# Synchronized Drone and Truck Routing Problem: A Multi-Stakeholder Perspective

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Abstract: This paper introduces a synchronized truck and drone routing problem consisting a fleet of capacitated trucks and drones dispatching last-mile deliveries. Each truck, while traveling on its route to serve customers, could stop and launch drones which perform multiple back and forth trips between the truck and one or more delivery destination, serving one customer at a time. The synchronization between trucks and drones moves is mandatory since the drone is launched and retrieved by the truck, that should wait for delivery completion and drone retrieval. Following a multi-stakeholder perspective, different customer- and business-oriented objectives are included to account for the presence of different (public an private) actors and end-users with conflicting interests and preferences. We formulate the problem as a mixed-integer program to determine the optimal truck routes and sequence of drone trips under the synchronization assumption. The proposed model is then solved by a meta-heuristic solution approach.

## 1 INTRODUCTION

The last few years have seen a sharp increase of the paradigms of on-demand economy and e-commerce. New emerging business models are no longer driven by suppliers, but are more and more influenced by customers' preferences and expectations in terms of time and cost, with a consequent disruptive impact on the delivery process (Perboli and Rosano, 2019). To survive in such a competitive market, e-commerce companies should face the upward trend for fast and cheap deliveries, optimizing the last-mile process. It is well-recognized that routing inefficiencies, in the last leg of of the distribution, may contribute to delayed deliveries, loss of revenues and profits and above all, unsatisfied customers. To catch up with these trends, in the last decade, new delivery systems, exploiting the complementary nature of trucks and drones, have been investigated with the aim of assessing the value of using drones within logistics chain. Drones are considered as a potential solution to the last-mile challenges, because of their high travel speed and ability to access areas regardless of road infrastructure, to deliver small packages in a fast and sustainable way, significantly accelerating delivery times and reducing human intervention. Even though the speed of drones can offer significant time savings with respect to the traditional vehicles traveling congested routes, drone-aided delivery systems are challenged by intrinsic characteristics of aerial vehicles, such as limited payload capacities, battery endurance and sensitivity to weather conditions. Moreover, the debate on the regulatory and safety issues of air control administrations and long-term viability, is far to be resolved. Despite all these issues, the idea of drone-aided delivery is gaining ground from both practitioners, persuaded to apply sustainable, cost- and time-efficient transport alternatives, and researchers, promoting multi-modal and collaborative delivery systems combining terrestrial (such as trucks) and aerial vehicles (Unmanned Aerial Vehicles (UAVs) or drones).

The design of an efficient multi-modal joint delivery system is not straightforward for the main challenges of coordinating and synchronizing trucks and drones, especially when a set of truck routes needs to be synchronized with the drones movements. In

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a synchronized multi-truck and multi-drone model, a mixed fleet of homogeneous capacitated trucks, that deliver heavy packages, and multiple sidekick drones that carry out lightweight deliveries are employed. Each truck dispatched from the depot travels a route starting from a central depot, visits a subset of customers and returns back to the depot after the last delivery completion. The truck also serves as a mobile depot and launch and retrieve platform for the sidekick drones and moves them to the proximity of the drone delivery area, where the truck stops, launches the drone to deliver a single customer order and retrieves it back once the delivery mission is completed. The drone is allowed to perform multiple one-to-one delivery trips between the stationary truck and customer locations as long as its battery is not depleted. Due to safety regulations and to better monitor the drone moves, the truck driver awaits at the location until all scheduled multi-trip deliveries are performed and the drone is retrieved. This fundamental assumption makes the relative movements non-simultaneous, however, the synchronization is still relevant since the truck departure can be scheduled only after the drone retrieval. Obviously, this joint scheme requires more complex evaluation and planning models and procedures, compared to those existing in the literature as not only the operations of each transport mode should be optimized, but also the interactions between different vehicle types, such as the synchronization and coordination of the traditional vehicle with the drones are involved. That is the focus of the present study. We extend the synchronized drone and truck delivery with non-simultaneous relative movements between one truck and drones to the case with multiple trucks.

On the other hand, the complexity of drone-aided delivery applications goes far beyond the synchronization problem since the social and environmental concerns of the public stakeholder (in terms of pollution, traffic congestion, and other externalities), the economic interests of the delivery system owner, and the expectations of customers call for a multi-stakeholder optimization approach. To fulfill this goal, we adopt a multi-objective perspective and model the synchronized drone and truck routing problem considering the following four objective functions of *i*) total profit, (assuming that each delivery brings a profit to the stakeholder that should decide which customers to serve), *ii*) total traveling cost for trucks (it may also represent environmental costs), *iii*) sum of arrival times to each customer visited by a truck or a drone (also called latency) reflecting the customers' satisfaction and finally *iv*) number of trucks dispatched from the depot (cost-efficiency of the transport system). Since the fleet cost –proportional to the fleet size– is a considerable contribution to the operating costs, the decision maker could optimize the number of trucks to be employed. Except the latency goal, that is a customer-oriented objective, the other three goals are business-oriented. In general, not all the delivery requests are profitable, especially those prolonging the arrival time of other requests, and therefore, some requests might be skipped. This imposes a selective structure to the problem exacerbating its complexity.

The complication of drone-aided deliveries is also linked to intrinsic drone-related features –such as limited drone payload, battery capacity, and variable energy consumption in drone battery due to wind and weather condition– restricting the drone delivery range and number of allowed back and forth trips between the truck and customer locations. The literature is abundant in contributions that treat the drone-related issues as those in the traditional terrestrial vehicle routing problems, either by setting a maximum drone endurance in terms of travel distance/time or approximating the energy consumption as a linear function of drone payload and travel time that later brings the validity and applicability of the obtained solutions into question. To fill this gap, we model the energy consumption in drone battery as a non-linear function of drone payload and travel time and adopt a distributionally robust optimization approach to capture the uncertainty of energy consumption due to variations in drone speed and travel time.

The contributions of this paper are manifold. We address a novel multi-trip synchronized truck and drone routing problem, under a multi-criteria setting addressing both business- and customer-oriented goals where the realistic drone-related features in terms of load-dependent energy consumption rates and the fluctuations in weather condition causing speed and travel time variations are taken into account. To solve the problem, we apply an evolutionary meta-heuristic algorithm that efficiently handles instances of reasonable size, as shown in the computational experiments.

The remainder of this paper is organized as follows. Section 2 presents a detailed review on the relevant literature. Section 3 describes the problem setting and the mathematical formulation. Section 4 proposes the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), as a well-known meta-heuristic for multi-objective problems. Section 5 presents computational results evaluating the validity of the proposed model and the efficiency of the solution approach. Finally, Section 6 concludes the paper and summarizes some directions for future research.

## 2 LITERATURE REVIEW

In the last decade, a large body of the operations research literature has focused on routing problems for drone delivery. Several new challenges, derived from the multi-modal nature of delivery system combining the terrestrial and aerial vehicle types with extremely different characteristics, has stimulated a rising interest in the optimization community unveiling different drone integration schemes in the last-mile delivery context. The flourishing literature on drone delivery involves different problem variants categorized based on problem features, such as number of trucks and drones, the number of trips allowed for the drones and/or trucks, the interrelation between trucks and drones as independent or sidekick working units that brings the parallel (unsynchronized) or synchronized movements into question, different launch and retrieve policies (either at the depot or while the truck is en-route) simultaneous and non-simultaneous relative movements.

When the routing problem combines one truck and one or more drones, it can be view as a variant of the traditional Traveling Salesman Problem (TSP). Depending on the synchronization level between the vehicles, it is referred to as the Flying Sidekick Traveling Salesman Problem (FSTSP) or Parallel Drone Scheduling TSP (PDSTSP). The fundamental difference between these two problems is the synchronization issue. While in the FSTSP problem trucks and drones operations must be coordinated, in the PDSTSP the synchronisation issue is not relevant as truck and drones work independently. In the FSTSP, the truck carries the drone and it can decide to launch the drone to deliver the orders of a few customers in the nearby while the truck could continue its route to serve other customers and finally meet the drone at a rendezvous location, with the objective of minimizing the makespan, that is the time required by the truck to return to the depot. In the PDSTSP, the drones are directly deployed from the depot, serving one customer at a time but possibly performing multiple trips.

In this Section, we focus on the literature on PDSTSP since our contribution essentially belongs to the class of PDSTSP in which the synchronization issues are also incorporated. Following the research stream on PDSTSP, Murray and Chu (2015) proposed an MILP formulation and a heuristic method for PDSTSP, tested on small instances with 10 and 20 customers. The heuristic builds a TSP tour for customers visited by the truck and after assigns the remaining customers to drones. Mbiadou Saleu et al. (2018), proposed the first iterative two-step heuristic for the problem. First, the customer sequence is determined and then, it is decomposed into a tour for the truck and a set of trips for the drones. DellAmico (2020) presented a simplified mixed integer linear programming model for the PDSTSP and a set of matheuristic algorithms tested on instances with 48–229 customers. Several PDSTSP variants have been also introduced and studied in the literature. Kim and Moon (2019) considered a variant in which drones can be deployed from the depot but also from dedicated drone stations to address the limitations of the drone flight range. Ham (2018) studied a multi-truck multi-depot pickup and delivery variant of the PDSTSP where a drone, after the delivery task, can either fly back to the depot or reach another pickup customer. Several publications in the literature have investigated the objective function of minimizing the total transportation cost in routing problems using the truck-drone combination for delivery. Moshref-Javadi et al. (2020a) extended the PDSTSP, implementing a different operating condition, to better reflect the realities associated with the complex nature of last-mile distribution logistic problems. Specifically, this variant of the problem considers that drones can either take off from the depot or to a node reached by the by the truck (this node could be a customer or a parking area or a locker point). The drone delivers a set of packages, servicing one customer at a time performing back and forth trips, and returns to the truck, waiting for the return of all the drones launched. An efficient ALNS meta-heuristic was designed to solve real-world-size instances and tested on several small instances in the benchmark that found near-optimal solutions within low computational time. The model and solution approach were also tested on a real-world case study of e-commerce deliveries in Sao Paulo, Brazil. They compare their model with the classical traveling repairman problem, showing the effectiveness of using a multi-modal system delivery compared to the traditional delivery system with terrestrial vehicle. Moshref-Javadi et al. (2020b) propose a hybrid tabu search-simulated annealing algorithm for solving their variant on real-world-size problem instances.

The present paper extends the PDTSP problem along several dimensions. First of all, more than one truck is considered. Secondly, this variant of the problem considers synchronized shipping operations, where the drones can be launched at any truck stop. Different constraints for the trucks and the drones are also considered. First, the total weight of parcels loaded into the truck should not exceed the truck capacity and drones have limited payload. Second, we impose a restriction on the energy consumed by each drone during the whole service. We should notice that, since drones are faster than trucks, any solution which ignores the battery endurance, will extensively employ more drones against trucks. We remove the restrictive (and often unrealistic) assumption that the drone battery is fully charged/swapped while the truck is moving, rather considering that the drone batteries will be charged at the end of the service, when the truck comes back into the depot.

Previous studies do not consider neither truck capacity constraints nor intrinsic characteristic of drones.

# 3 SYNCHRONIZED MULTI-TRIP DRONE AND TRUCK ROUTING PROBLEM

## 3.1 Problem Description

In the Synchronized Multi-Trip Drone and Truck Routing Problem (SMTDTRP), a fleet of capacitated trucks, each hosting at least one drone, departs from a single depot to service a subset of potential customers. Some customer orders are required to be delivered only by truck (cases where the order volume and mass is beyond the drone payload capacity, the travel time to reach the delivery location by a drone violates the drone maximum endurance, or the local meteorological at the delivery site prevents the use of drone) while other customers, ordering light packages, can be served by drones. A profit is associated with each customer and the vehicles can skip serving some customers, depending on the profit rate, thus framing the problem as a selective one. Clearly, adding the decision on the selection of customers to be served exacerbates the problem complexity. The trucks are able to dispatch drones from the vehicle roof and, starting from the depot, visit every customer exactly once. Drones can be dispatched from the truck delivering light packages to nearby customers while the truck is servicing a truck-only customer and then waits for the drone to retrieve it. The drone is allowed to perform multiple back and forth trips (but can serve only one customer per operation), and then returns to the truck from which the drone started its mission. The truck should wait until the dispatched drones have completed the delivery operations. The drones, with limited payload and battery capacity, are fully charged at the beginning of the service and the battery cannot be recharged nor swapped until the truck returns to the depot. The non-simultaneous relative movements between truck and drone holds in many applications especially those in which the drone track should be frequently monitored due to safety regulations. Figure 1 represents a possible routing plan for an example with two trucks. One truck serves customers 4, 15, 9 and 10 and hosts one drone (Drone 1) performing deliveries to customers 18, 13, 11, and 12. The other truck (Truck 2) visits customers 5, 6, 7, and 8 and hosts two drones that deliver the orders of customers 1, 2, and 19 (by Drone 2) and customers 3, 17, and 20 (by Drone 3).

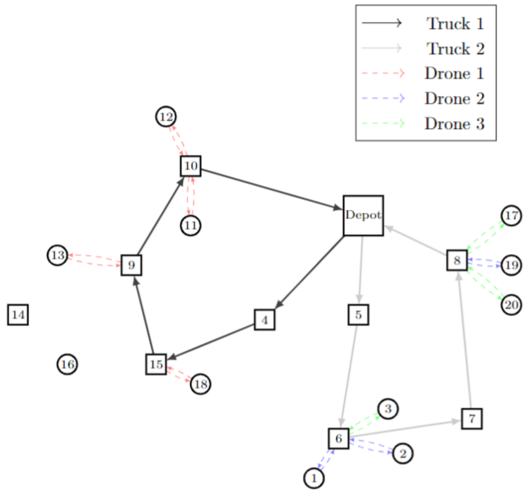



Figure 1: A nominal routing plan.

The energy consumption in drone battery depends (linearly) on travel time, and (non-linearly) on drone frame mass ($W$), battery mass ($m$), and payload ($p$). Assuming that the drone battery capacity is denoted by $C$, the total drone energy consumption within a trip $r$, with travel time $d^r$, to deliver a parcel of mass $p^r$ can be evaluated as follows.

$$\mathcal{E}^r = k'(W+m+p^r)^{3/2}d^r + k'(W+m)^{3/2}d^r \quad (1)$$

where $k'$ is a constant depending on the air density, the area of the spinning blade disc and the gravity. The first term in (1) represents the energy consumption during the trip towards the customer's location while the drone is carrying the order and the second term denotes the energy consumption during the drone return trip to the truck when the order is delivered and thus drone payload is zero.

We assume that drones perform one-to-one delivery trips $r \in R$ until the battery is depleted, i.e., $\sum_{r \in R} \mathcal{E}^r \leq C$. Uncertain weather conditions, i.e., wind speed and direction, could drastically affect the energy consumption. To guarantee that under different weather scenarios, the drones operate in a safe and efficient fashion, we adopt a distributionally robust optimization framework in which we suppose the battery consumption is uncertain and although its probability distribution is not completely specified, we have some partial information on its distribution function knowing that it belongs to a class of distributions with known mean and covariance. This assumption of course broadens the applicability of the approach, that can be applied to different real-life scenarios. It is worthwhile mentioning that the selection of the appropriate distribution functions for energy consumption is not straightforward (for more information on energy consumption functions in drone battery see Zhang et al. (2021)).

Knowing this, we may apply the probabilistic chance constraint (2) to account for both the uncertainty of energy consumption and limited battery capacity.

$$\mathbb{P}\Big(\sum_{r\in R} \mathcal{E}^r \leq C\Big) \geq 1-\alpha \tag{2}$$

where $\alpha \in [0,1]$ is the risk level and thus $1-\alpha$ denotes the decision maker's risk-aversion tendency. Under this assumption, the distributionally robust counterpart for constraint (2) can be written as

$$\mu + \sqrt{\frac{1-\alpha}{\alpha}}\,\sigma \leq C \tag{3}$$

where $\mu = \sum_{r\in R} \mu(\mathcal{E}^r)$ represents the expected value corresponding to the total energy consumption and $\sigma = \sum_{r\in R} \sigma(\mathcal{E}^r)$ is the total variance (Lam, 2019; Calafiore and Ghaoui, 2006).

The problem consists in deciding the subset and the sequence of potential customers that should be serviced by trucks and drones, as well as possible assignments of customers to drones performing back and forth trips. In particular, four objectives are of our interest: maximizing the total profit assigned to delivered orders, minimizing the total latency (arrival time to customers), minimizing the total travel cost, and minimizing the number of deployed trucks.

### 3.2 Mathematical Model

The formulation makes use of the notation in Table 1 and the mathematical model is cast as (4)-(27).

$$\max \sum_{i\in V}\sum_{j\in V'}\sum_{k\in K} \pi_j x_{ij}^k + \sum_{i\in V}\sum_{j\in V'}\sum_{k\in K}\sum_{u\in U}\sum_{r\in R} \pi_j f_{ij}^{kur} \tag{4}$$

$$\min \sum_{i\in V'}\sum_{k\in K} (t_i^k + \hat{t}_i^k) \tag{5}$$

$$\min \sum_{i\in V}\sum_{j\in V'}\sum_{k\in K} c_{ij} x_{ij}^k \tag{6}$$

$$\min \sum_{j\in V'}\sum_{k\in K} x_{0j}^k \tag{7}$$

$$\sum_{j\in V} x_{ij}^k = \sum_{j\in V} x_{ji}^k \quad i\in V, k\in K \tag{8}$$

$$\sum_{j\in V'} x_{ij}^k \leq 1 \quad i\in V, k\in K \tag{9}$$

$$\sum_{j\in V'}\sum_{u\in U}\sum_{r\in R} f_{ij}^{kur} \leq M y_i^k \quad i\in V, k\in K \tag{10}$$

$$\sum_{i\in V} x_{ij}^k \geq y_j^k \quad j\in V', k\in K \tag{11}$$

$$t_i^k + z_i^k + d_{ij} - M(1-x_{ij}^k) \leq t_j^k \quad i\in V, j\in V', i\neq j, k\in K \tag{12}$$

$$\sum_{j\in V'}\sum_{r\in R} (\hat{d}_{ij} + \hat{d}_{ji}) f_{ij}^{kur} \leq z_i^k \quad i\in V, k\in K, u\in U \tag{13}$$

$$\sum_{j\in V'} f_{ij}^{kur} \geq \sum_{j\in V'} f_{ij}^{ku(r+1)} \quad i\in V, k\in K, u\in U, r\in R \tag{14}$$

$$\sum_{i\in V}\sum_{u\in U}\sum_{r\in R}\sum_{k\in K} f_{ij}^{kur} + \sum_{i\in V}\sum_{k\in K} x_{ij}^k \leq 1 \quad j\in V' \tag{15}$$

$$\sum_{j\in V'} f_{ij}^{kur} \leq 1 \quad i\in V, k\in K, u\in U, r\in R \tag{16}$$

$$t_i^k + \hat{d}_{ij} - M(1-f_{ij}^{kur}) + \sum_{j'\in V'}\sum_{\substack{r'\in R\\ r'<r}} (\hat{d}_{ij'} + \hat{d}_{j'i}) f_{ij'}^{kur'} \leq \hat{t}_j^k \; i\in V, j\in V', i\neq j, u\in U, r\in R, k\in K \tag{17}$$

$$\sum_{i\in V}\sum_{j\in V'}\sum_{k\in K}\sum_{r\in R} (e_{ij}^1 + e_{ji}^2) f_{ij}^{kur} \leq C \quad u\in U \tag{18}$$

$$\sum_{i\in V}\sum_{j\in V'} q_j x_{ij}^k + \sum_{i\in V}\sum_{j\in V'}\sum_{u\in U}\sum_{r\in R} q_j f_{ij}^{kur} \leq Q_k \quad k\in K \tag{19}$$

$$\sum_{k\in K} f_{ij}^{kur} \leq 1 \quad i\in V, j\in V', r\in R, u\in U \tag{20}$$

$$f_{ij}^{kur} \geq M \sum_{\substack{k'\in K\\ k'\neq k}} f_{i'j'}^{k'ur'}, \; i, i'\in V, j, j'\in V', r, r'\in R, u\in U, k\in K \tag{21}$$

$$f_{ij}^{kur} = 0 \quad i\in V, j\in V_K, k\in K, u\in U, r\in R \tag{22}$$

$$x_{ij}^k = 0 \quad i\in V, j\in V_D, k\in K \tag{23}$$

$$x_{ij}^k \in \{0,1\} \quad i\in V, j\in V', k\in K \tag{24}$$

$$f_{ij}^{kur} \in \{0,1\} \quad i\in V, j\in V', k\in K, u\in U, r\in R \tag{25}$$

$$y_i^k \in \{0,1\} \quad i\in V, k\in K \tag{26}$$

$$z_i^k, t_i^k, \hat{t}_i^k \geq 0 \quad i\in V, k\in K \tag{27}$$

Objective (4) maximizes the total profit of visited customers and encompasses two terms corresponding to the profit of customers visited by trucks and drones; objective (5) minimizes the total latency, defined as

Table 1: Notation for the mathematical model.

| | |
|---|---|
| *Sets* | |
| $V'$ | Set of customers |
| $V = V' \cup \{0\}$ | Set of nodes including the depot (0) indexed by $i$, $j$, $j'$ |
| $V_K \subset V'$ | Set of customers to be visited by trucks |
| $V_D \subset V'$ | Set of customers to be visited by drones |
| $U$ | Set of drones indexed by $u$ |
| $K$ | Set of trucks indexed by $k$ |
| $R$ | Set of drone trips indexed by $r$, $r'$ |
| *Parameters* | |
| $q_i$ | Demand of customer $i$ |
| $\pi_i$ | Profit associated to customer $i$ |
| $Q_k$ | Capacity of truck $k$ |
| $c_{ij}$ | Time-dependent travel cost (such as environmental cost) |
| $d_{ij}$ | Travel time for truck between node $i$ and $j$ |
| $\hat{d}_{ij}$ | Travel time for drone between node $i$ and $j$ |
| $e^1_{ij} = k'(W+m+q_i)^{3/2}\hat{d}_{ij}$ | Energy consumption of a drone launched from node $i$ to deliver the order of customer $j$ |
| $e^2_{ji} = k'(W+m)^{3/2}\hat{d}_{ji}$ | Energy consumption of a drone on its return trip after delivering order of customer $j$ and coming back to the launch node $i$ |
| $C$ | Drone battery capacity |
| $M$ | A sufficiently large number |
| *Decision variables* | |
| $x^k_{ij}$ | Binary variable that takes 1 if truck $k$ travels from node $i$ to reach node $j$ |
| $f^{kur}_{ij}$ | Binary variable that takes 1 if truck $k$ stops at node $i$ and launches drone $u$ to visit customer $j$ in its $r$th trip from node $i$; otherwise, 0 |
| $y^k_i$ | Binary variable takes 1 if truck $k$ stops at node $i$ to launch at least one drone; otherwise, 0. |
| $z^k_i$ | Waiting time of truck $k$ at node $i$ |
| $t^k_i$ | Waiting time of customer $i$ served by truck $k$ |
| $\hat{t}^k_i$ | Waiting time of customer $i$ served by a drone launched by truck $k$ |

the sum of customers' arrival times visited by either trucks or drones; Objective (6) minimizes the total truck travel cost, and objective (7) minimizes the total number of dispatched trucks. Constraints (8) ensure the continuity of flow for each truck; Constraints (9) ensure that the each truck can exit each customer at most once. Constraints (10) relates the variables $y^k_i$ and $f^{kur}_{ij}$ and ensures that if a customer is supposed to be visited by a drone, then it is mandatory that the truck stops at a customer to launch the drone. Constraints (11) ensure that a truck can only stop at a customer location to launch a drone, only if the truck serves that customer. Constraints (12) define the arrival time of a customer visited by a truck. Constraints (13) define the waiting time of each truck as the maximum delivery time of all drones launched from that truck. Constraints (14) sets the logical relation between the order of drone trips; so a drone can operate its $r+1$ tour only if it has already performed $r$ trips. Constraints (15) show that each customer can be served at most once either by a truck or a drone. Constraints (16) indicate that the drones can serve at most one customer within each trip. Constraints (17) defines the arrival time of customer $j$ visited by a drone in terms of arrival time of the customer $i$ that the drone was launched from, and the time that the drone spent to serve customers served before $j$. Constraints (18) define the limited drone battery over all missions. Constraints (19) require that the total payload of each truck over its tour is below the truck capacity. Constraints (20) ensure that each drone is assigned to at most one truck. Constraints (21) ensure that if a drone is deployed by a truck it cannot be used by any other truck. Constraints (22) requires that those customers allowed to be served only by trucks cannot be visited by drones. In a similar way, Constraints (23) ensure that the those customers allowed to be served by drones cannot be visited by trucks. Finally, constraints (24)-(27) define the nature of variables.

# 4 SOLUTION METHODOLOGY

In this section, we present the sketch of the NSGA-II solution algorithm that we apply to solve the proposed model. Known as the multi-objective variant of the genetic algorithm, the NSGA-II is one of the most popular and promising evolutionary algorithms. The algorithm efficiency is supported by the low computational complexity, limited to $O(MN^2)$, where $M$ and $N$ are, respectively, the number of objective functions and the population size. The algorithm is based on the main idea of finding multiple non-dominated solutions in a single simulation run as common in multi-objective evolutionary algorithms. The NSGA-II benefits from the elitism concept and does not require any sharing parameter that significantly contributes to its credibility (Deb et al., 2002). In a nutshell, the algorithm main elements are: *a fast non-dominated sorting mechanism* and *a fast crowded distance estimation mechanism* acting as intensification and diversification tools. The fast non-dominated sorting mechanism sorts the population individuals into different fronts, where the front index represents the non-domination level (rank) of the solutions in the front. All the solutions in the first front are not dominated by any other solution in the population and

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 5 | 6 | 7 | 8 | 0 | 4 | 15 | 9 | 10 |

| | | | | |
|---|---|---|---|---|
| $(6,1,2,3)$ | $(8,17,19,20)$ | $(15,18)$ | $(9,13)$ | $(10,11,12)$ |

Figure 2: Chromosome representation for solution in Figure 1.

dominate all elements in the other fronts; the elements in the second front are dominated only by the solutions in the first front and dominate all solutions in the third fronts; in a similar way, the elements in the third front are dominated only by those in the first and the second front, and so on. Instead, the crowding distance estimation mechanism is used to maintain diversity in NSGA-II. The crowding distance provides the density of solutions surrounding a particular solution in a nondominated set. The solutions in a nondominated front are first sorted in an ascending order of magnitude, according to each normalized objective function value. Then, for each objective, to the solutions with smallest and largest objective function values is associated a distance equal to infinity. For the remaining pairs of adjacent solutions, the distance value is evaluated as the absolute normalized difference in the corresponding objective function values. The overall crowding-distance value is the sum of distance values corresponding to each objective. In what follows, we present the details on applying the NSGA-II algorithm for the SMTDTRP.

## 4.1 Solution Representation

The population $P$ includes $N$ individuals corresponding to solutions of the problem. Each solution contains a set of tours, one tour for each truck, and each tour is an ordered list of visited customers. In the solution representation, to each drone is associated an ordered list of nodes allowed to be visited. Each element in the list contains the launch point of the drone (necessarily a node in set $V_K$, a truck-eligible customer) followed by the set of customers visited in the ordered trips.

Figure 2 displays the encoded chromosome corresponding to the solution in Figure 1.

## 4.2 Initial Population Generation

To generate a population the following steps are followed.

Each solution in the initial population is generated following steps 1-6:

1. Select a random integer number $N_k \in [1,|K|]$ representing the number of deployed trucks (tours) in the current solution.
2. To each truck $k$, assign a random integer value $u_k$ that specifies the number of drones assigned to the truck.
3. For each customer in $V_K$, repeat *i* to *iii* that builds the truck tours:
   - *i*. select randomly a customer $i \in V_K$, to be removed from $V_K$ and update $V_K$.
   - *ii*. select randomly a truck with free capacity to add the order of customer $i$ to.
   - *iii*. Add customer $i$ to the end of tour of truck $k$.
4. For each customer in $V_D$, repeat *i'* to *vi*:
   - *i'*. select randomly a customer $i \in V_D$, remove it from set $V_D$ and update $V_D$.
   - *ii'*. select randomly a truck $k^o$ with residual capacity greater than payload of the order of customer $i$.
   - *iii'*. Randomly select a customer $i^o$ within the tour of truck $k^o$ as the drone launch point
   - *v*. Select randomly an available drone $u^o$ assigned to truck $t$
   - *vi*. If the drone energy consumption is not violated, add customer $i$ to the path of drone $u^o$.
5. Update the objective function values and add the solution to the population.

## 4.3 Fitness Evaluation

The fitness of the individuals is evaluated based on the non-dominance rank and the crowding distance measure.

The crowding distance of a solution $sol_i$ that belongs to front $\mathcal{F}_l$ with rank $l$ is defined as:

$$cd(sol_i) = \sum_{m=1}^{M} \frac{f_m^{i+1} - f_m^{i-1}}{f_m^{max} - f_m^{min}} \tag{28}$$

where $f_m^i$ is the objective value of $sol_i$ with respect to objective $m$ and $f_m^{max} = \max_{sol_i \in \mathcal{F}_l} f_m^i$ and $f_m^{min} = \min_{sol_i \in \mathcal{F}_l} f_m^i$, respectively, represent the highest and the lowest objective function among all individuals in $\mathcal{F}_l$.

## 4.4 Parent Selection

As common in the classical genetic algorithm, a tournament selection procedure is applied that chooses a pair of individuals (parents) from the population to be recombined using the crossover operators and later modified by the mutation operations. The $N$ new individuals are then merged into the population: next, this extended population with size of $2N$ is sorted thanks to the non-dominated sorting procedure. To shrink the size of the population to $N$ individuals, starting from the first rank, all the solutions in the front are added in the new population. If the resulting number of solutions in the front is still less than $N$, the solutions of the subsequent fronts in the order of their ranks are inserted to complete the population. In case the cardinality of a front is above the number of individuals needed to be added to the population set, the crowded-comparison feature breaks the tie in favor of solutions with higher crowding distance. This procedure respects the elitism as the non-dominance sorting is applied on both the parents and offsprings.

### 4.5 Crossover Operators

The Crossover is one of the main operators in the genetic algorithm that uses the information of two individuals (current solutions) to produce offsprings, representing new solutions. Given a crossover probability $p^{crossover}$, the *single truck* and *multi-truck* crossover operators could be applied. To this end, we first need to explain the notion of *Complementary truck and complementary map*:
Two trucks are *complementary iff* the truck (indecies) and the set of visited customer are different (they do not have any visited node in common).
Let $I$ and $I'$ be two individuals, the *complementary map* of $I$ is a list that includes all set of trucks from $I'$ which are complementary to the trucks in $I$.
*Crossover single truck*
Let $I$ and $I'$ be two individuals, their offspring is generated by starting from the tour of one of the two individuals followed by adding the tour of the second one skipping the customers already present.
*Crossover multi-truck*
In this case, one of the individuals is randomly selected as the first parent ($p_1$) and the other would be the second one ($p_2$). We create a map $\mathcal{M}$ in which for each truck in the first individual, we store all the complementary trucks belonging to the second individual. We choose a random truck $v$ and we add it to the solution. From the map $\mathcal{M}$ we take the complementary list relating to vehicle $v$. If this list is empty, the crossover ends. Otherwise we choose a random number $nc$ of complementary vehicles to add to the solution. This number can range from 1 to $NC$, where $NC$ is the size of complementaries. We randomly take $nc$ vehicles from complementaries and add them to the solution.

### 4.6 Mutation

With probability $p^{mutation}$ the following mutation operators are applied.

- *Intratour swap*
  This operator swaps the order of two randomly selected customers within the truck tour. The swap is done at least once and up to $L$ times where $L$ denotes the length of truck tour.
- *Delete nodes*
  This operator randomly deletes a prespecified number of customers, let say $D$, from the tour of a given truck where $0 \leq D \leq L-2$

## 5 COMPUTATIONAL RESULTS

In this Section, we report the the computational experiments carried out on a set of benchmark instances adapted from the literature in order to investigate the efficiency of NSGA-II algorithm for the proposed mathematical model.
All the experiments were executed on an Intel Core i7-4700HQ, with 2.40 GHz CPU, 16 GB RAM and the NSGA-II algorithm was coded in Java language Arnold et al. (2005). In the following, we describe the adopted test beds and present the computational results.

### 5.1 Data Sets and Parameter Settings

As the benchmark, we used the set of instances from Dewilde et al. (2013) originally designed for the traveling repairman problem with profits. In particular, we considered four classes of instances with 50, 100, 200, and 500 customers and selected the first two instances of each class. We modified the instances appropriately to account for the presence of drones and variations in travel speed. In our setting, it is assumed that up to 75% of customers can be visited by trucks and the remaining ones by the drones ($|V_K| = \lfloor 0.75V' \rfloor$, $|V_D| = |V'| - |V_K|$). Regarding the uncertainty of drone energy consumption, we randomly generated the variance of the energy consumption in each drone trip as $\sigma^2 = \chi\mu$ where $\mu$ is the expected energy consumption and $\chi$ is a randomly generated value where $\chi \in [0.1, 0.3]$. To reflect the highly risk-averse attitude of the decision-maker, parameter $\alpha$ was set to 0.1. We considered a homogeneous fleet of drones with a fully charged battery of 0.27 $KW/h$, payload capacity of 1 $kg$, where the drone speed is set to 43.2 $km/h$ (12 $m/s$). Other drone-related features are as follows:

Table 2: Parameter settings.

| Parameter | Value |
|---|---|
| Population size $N$ | 200 |
| Number of iterations | 250 |
| $p^{crossover}$ | 0.8 |
| $p^{mutation}$ | 0.5 |

Table 3: Computational results.

| Instance | TP | TL | TTD | TNDT | CPU |
|---|---|---|---|---|---|
| 50-1 | 28931.9 | 80008.2 | 184046.9 | 3.5 | 5 |
| 50-2 | 32039.7 | 96638.0 | 209477.7 | 3.6 | 3 |
| 100-1 | 89579.3 | 165380.7 | 325997.0 | 5.2 | 7 |
| 100-2 | 74263.8 | 159259.4 | 299150.4 | 4.4 | 7 |
| 200-1 | 316691.3 | 363168.8 | 634370.7 | 8.5 | 24 |
| 200-2 | 330863.0 | 429824.7 | 701401.6 | 8.2 | 28 |
| 500-1 | 1484141.8 | 2525309.0 | 3915138.7 | 11.2 | 42 |
| 500-2 | 1573664.9 | 2388172.2 | 4185311.2 | 12.9 | 41 |

TP: Total Profit, TL: Total Latency, TTD: Total Traveled Distance, TNDT: Total Number of Dispatched Trucks.

The drone frame and battery mass are both equal to 1.5 $kg$, constant $k'$ was calculated as a function of $k' = \sqrt{\frac{g^3}{2\rho\xi h}}$ where the gravity $g$ is set to 9.81 $(N/kg)$, the fluid density of air $\rho$ is set to $1.204 kg/m^3$; the area of spinning blade disc $\xi$ is $0.0064 m^2$ and each drone has eight rotors $h = 8$. For all instances, we set a fleet of five trucks and two drones. The truck speed was set to 29.88 $km/h$ and the capacity of trucks dependent on the instance were set as the eighty percent of total demands divided by the size of terrestrial fleet. Also, the travel distance between nodes $i$ and $j$ across arc $(i, j)$ is calculated following the Euclidean norm. Other algorithm-related parameter settings are as reported in Table 2.

Table 3 reports the average of best results within three random executions for each objective (Columns 2-5). Column 6 presents the algorithm CPU time in seconds. Figure 3 displays the algorithm computational time in seconds confirming the high performance of NSGA-II. Also, as expected, with the increase in problem size, the computational time also increases. Figure 4 illustrates the number of Pareto-optimal solutions found by the algorithm for each instance. We observe that the size of approximate Pareto-optimal set increases with the increase in the number of customers. This also justifies the increase in the computational time since provides the decision-maker with more choices.

In order to present some insights on the impact of problem size (in terms of number of customers) on the problem objectives, we consider the two cases with 50 customers as the baseline and report the ratio of change (depicted by $\Delta$. in Table 4) with respect to each criterion for cases with more than 50 customers. For example, the value of 50.2 in the last row indicates that the total profit of the logistics manager is multiplied 50 times as the size of customers increase from 50 to 500. The ratio of changes in the fleet size in also low while the increase in total traveled distance and latency criteria remains acceptable. This shows that it is beneficial for the logistics stakeholder to enlarge the business size and service area.

Table 4: Sensitivity analysis with respect to the problem size.

| Instance | $\Delta\lvert V'\rvert$ | $\Delta$ Profit | $\Delta$ Latency | $\Delta$ Distance | $\Delta$ Fleet Size |
|---|---|---|---|---|---|
| 100 | 2.0 | 2.7 | -1.9 | -1.6 | -1.4 |
| 200 | 4.0 | 10.6 | -4.5 | -3.4 | -2.4 |
| 500 | 10.0 | 50.2 | -28.1 | -20.6 | -3.4 |

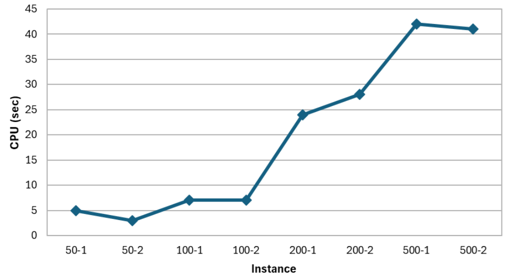



Figure 3: NSGA-II: Computational time.

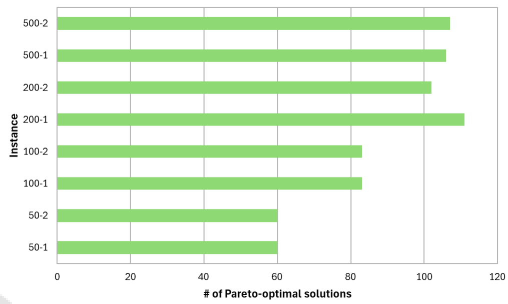



Figure 4: NSGA-II: Number of Pareto-optimal solutions.

Figure 5 illustrates the percentage of customers served by drones and trucks for each instance, verifying that no matter what the problem size is, on average around 70% of customers are served by the trucks.

In order to better understand the relation among

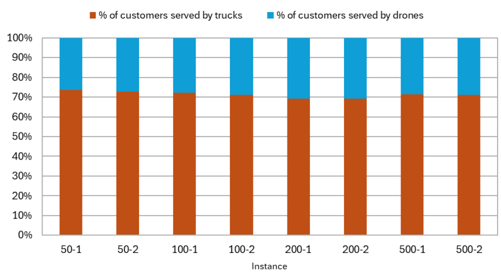
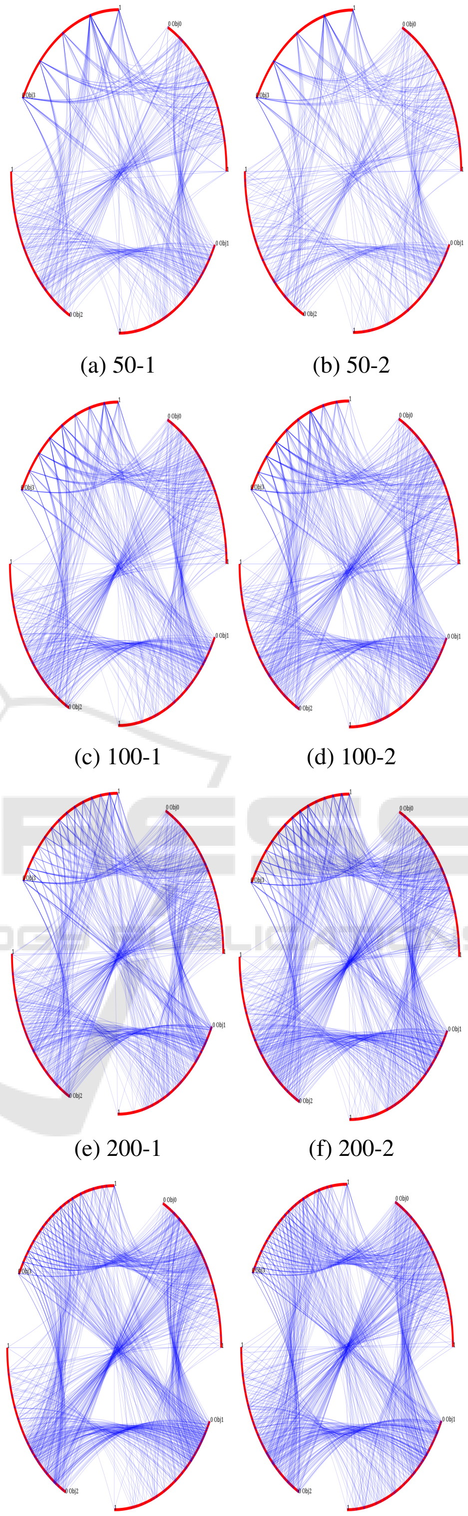



Figure 5: Percentage of customers served by trucks and drones.

different criteria (in terms of harmony or conflict), Figure 6 visualizes the trade-off among the Pareto-optimal solutions for all cases, thanks to the chord chord diagram Koochaksaraei et al. (2017). We should clarify that $obj0$, $obj1$,$obj2$, $obj3$, respectively, correspond to the profit, total traveled distance, latency, and the fleet size objectives. Our first observation is on the conflict of the profit criterion with the latency and travel distance objectives supported by links in the end (first) point of the $Obj0$ connected to the first (end) points of $Obj1$, $Obj2$, and $obj3$ and that makes sense since higher profit gains require, serving more customers, and this requires traveling more distance, increasing the waiting time of customers, and of course more vehicles. In addition, the presence of many links between the end (first) points of the $Obj0$ and $Obj2$ shows that there is a strong conflict with the profit and traveled distance. In general, we observe a harmony among the all objectives, but the profit. Fortunately, there are links connecting the middle middle bound of each objective and such area is dense enough confirming the possibility to find a trade-off among all objectives. Last but not least, we observe that the chord diagrams gets denser with the increase of the number of customers that is quite reasonable since in general we expected with the increase of problem size, the number of Pareto-optimal solutions increase. This means that the decision-maker has more choices to select among. We should emphasize that in all cases, almost all the points on red arches are fully covered and connected by some links to other points in other arches. This also confirms the diversity of solutions and the fact that the objective range (feasible region) is covered appropriately.

In Figure 7, we illustrate the Pareto-optimal frontier as a three-dimensional scatter plot, where the color of each point, mapped into the color bar, refers to the forth objective. We can see that there are plenty of solutions in the middle of the three-dimensional plot which are colored in Yellow and Orange that correspond to those solutions in which all objectives are more or less balanced. The density of the solutions and its wide coverage are promising results, confirming the efficiency and validity of the NSGA-II for the proposed model.



(a) 50-1 (b) 50-2

(c) 100-1 (d) 100-2

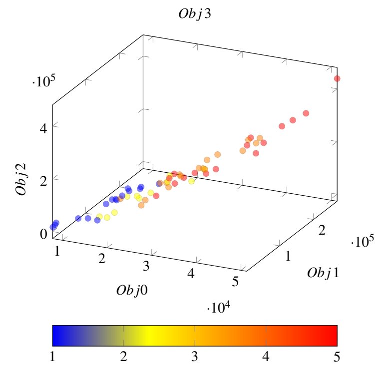
(e) 200-1 (f) 200-2

(g) 500-1 (h) 500-2

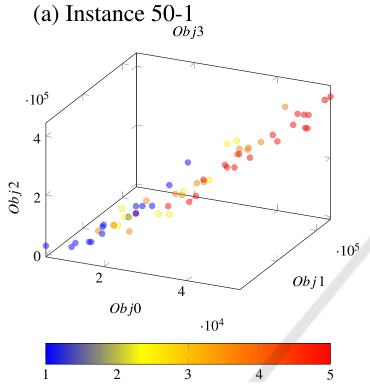
Figure 6: Visualization of the relation among objectives: chord diagram.

## 6 CONCLUSIONS

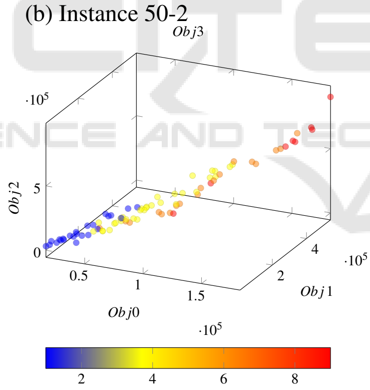
In this paper, we studied the synchronized last-mile delivery problem under a joint and collaborative system consisting of terrestrial and sidekick aerial vehicles. This novel variant, requiring the timing synchronization between drone and truck, can be classified as



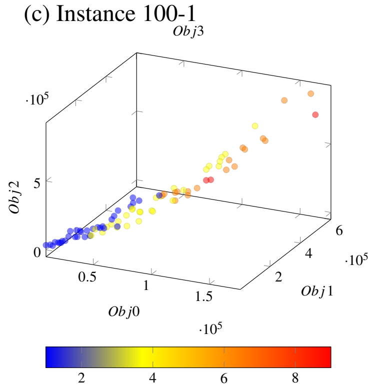

(a) Instance 50-1



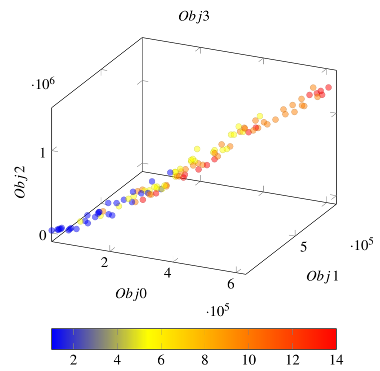

(b) Instance 50-2



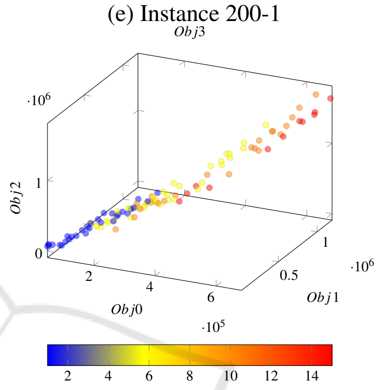

(c) Instance 100-1



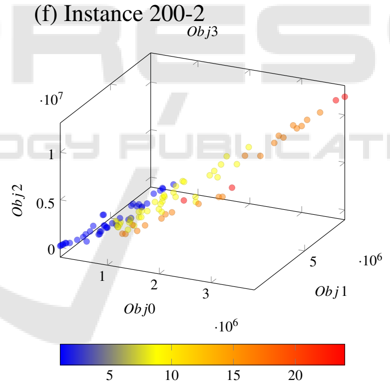

(d) Instance 100-2



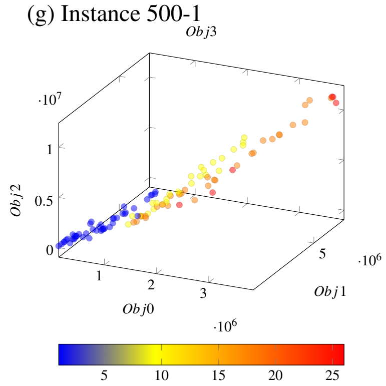

(e) Instance 200-1




(f) Instance 200-2




(g) Instance 500-1




(h) Instance 500-2

Figure 7: Scatter plot representing the Pareto-optimal frontier in 4D.

a synchronized version of parallel drone scheduling vehicle routing problem. We formulated the problem as a multi-objective model involving both business and customer-oriented goals and developed an evolutionary-based meta-heuristic approach to solve the model. The efficiency of the solution approach was investigated through computational experiments carried out on different instances adopted from the benchmark. Several interesting research avenues are open for further investigation. One relates to the design of exact solution methods or matheuristics and compares the solutions of such methods with those presented in this study. Another interesting research topic could be focused on the extension of the present model to the case where drones can serve more than one customer per trip or being retrieved at arbitrary locations besides customer sites.

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