenario, with an improved capacity ratio of 25.75 percentage points.

## 35 RECOMMENDATIONS

36 Once results showed that the introduction of drones would bring substantial improvements in the  
37 logistic operations of last-mile delivery for the pharmacy BENU 't Slag, several scenarios alter-  
38 natives were hypothesized, to check the extent to which different network configurations would  
39 provide different performance indicators. A fully-drone configuration, a combination of EVs and  
40 drones configuration and a multiple depot configuration were suggested. First results showed that  
41 a homogeneous fleet of only drones brought a considerable increase in cost per item. Environ-  
42 mental benefits were undoubtedly interesting, with a drop of CO<sub>2</sub> emission and fuel consumption  
43 down to zero. Same environmental results were obtained with a fully electric heterogeneous fleet

1 composition, with 2 e-vans and 1 drone. Moreover, with 2 e-vans and 1 drone, cost per item was  
2 considerably reduced, as well as the cost of power supply. Lastly, the test scenario with multiple  
3 depot showed that, in comparison with the situation where only one depot is arranged, service time  
4 could be reduced by 12% and cost of power supply by 33%. Therefore, the main recommendation  
5 for further research is the implementation of the scenario with a fully electric heterogeneous fleet,  
6 composed by e-vans and drones, with multiple depot locations.

7 For what concerns the implementation method, the research can be extended including the  
8 usage of different solution approaches that account for multiple distance computations and average  
9 vehicle speed in the same implementation setup. Examples are Simulated Annealing or Genetic  
10 Algorithms implemented in Matlab or Python. Comparing the results obtained with the one of  
11 this research might provide a better insight on the feasibility assessment of drones for last-mile  
12 logistics. Moreover, it is recommended to undertake some practical test as soon as regulations will  
13 allow drones to fly.

14 Under a technical perspective, it is interesting to further investigate on some technical charac-  
15 teristics of the vehicle fleet. As an example, fuel consumption was assumed to be static, fixed at 5  
16 liters/100km. In reality, this value changes dynamically based on vehicle speed and traffic conges-  
17 tion (i.e. if the vehicle needs to stop and re start the engine several times). Another characteristic  
18 that is worth investigating, is the effect of weather condition on drone flight performances, e.g.  
19 how wind or rain might affect the possibility of drones to reach customers locations.

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