Energy-efficient coordinated electric truck-drone hybrid delivery service planning

Energy-Efficient Coordinated Electric Truck-Drone Hybrid Delivery Service Planning

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***Abstract*—Recent works have shown that a coordinated delivery strategy in which a drone collaborates with a truck using it as a moving depot is quite effective in improving the performance and energy efficiency of the delivery process. As most of these works come from the research community of logistics and transportation, they are instead focused on the optimality of the algorithms, and neglect two critical issues: (1) they consider only a planar version of the problem ignoring the geographic information along the delivery route, and (2) they use a simplified battery model, truck, and drone power consumption model as they are mostly focused on optimizing delivery time alone rather than energy efficiency.**

In this work, we propose a greedy heuristic algorithm to determine the most energy-efficient sequence of deliveries in which a drone and an EV truck collaborate in the delivery process, while accounting for the two above aspects. In our scenario, a drone delivers packages starting from the truck and returns to the truck after the delivery, while the truck continues on its route and possibly delivers other packages. Results show that, by carefully using the drone's energy along the truck delivery route, we can achieve 43-69% saving of the truck battery energy on average over a set of different delivery sets and different drone battery sizes. We also compared two "common-sense" heuristics, concerning which we saved up to 42%.

***Index Terms*—Electric Truck Delivery, Drone Delivery, Vehicle Power Modeling and Simulation, Vehicle Routing, Drone Routing, Hybrid Vehicle-Drone Routing, Heuristic Algorithm, SystemC.**

I. Introduction

EV trucks are expected to replace traditional Internal Combustion Engine (ICE) ones progressively; besides the obvious environmental benefits, they also have better performance thanks to the high-efficiency electric motor characteristics, which provides high torque at low Rotations Per Minute (RPM). Also, 98% of the kinetic energy can be restored during regenerative braking, making the electric truck even more energy efficient.

In the context of a package delivery business in a small-to-medium geographic scale, EV trucks' efficiency can be significantly improved by assisting drones, both in terms of delivery time and energy efficiency [1]. While delivery trucks can cover vast distances and carry heavyweights, their energy efficiency is strongly affected by the road slope, and delivery time can be limited by narrow, rough roads and the traffic. On the other hand, drones can carry limited weights but are unrestricted by traffic and terrain, and can travel in a straight line. By combining the two vehicles, we can achieve a complementary "virtual vehicle" that can reduce the total route time and energy.

A typical situation in which this collaborative scenario is practical is when customers were grouped in one area (typical of districts with high-density housing) and just a few customers scattered outside these areas. In this case, the drone will deliver to the outliers while the truck carries out the delivery in the main areas. Previous work has shown that a truck-drone combination can yield 30 % faster deliveries in the case of favorable distribution of the locations [2].

An orthogonal dimension of this scenario is when we also consider the altitude of the locations or road conditions. The last-mile delivery by a drone is incredibly efficient for locations that exhibit significant altitude differences from the current position. As the battery discharge depends non-linearly on the drawn power, steep uphills impact the truck battery more significantly than the drone one.

While some works have addressed collaborative truck-drone delivery, they mostly focus only on a subset of the involved variables. The vast majority focuses only on the improvement of delivery time as the sole metric of cost and does not consider the energy efficiency of the delivery schedule [3], [4], [5]. Those including energy in the metric [4], [6], [7] assume a simplified battery discharge model not based on an accurate vehicle-drone power consumption models. Moreover, the 3D topographic information is ignored in previous works; the problem is solved as a planar instance where all the locations are at the same altitude. However, altitude has a significant impact on the EV truck's energy consumption, while it is less critical for the drone.

In this work, we devise a heuristic algorithm to determine the most energy-efficient sequence of delivery tasks in which a drone and a truck collaborate in the delivery. We adopt the drone and the truck's accurate power models, and the battery model is sensitive to the current discharge dynamics. We also consider road information. The combined truck-drone route is determined offline before the delivery service starts and is derived by perturbing an initial solution based on a Traveling Salesman Problem (TSP) referred to as a truck-only delivery. From this initial route, the estimated deliveries to draw the most energy from the truck battery are greedily selected and assigned to a drone, provided that the corresponding weights can be handled.

Results show that, depending on the size of the delivery area, the number of locations, the altitude profile, and the drone's battery capacity, battery energy savings of up to 69% can be achieved. We have tried two "common-sense" heuristics, as it was not possible to implement complex solutions in the literature based on sharply different assumptions concerning ours. The proposed method shows up to 42% energy saving.

II. Motivation and Background

A. Motivation

In the literature, the advantages of a coordinated truck-drone delivery have been mainly focused on the benefits deriving by shifting part of the packages to drones. Therefore, the emphasis has on the "last mile" aspect of the delivery problem. The drone higher energy efficiency and small weight allowance are exploited for delivering packages to a single destination entirely off the main truck driving route or several light packages geographically close locations.

When considering the topographic details of the delivery area, several variables should be taken into account. Observing the instance depicted in Fig.1, where five locations along a delivery route are shown together with their altitude location. It is evident (Fig.1-(a)) that because of altitude differences, the roads will consist of bends and possibly steep uphills, which will significantly deplete battery charge from the truck.

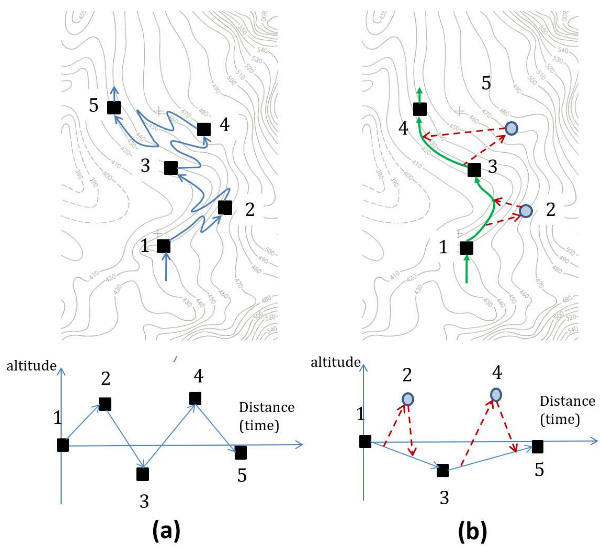

Figure 1: Truck-only (a) and truck-drone scenarios (b).

The non-straight-line distance between locations can quickly be taken into account even in a planar instance of the problem: it would suffice to replace road information and label distances with the actual length. For example, two locations on a 2-D map may have a Euclidean distance of 1 mile, but the road connecting them is 1.5 miles. Concerning the traditional planar analysis, it would not be able to model the different altitudes of the locations: in a planar model, two locations that are 1 mile apart would be modeled in the same way regardless of their altitude difference. Therefore, it is intuitive that offloading deliveries to locations with relatively high altitude differences to drones would be more energy efficient.

The case of Fig.1 shows one such (somewhat extreme) example; in a truck-only delivery (Fig.1-(a)), the truck will have to go up and down (see the profile in the bottom part of the figure) to serve the destinations in sequence. In Fig. 1-(b), destinations 2 and 4 are served by a drone, which will return to a truck while it is moving. In this way, the truck can follow an almost flat route to serve destinations 1,3 and 5, approximately at the same altitude.

The reduced battery stress and several stops for the truck can either use a smaller truck for the same set of deliveries, or for the given battery size, to add one destination within a planned delivery route.

B. Related Work

Although research on the application of truck-drone collaborated delivery in logistics is still in its infancy, the results so far have been promising. According to the optimization target, the previous works can be classified into two main categories: reducing delivery time or improving energy efficiency.

[3] proposed a continuous approximation model for a disaster-affected region where drones can be considered potential transportation except trucks to transport emergency supplies. Although the work set the delivery time as the critical point, it ignores the combined truck-drone delivery system's energy efficiency. In [4], the authors proposed a multi-trip vehicle routing problem that considers battery and payload weight when calculating energy consumption. However, the battery model used in this work is vague, and the work concentrates on extending drone flight time by increasing the battery size and reducing available payload capacity, which does not consider the integrated truck-drone system's energy efficiency. [5] has the same limitation as to the previous two; it simulates truck-drone delivery analysis only considering delivery time. In addition to the simulation-based method, [8] combines a theoretical analysis in the Euclidean plane with real-time numerical simulations on a road network, but they only provide data on delivery time.

Besides the works focus on delivery time optimization, another type of research focuses on the drone-truck system's energy savings compared to the truck-only system. However, most of them use a simplified battery discharge model to run the simulation, such as [4], or use the simplified truck and drone power models. One example is provided in [6], which proposes an optimization algorithm that determines the optimal number of launch sites and locations, and the number of drones per truck to increase the total energy efficiency. This work focuses on implementing an optimization algorithm without using accurate models. Most of the existing works under this category have the same issue [7], they focus on improving the algorithm to achieve better energy efficiency performance while neglecting the fundamental characteristics of power consumption in the whole system.

Besides the inaccurate models adopted, the existing works usually assume the delivery locations in a two-dimension plane with uniform or non-uniform distributions and ignore the geographic information. However, the road slope strongly affects trucks' power consumption, and the amplitude of location is the crucial point to decide how to partition the delivery tasks between trucks and drones.

III. System Modeling

A. Electric Truck Powertrain Model

When a vehicle drives on a road, four resistances act on the vehicle: rolling resistance F_R, gradient resistance F_G, inertia resistance F_I, and aerodynamic resistance F_A. Power consumption to overcome the resistances P_{res} is a function of torque T and angular speed ω as shown below equation. All resistances except F_A are linearly proportional to vehicle mass m.

$$P_{res} = T\omega = Fds/dt = (F_R + F_G + F_I + F_A)v$$
$$F_R \propto C_{rr}mg, \; F_G \propto mgsin\theta, \; F_I \propto ma, \; F_A \propto \frac{1}{2}\rho C_d A v^2$$

where v is the vehicle speed, C_{rr} is coefficient of rolling resistance, m is total weight of EV, g is gravity, θ is road slope, a is vehicle acceleration, C_d is coefficient of drag, and A is the area of the front side.

Practical power consumption by electric motors P_{EV} is sum of the power to overcome the resistances P_{res} and power loss P_{loss} from the motor rotation, the detailed model data refer to [9]. The P_{EV} depends on m, θ, v, and a:

$$P_{EV} = P_{res} + P_{loss} = f(m, \theta, v, a)$$

B. Electric Drone Powertrain Model

A typical drone power model [10] consists of three forces act on a quadcopter. F_W pulls down the drone by gravity and horizontal and vertical movements of a drone are resisted by dragging forces F_{DH} and F_{DV}, respectively. Thrust F_T opposes these three forces to keep the drone flight constant. F_W, F_{DH} and F_{DV} are modeled as functions of drone weight w_d, payload w_p and horizontal and vertical drone flight speeds v_h and v_v:

$$F_W = (w_d + w_p)g, F_{DV} = \frac{1}{2}\rho A_t C_d v_v^2, F_{DH} = \frac{1}{2}\rho A_f C_d v_h^2$$

where g is gravity; A_f and A_t are cross sectional areas in horizontal and vertical directions; C_d is drag coefficient; ρ is air density.

Required thrust to oppose above three forces is

$$F_{T,v} = F_W + F_{DV} \text{ and } F_{T,h} = \sqrt{F_W^2 + F_{DH}^2}$$

and modeled as a function of motor angular speed:

$$F_T = 0.5\rho A_p C_t (\omega r)^2$$

where A_p is the disk area of propellers; C_t is a thrust coefficient; ω is angular speed of motors; r is radius of propellers. We can derive the required angular speed while take-off, horizontal flight and landing with above equations by following a modeling methodology described in [9].

We assume a simple drone flight model, which consists of (i) take-off from a place with constant vertical speed to a given height, (ii) flight horizontally during distance with a constant speed and (iii) landing with the same vertical speed on a destination. The drone returns to the starting point after taking down a package.

C. Non-linear Dynamic Battery Model

The battery pack model must be able to account for the non-ideal discharge characteristics of the battery. We model a single battery cell using a circuit equivalent model that considers the capacity dependencies on the current magnitude and dynamics [11]. As shown in Fig.2, the circuit equivalent model consists of a battery lifetime model on the left-hand side and a battery voltage model on the right-hand side, respectively. In the battery lifetime model, a capacitor C represents the battery capacity, and a current generator I_{batt} represents the discharge current. Two voltage generators $V_{lost}(f_{load})$ and $V_{lost}(I_{load})$ are used to express dependencies on the amplitude and frequency of the load current. Both larger amounts and higher frequency of the load current decrease state of charge (SOC). Battery voltage V_{batt} on the right-hand side is then calculated based on the SOC, battery internal resistance $R(SOC)$, and two RC pairs tracking the time constants of an instant response.

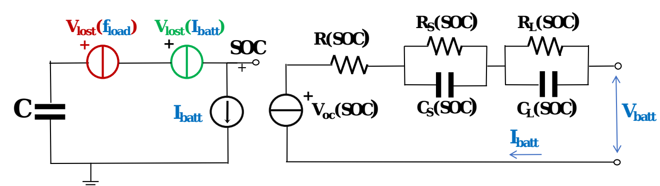

Figure 2: Adopted circuit-equivalent model for battery cell.

We adopt the commonly used method that assuming all the cells behave identically within the battery pack. Therefore, we built the pack model for both truck and drone by ideally scaling all electrical parameters according to the serial and parallel connectivity of the battery cells within the pack. In this way, not all the cells have to be simulated individually.

IV. Energy-Efficient Coordinated Scheduling

A. Scenario Definition

We assume the following delivery scenario: we have a truck equipped with one drone, supposed to deliver n of packages to a set of n destinations. The truck starts from a depot node; it visits all customers once from the depot and returns to the depot again. The overall delivery task is denoted by $\mathbf{T} = \{t_1, \ldots, t_n\}$ and is defined upfront. Each delivery task t_i to destination i is a 4-tuple (w_i, x_i, y_i, z_i), where w_i is the package weight, and x_i, y_i, z_i are the Cartesian coordinates of the location. We assume that the graph describing the locations is fully connected, i.e., there exists a route between any two locations, including the depot. The distance between each node pair corresponds to the actual driving distance.

Concerning the movements of the two vehicles, we assume that the drone has a payload capacity of one package and hence must return to the truck after each delivery. Moreover, there is no drone battery replacement, and the drone will be used until it is totally depleted. The truck must follow a given speed on each road and not temporarily stop on the road; it can only stop at the depot or customer locations for delivery. Our objective is to maximize the utilization of drone delivery and therefore deplete it as much as possible.

B. Algorithm

The problem under analysis is challenging to solve to optimality because it is a generalization of the TSP that requires considering the locations where the truck and the drone can meet. For this reason, we propose a greedy heuristic that meets the above-described constraints of our scenario.

Fig. 3 sketches our coordinated truck-drone delivery algorithm. Its objective is to find the optimal sequence of delivery tasks for the truck and drone minimizing *energy consumption of the truck* under a given drone battery size. It takes as inputs the set $\mathbf{T} = \{t_1, \ldots, t_n\}$ of n deliveries, the distance matrix $\mathbf{D}$ between any of the $n+1$ vertices (including the depot), and the drone battery capacity E_D; it outputs the list of deliveries carried out by each vehicle (S_D and S_T).

INPUT: $\mathbf{T} = \{t_1, \ldots, t_n\}$, $\mathbf{D} = \{d_{ij}\}$, E_D
OUT: Sequences of delivery tasks by truck S_T and drone S_D
1. $P = (p_0 \rightarrow \ldots \rightarrow p_{n+1}) = TSP(\mathbf{D})$
2. $S_D = \{\ \}$; $S_T = \mathbf{T}$
3. **while** ($E_d > 0$)
4. Calculate $\Delta E_T = [\Delta E_{T,1}, \ldots, \Delta E_{T,n+1}]$ and $\Delta E_D = [\Delta E_{D,1}, \ldots, \Delta E_{D,n+1}]$ based on the schedule P
5. $p_m \leftarrow$ pick the edge with largest ΔE_T and that is compatible with drone constraints
6. if (no edge is compatible) **break**;
7. update E_d
8. add t_k to S_D and remove t_k from S_T
9. update P removing the edges corresponding to p_m
10. **endwhile**

Figure 3: Algorithm for coordinated truck-drone delivery.

As our method is based on the selective replacement of some truck deliveries using the drone, we need to start from an initial P schedule. The initial P is obtained by running a conventional TSP algorithm (Line 1). We use one of the state-of-the-art TSP heuristics for directed graphs, which relies on calculating the Minimum Spanning Tree (MST) algorithm as a pre-processing step [12]. This step yields a path $P = (p_0 \rightarrow \cdots \rightarrow p_{n+1})$ in the distance graph D, where $p_0 \equiv p_{N+1}$ is the depot. We then initialize (Line 2) the two delivery lists by assuming all deliveries are served by the truck.

Given the initial schedule, we calculate (Line 4) the amount of energy required by each delivery, according to the order defined by P, for both the truck and the drone. More precisely, for an edge $p_i \rightarrow p_{i+1}$, the energy required to deliver the corresponding package is calculated using both the truck and the drone energy models. It is essential to observe that for the truck, and this calculation must *account for its current weight*: at step i, the truck will have delivered some packages but still carry the remaining ones, so the energy consumption depends on the "state" of the delivery sequence. Conversely, the drone delivers each package individually, so only the individual delivery's energy is considered.

This generates two lists of energy values ΔE_T and ΔE_D, with one entry for each of the $n+1$ edges (i.e., legs of the schedule). We then pick from ΔE_T the leg p_m that incurs in the most massive energy demand for the truck **and** that is *compatible* with a drone delivery (Line 5). This represents a delivery that a drone can carry out, and that relieves the truck maximally. Compatibility with the drone delivery consists of two conditions: (1) the corresponding package should not exceed the maximum carrying capacity, and (2) the requested energy for the delivery is still available.

If one such leg exists, the corresponding energy is subtracted from the drone energy. Let the two nodes connected by p_m be i and j, with j is followed by node k in the schedule P. Thus, node j is selected to be served by the drone. As the latter needs to fly back to the truck, the actual energy drawn to serve j implies flying back and forth. As the exact takeoff/landing time and location of the drone depends on the remaining route, we approximate this by assuming that the drone leaves when the truck leaves i and returns before the truck reaches k. As a conservative estimate, we subtract the energy from the drone required to fly from i to j and j to k (Line 7). We then add the corresponding delivery task t_k to the set S_D and subtract it from truck deliveries S_T.

The assignment of one delivery to the drone results in the removal of two edges ((i,j) and (j,k)) from the original sequence; the route includes now a new edge (i,k) that was not initially there. Therefore we need to update the route (Line 8). It implies removing the two edges (i,j) and (j,k) from P and replacing them with the corresponding bypass edge (i,k). In the next iteration, the values of ΔE_T are recomputed for all the edges of the new P. The process is repeated until there is residual energy in the drone.

V. Simulation Results

A. Simulation Setup

1) Truck Powertrain Model: We select the Tesla Semi truck in our simulation; this is currently the only source of information for the specs as Tesla is preparing to release the Semi [13]. We implement powertrain and battery pack models based on the released information: A powertrain system consists of four 192 kW electric motors, and a battery pack capacity is 156 Ah with 346 V of battery voltage. We assume Semi's curb weight as the sum of the typical weight of class 8 truck and battery pack weight. Coefficients of the Tesla Semi truck powertrain model are obtained from [14].

2) Drone Powertrain Model: For our simulations, we selected a quadcopter DJI Matrice 100 as a delivery drone. The maximum weight to take off is 3.4 kg and the longest flight time is 16 minutes with one kg payload. The maximum speed is 79 km/h without payload. We obtained measurement data from [15], which includes the required angular speed of the rotors by thrust and related battery voltage and current consumption. We implement the drone powertrain model as a function of drone speed and weight [10].

3) Non-linear Battery Pack Model: We choose a DJI TB48D LiPO battery pack, in which six battery cells are connected in series. Nominal battery capacity is 5700 mAh and nominal voltage is 22.8 V. We use physical parameters of a 5700 mAh LiPO single cell from [16]. Then, we build the battery pack model as described in Section III-C. Concerning the electric truck battery pack model, we adopted the same model used in [12].

4) Delivery Task Model: In this paper, we evaluate the overall energy saving with respect to battery size for a set of different delivery area and range of altitude. The deliveries refer to:

- A set of 30 locations uniformly distributed within 10 km by 10 km, 20 km by 20 km, and 30 km by 30 km area;
- A set of range of altitude of 0 (float road), ± 100 m and ± 200 m;
- A set of package weights uniformly distributed between 100 g to 300 g.

We assume that the truck's speed is 20.76 km/h, which is an average rush-hour speed on urban arterial streets in San Francisco [17]. Although the speed variations impact the battery energy consumption, for the purpose of our analysis, the assumption is reasonable. Moreover, adding time-dependent speed values would yield results too much dependent on the specific speed profile. Our framework can be adapted to actual speed traces or estimates using traffic-aware navigation data (e.g., as done in [9]). We assume that the drone flight speed is 40 km/h, half of the maximum speed of DJI Matrice 100. Alternatively, we can adapt energy-optimal speed as done in [9]. We choose the drone's height during horizontal flight is 40 m over the ground level, which is the 33% of the maximum allowable height to fly the drone in Europe by the European Aviation Safety Agency (EASA) [18].

B. Delivery Schedule of Coordinated Truck-Drone Delivery

Fig.4 shows a schedule P of the truck delivery for two different the drone battery sizes with altitude on the y-axis and distance on the x-axis. Black dots and lines in each subgraph indicate $n+1$ deliveries as in the initial schedule. Intuitively, where altitude changes are large, we expect a larger energy demand for the truck than for the drone.

In the middle plot, orange lines and circles denote the revised truck schedule of the truck when the battery size of the drone is 50% of its nominal battery size (5.8Ah). The remaining black dots in the second subgraph are served by the drone. In the bottom plot, we can see how doubling the battery size allows to serve more tasks with the drone, with the truck following a route with much lower total altitude difference. We save 43% and 61% of truck energy consumption with the truck schedules in the middle and bottom plots.

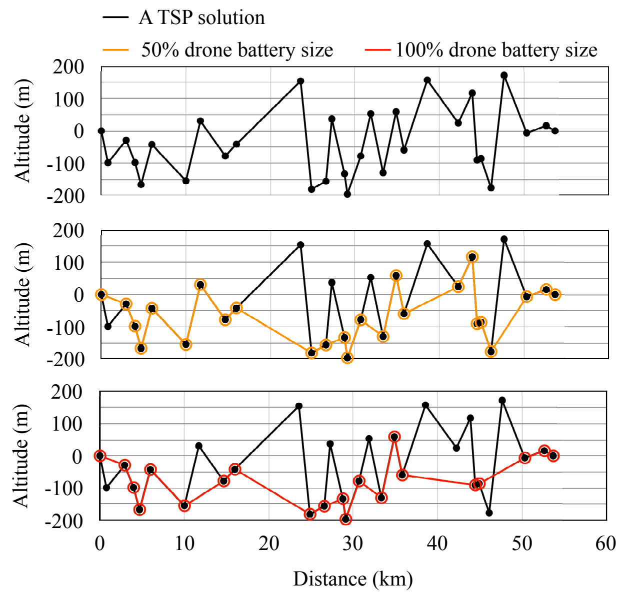

Figure 4: P of the truck by different battery size of the drone.

C. Truck energy saving by different delivery task set

Fig.5-(a) shows energy saving of the truck by different ranges of altitude and battery size of the drone. The delivery area is set as 10 km by 10 km. X-axis in the subgraph means size of the drone battery, and Y-axis means the energy saving of the truck compared with the initial schedule of the truck delivery. Each dot means a simulation result of each delivery set. Each color indicates different ranges of altitude: green color means ± 200 m range of altitude; blue means ± 100 m range of altitude; red color means flat roads. Lines of each color mean average energy savings in different drone battery size. The energy saving on ± 200 m and ± 100 m ranges of altitude and flat road with 100% of drone battery size is from 43% to 69%, 28% to 61%, and 21% to 39%, respectively. Also, the average energy gain in each range of altitude is 59%, 50% and 31%, respectively.

As the range of altitude gets larger, average slope of roads also increases. However, the energy demand of the truck is too much because tasks located on too high or too low altitude are served by the drone. On the other hands, energy demand by the initial schedule increases by the increase in slope of roads. Therefore, the energy saving on ± 200 m range of altitude is nearly double of that on flat road.

Fig.5-(b) shows energy saving of the truck on different delivery area and drone battery size. The range of altitude is set as $\pm$ 200 m. The delivery set on 10 km by 10 km delivery area is the same as the results on ± 200 m range of altitude in Fig.5-(a). The energy saving on delivery area of 20 km by 20 km and 30 km by 30 km with 100% of drone battery size is from 23% to 51% and 18% and 39%, respectively.

As the delivery area becomes larger, the average distance among locations increases. Therefore, the slope of the road between locations decreases, which reduces the impact of drone delivery on energy saving.

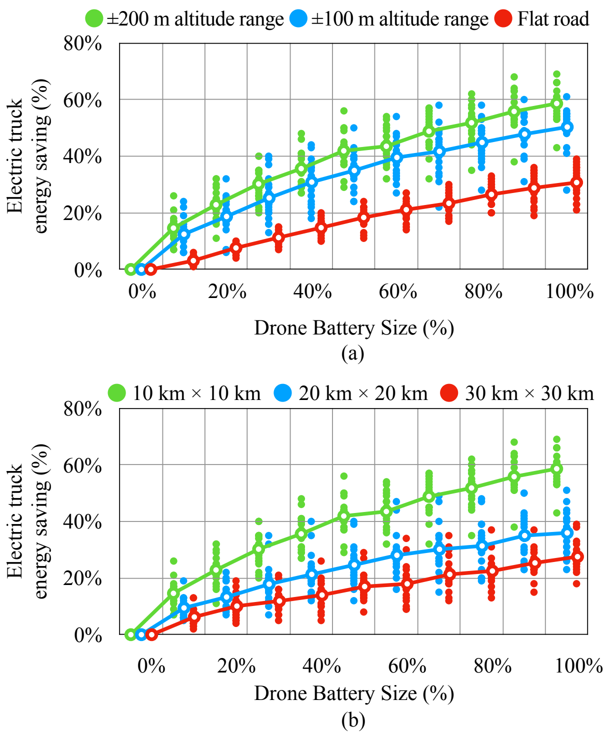

Figure 5: Electric truck energy saving by different drone battery size, range of altitude and delivery area.

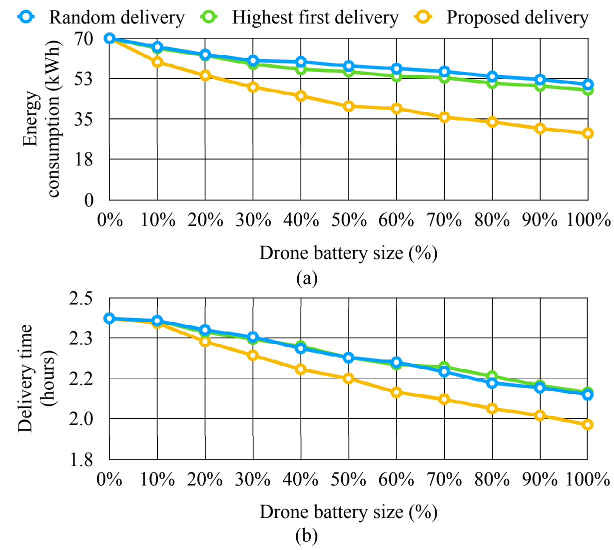

Figure 6: Energy (a) and delivery time (b) comparison among drone random, highest first and the proposed delivery.

D. Truck energy saving comparison with baselines

We implement two "common-sense" heuristics to explore strongly different assumption with respect to ours. In the first one, the drone serves 'random' locations, i.e., locations that can be served between two truck destinations: we call this one **random delivery.** In the second one, the drone serves locations at the highest altitude first (we call **highest-first delivery**). We first sort locations by their altitude, then pick as many as possible that can be served. We performed the three algorithms on 20 delivery instances in which a truck and a drone serve 30 deliveries on 100 km^2 area with $\pm$200 m altitude range). Fig.6-(a) shows the average energy savings by three algorithms as the battery size of the drone increases. The proposed method shows up to 42% and 39% more energy saving compared with the random and highest-first deliveries, respectively. This means the proposed method utilizes drone assistance most efficiently among them. The delivery results by the highest-first delivery method does not show better results compared with random delivery. If the altitude of the current truck destination is very low, it needs to ascent significantly to move to the next destination. Fig.6-(b) shows the average time savings by the drone assistance. The proposed method also saved 5 to 6% more time than others.

VI. Conclusions

Coordinated delivery strategies in which a drone collaborates with a truck have been focused on the optimality of the algorithms in terms of distance of delivery route on a plane or overall delivery time. However, altitude of the locations or road conditions makes climbing steep uphill more energy consuming, and which is more energy efficient with a drone delivery. In this work, we propose a heuristic algorithm to determine the most energy-efficient sequence of deliveries in which a drone and an EV truck collaborate in the delivery process. Simulation results with accurate model of energy consumption of both the drone and the truck, as well as a battery model show up to 69% achievement of electric truck energy saving on average.

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