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Multi-Criteria Coordinated Electric Vehicle-Drone Hybrid Delivery Service Planning

Young Hoo Cho, *Member, IEEE*, Donkyu Baek*, *Member, IEEE*, Yukai Chen*, *Member, IEEE*, Min Jae Jung, *Member, IEEE*, Sara Vinco, *Senior Member, IEEE*, Enrico Macii, *Fellow, IEEE*, Massimo Poncino, *Fellow, IEEE*

Abstract—**According to recent works, a coordinated delivery strategy in which terrestrial and aerial electric vehicles work together effectively improves delivery throughput and energy efficiency. However, most research on logistics and transportation focuses on delivery performance and does not care about energy efficiency, with three main limitations: 1. Most of these works ignore geographic information along the delivery route, while road slope is one of the most critical energy consumption components. 2. Vehicle and drone power consumption models are simplified as driving mileage, while the delivery time is a significant concern. 3. The battery model is simplified as a linear model even though practical batteries have non-linearity properties. This work proposes a framework to provide energy- and time-efficient delivery schedules with a hybrid delivery service with terrestrial and aerial electric vehicles. We first implement accurate electric van and drone power models and a battery model based on manufacturers' system specifications and experimental data. Then, we propose a heuristic delivery scheduling algorithm to determine the electric van and drone delivery schedule. We also introduce various cost functions to evaluate the delivery scheduling results regarding time, energy, the weighted sum of time and energy, and the economic model. The proposed framework is validated on randomly implemented delivery missions and delivery scenarios in existing cities. Results indicate that the coordinated delivery saves delivery costs up to 27.25% in terms of the economic model compared with the electric van-only delivery schedule.**

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

I. Introduction

Terrestrial electric vehicles (we call EVs shortly in this paper) are expected to progressively replace traditional Internal Combustion Engine (ICE) vehicles thanks to the high-efficiency characteristics of electric motors, high torque at low Rotations Per Minute (RPM), relatively low operating noise and vibration, and simple maintenance. The operation of the regenerative braking system, which transfers kinetic energy from the wheels to electric energy, also improves the efficiency of EVs. Due to the advantages in terms of efficiency, new vehicle manufacturers [1], [2] as well as traditional vehicle manufacturers [3], [4], [5] start to build electric vehicles for delivery, and delivery companies have gradually started to use electric vans for their delivery services [2], [5].

In the context of a package delivery business on a small-to-medium geographic scale, delivery efficiency can be significantly improved by assistance from aerial electric vehicles (we call drones shortly) in terms of both delivery time and energy efficiency [6]. While EVs cover long distances and heavy parcels, their energy efficiency is strongly affected by road traffic and geographical condition, like road slopes, narrow lanes, and rough road conditions. On the other hand, drones are unrestricted by traffic and terrain, ignoring geographical conditions. Coordinated delivery with the two types of vehicles can thus achieve a complementary "virtual vehicle" that can efficiently reduce the total delivery time and energy.

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

Several variables should be considered when considering the topographic details of the delivery area. Figure 1 describes one delivery instance to illustrate the motivation of this work, where five locations along a delivery planning route are shown together with their altitude location. It is evident (Figure 1(a)) that because of altitude differences, the roads consist of bends and possibly steep uphill roads, which will significantly deplete more battery charge from the EV than the EV driving on a flat and straight road.

The non-straight-line distance between locations can quickly be taken into account in 2D planar scenarios: it would suffice to replace road information and label distances with the actual length. For instance, two locations on a 2D map may have a Euclidean distance of 1 mile, but the road connecting them is 1.5 miles due to the natural terrain. Concerning the traditional planar analysis, they do not consider altitude as its effect on the distance; distance is not just the geometric distance but also considers the impact of altitude. Therefore, it is intuitive that offloading deliveries to locations with relatively high altitude differences to drones would be more energy efficient.

Y. H. Cho and M. Jung are with the School of Electrical Engineering, Korea Advanced Institute of Science and Technology (KAIST), Korea. (E-mail:younghoo@kaist.ac.kr, jmj0313@kaist.ac.kr). D. Baek is with the School of Electronics Engineering, Chungbuk National University, Korea. (E-mail: donkyu@cbnu.ac.kr). Y.k. Chen is with the Compute System Architecture (CSA) R&D unit, IMEC, Belgium. (E-mail: yukai.chen@imec.be). S. Vinco and M. Poncino are with the Department of Control and Computer Engineering (DAUIN), Politecnico di Torino, Italy. (E-mail: sara.vinco@polito.it, massimo.poncino@polito.it). E. Macii is with the Interuniversity Department of Regional and Urban Studies and Planning (DIST), Politecnico di Torino, Italy. (E-mail: enrico.macii@polito.it)

* Corresponding Authors

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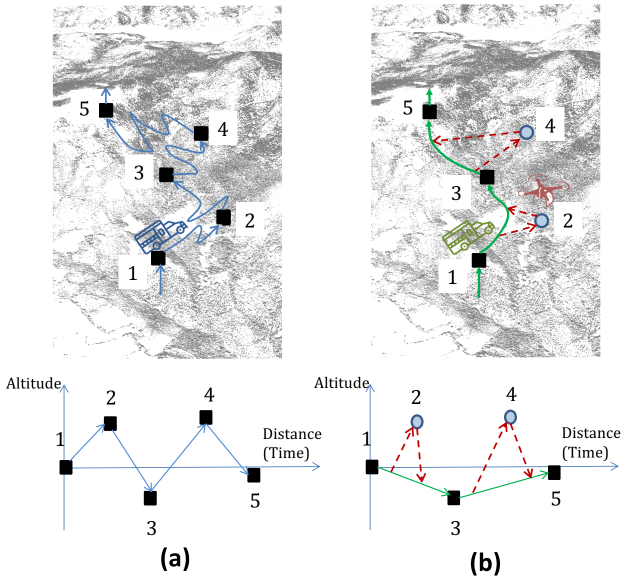

Figure 1. EV-only planning path (a) and EV-drone planning paths (b) (solid lines for EVs, dashed lines for drones).

The case of Figure 1 shows one such (somewhat extreme) example; in an EV-only delivery (Figure 1(a)), the EV will have to go up and down (see the profile in the bottom part of the Figure 1) to serve the destinations in sequence. In Figure 1(b), destinations 2 and 4 are served by a drone, which will return to the EV while it is moving. In this way, the EV can follow a much flatter route than the previous route to serve destinations 1, 3, and 5, approximately at the same altitude. In addition, less battery usage reduces battery stress. With the reduced battery stress and several stops, the EV can either use a smaller vehicle for the same set of deliveries or add more destinations within a planned delivery route for the given battery size.

A typical situation adopting the coordinated delivery scenario considers customers who are grouped in a *densely populated area* (districts with high-density housing) and just a few customers scattered outside of the area. In this case, deliveries for the densely populated areas are covered by an EV, and a drone covers the outliers. Previous work shows that the coordinated delivery can yield 30% faster deliveries in the case of favorable distribution of the locations [7]. When existing works address coordinated delivery, they mainly focus on improving delivery time as the sole cost metric [8], [9], [10].

There is an orthogonal dimension in the delivery scenario when we also consider the *altitude of customers or road conditions*. The last-mile delivery by a drone becomes more efficient for customers with significant altitude differences than the customers in the same altitude plain because the delivery by a drone saves energy consumed by the EV on an uphill road. However, the three-dimensional (3D) topographic information is ignored in previous work even though the information significantly affects delivery efficiency; problems are solved as all customers are at the same altitude. In addition, since the battery is a typical non-ideal energy storage device, and it has multiple non-linear characteristics during the discharge [11], steep uphills drain the EV battery considerably more than the drone battery. Some work considers the energy consumption perspective as a metric with a simplified battery discharge model and vehicle-drone powertrain models [9], [12], [13]. However, the model accuracy of the vehicles and battery is one of the most critical factors in evaluating efficient delivery paths under the 3D topographic information. Accurate models are not required for the typical two-dimensional (2D) delivery problem without altitude information because the total delivery distance is mainly straightforwardly proportional to the total energy consumption or delivery time.

Another paramount concern of the coordinated delivery is the *cost function* definition for delivery schedule evaluation, given that delivery time and energy are both important factors. Time and energy consumption are inversely proportional and directly related, and should thus be considered simultaneously. As an example, in the coordinated delivery scenario, the use of the drone as the last-mile delivery may slow down the overall delivery time due to the waiting time for the drone's return, even though it saves significant energy consumption. Therefore, we should carefully evaluate which delivery plan is better regarding energy and time.

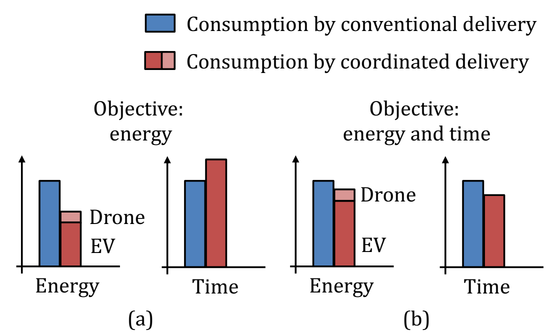

Figure 2. Coordinated delivery result with consideration of energy only (a) and of energy and delivery time (b).

The cost function of the delivery is another delivery issue. Generally, a drone delivery at the last mile may increase the delivery time because the drone speed is typically slower than the EV, and the EV should wait for the returning drone. Figure 2(a) shows a motivational example of this, showing that an energy-efficient coordinated delivery may increase delivery time because the drone speed is slower than the EV in typical; thus, the EV sometimes should wait for the drone to return. Therefore, we should consider both energy and delivery time for the coordinated delivery that, as shown in Figure 2(b), might identify a better energy-time trade-off.

This work proposes a framework to provide energy- and time-efficient delivery schedules with heuristic algorithms for the coordinated delivery service. The proposed framework considers 3D topographic information. Figure 3 shows the proposed overall coordinated delivery service planning framework, considering all aforementioned considerations. We first develop accurate models of a target EV powertrain, a target drone powertrain, and two vehicles' battery packs, respectively. An accurate battery model for the drone is mandatory to estimate an available flight time and utilization of the drone. So, we

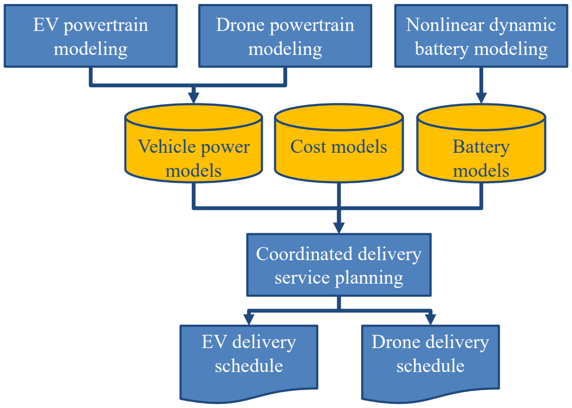

Figure 3. Framework of the coordinated delivery service planning.

implement a nonlinear dynamic battery model that can account for the battery capacity dependence on load variations. New cost functions are developed for the evaluation of coordinated delivery service plans are proposed. Coordinated delivery service planning outputs delivery schedules for the EV and the drone according to the specified cost function.

Technical contributions of this paper are:

1) Development and integration of accurate electric van and quad-copter drone powertrain models with an advanced battery model that accounts for multiple non-linear discharge characteristics; all these models are derived based on manufacturers' system specifications and experimental data.
2) Cost functions with a weighted sum of energy and time to analyze the trade-off relationship between the two objectives, energy and time.
3) A total cost function considering an economic model in which time and energy are converted to the exact expense based on typical delivery and electricity fee.
4) Evaluation of the proposed delivery scheduling results under various delivery scenarios with the accurate powertrain and non-linear battery models.
5) Validation of our van-drone delivery service planning framework in existing real cities.

The rest of this paper is as follows: Section II explains this research's motivation and related work. Section III describes how powertrain models, battery models, and cost functions are developed. Problem formulation and algorithm of our proposed scheduling framework are described in section IV. We introduce the simulation setup and present the framework validation with simulation results in section V. Section VI draws the conclusion of this work.

II. Related Work

Although research on EV-drone coordinated delivery in logistics is still in its infancy, the results 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.

The work [8] 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 sets the delivery time as the critical point, it ignores the combined truck-drone delivery system's energy efficiency. In [9], 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. [10] has the same limitation as the previous two; it simulates truck-drone delivery analysis only considering delivery time. In addition to the simulation-based method, [14] combines a theoretical analysis in the Euclidean plane with real-time numerical simulations on a road network. Still, they only provide data on delivery time. Recent work [15] starts to focus on the drone coordinated with the existing public transportation system for delivery; the authors propose a new service model to characterize the delivery time for customers, then the authors formulate and propose an algorithm to solve an optimal deployment problem to minimize the average delivery time for the customers.

Besides the works focusing on delivery time optimization, another type of research focuses on the truck-drone 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 [9], or use the simplified truck and drone power models. One example is provided in [12], 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 [13]; they focus on improving the algorithm to achieve better energy efficiency performance while neglecting the fundamental characteristics of power consumption in the whole system. Another example is [13]; it models truck-drone delivery as a TSP problem and develops several heuristics based on local search and dynamic programming. It improves performance by saving delivery time and energy compared with truck-only delivery. Still, the work does not adopt any drone and truck power models and ignores the battery's actual discharge characteristics.

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 the vehicle's power consumption, and the location's altitude is crucial for deciding how to partition the delivery tasks between trucks and drones.

III. System Modeling

A. Electric Vehicle Powertrain Model

Four resistances act on a vehicle when the vehicle drives on the road: rolling resistance F_R, gradient resistance F_G, inertia resistance F_I, and aerodynamic resistance F_A. Figure 4 shows the four resistances acting on a delivery van climbing a hill

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with δ degree. All resistances except F_A are linearly proportional to vehicle mass m. Power consumption to overcome the resistances P_{res} is a function of torque T and angular speed ω as shown below equation:

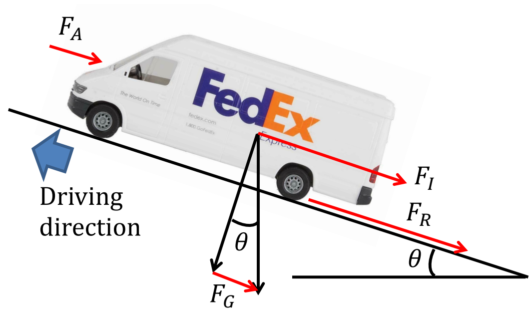

Figure 4. Forces acting on an electric van.

$$P_{res} = T\omega = Fds/dt = (F_R + F_G + F_I + F_A)v \quad (1)$$

$$F_R \propto C_{rr}mg, \;\; F_G \propto mgsin\theta, \;\; F_I \propto ma, \;\; F_A \propto \frac{1}{2}\rho C_d A v^2$$

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

Practical power consumption by electric motors P_{EV} is the sum of the power to overcome the resistances P_{res} and the power lost by the motor rotation mechanism P_{loss} [11]. P_{EV} thus depends on m, θ, v, and a:

$$P_{EV} = P_{res} + P_{loss} = f(m, \theta, v, a) \quad (2)$$

B. Electric Drone Powertrain Model

A typical drone power model [16] consists of three resistances that act on a quad-copter as shown in Figure 5. When the drone takes off and increases its altitude, as shown in Figure 5(a), there are two resistances: gradient resistance F_G pulling down the drone and dragging resistance in vertical direction F_{DV}. Thrust F_T generated by the rotor opposes these resistances to keep the drone flight constant. When the drone flies in the horizontal direction, as shown in Figure 5(b), the sum of two resistances F_G and F_{DH} (dragging resistance in the horizontal direction) act on the drone.

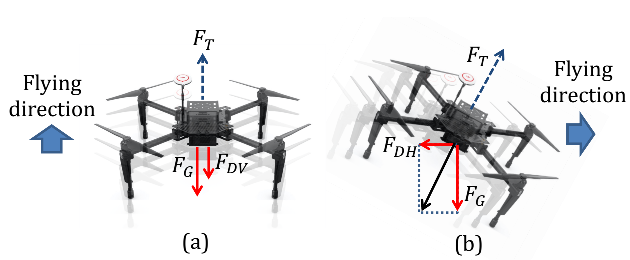

Figure 5. Forces acting on a drone when it takes off (a) and flies in the horizontal direction (b).

The required thrust to oppose the above resistances is thus:

$$F_T = F_G + F_{DV} \text{ and } F_T = \sqrt{F_G^2 + F_{DH}^2}. \quad (3)$$

where F_G, F_{DH} and F_{DV} are modeled as functions of drone mass w_d, payload w_p, and horizontal and vertical drone flight speeds v_h and v_v:

$$F_G = (w_d + w_p)g, \; F_{DV} = \frac{1}{2}\rho A_t C_d v_v^2, \quad F_{DH} = \frac{1}{2}\rho A_f C_d v_h^2 \quad (4)$$

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. Thrust is modeled as a function of motor angular speed:

$$F_T = \frac{1}{2}\rho A_p C_t (\omega r)^2 \quad (5)$$

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. Therefore, the required power for the drone delivery P_D becomes a function of angular speed with experiment-based linear modeling.

$$P_D = f(\omega(w_p, v_v, v_h)) \quad (6)$$

where ω is dependent to payload w_p, drone flight speed v_h and v_v.

We can derive the required angular speed ω during take-off, horizontal flight, and landing with a payload described in [11]. 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 until it reaches the destination with a constant speed, and (iii) landing with the same vertical speed on the destination. The drone takes off from the EV with one or multiple packages as a sidekick and returns to the EV after finishing the delivery.

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 [17]. As shown in Figure 6, the circuit equivalent model consists of a battery state of charge (SOC) model on the left-hand side and a battery voltage model on the right-hand side, respectively.

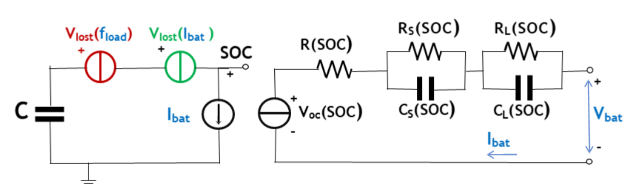

Figure 6. Adopted circuit-equivalent model for battery cell.

In the battery SOC model, a current generator I_{batt} represents the discharge current, and a capacitor C represents battery capacity, which is obtained by converting the nominal battery capacity C_{nom} (in Ah) using (7), where $1V$ is the initial voltage across the capacitor that defines a fully charged battery [18], represented by the 100% SOC of battery:

$$\mathbf{C} = \frac{C_{nom} \times 3600}{1V} \tag{7}$$

The voltage generator $V_{oc}(SOC)$ of the model describes the relation between SOC and voltage. $R(SOC)$ represents the battery's internal resistance. The methodology to extract these two quantities is described in [19]. The two pairs of RC groups in the series of the battery model account for the battery's sensitivity to the load dynamics. The first RC group (parallel between $R_S(SOC)$ and $C_S(SOC)$) defines the short-time constant $\tau_S = R_S \times C_S$ of the battery voltage response due to the double layer capacity effects; the second RC group (parallel between $R_L(SOC)$ and $C_L(SOC)$) defines the long-time constant $\tau_L = R_L \times C_L$ of the battery voltage response due to the characteristic diffusion effects in the electrolyte. The work in [19] provides the detailed steps to extract these RC groups' quantities from the battery datasheet, given that it provides the voltage trace of a pulse current. There are existing works that compute these parameters by conducting pulse current tests. However, since it is too difficult to obtain the parameters of these two RC groups and they do not affect the long-term simulation results, this circuit equivalent model is frequently used with only the $R(SOC)$ in the right part for the simulation as it does not focus on the instantaneous simulation results.

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 the higher magnitude and higher frequency of the load current decrease SOC. These two voltage generators bring a voltage drop at the SOC node, thus affecting the battery SOC. $V_{lost}(I_{batt})$ is derived by computing, at each simulation time step Δt, the following equation:

$$\Delta SOC(I_{Batt}) = \frac{I_{Batt} \times \Delta t}{C(I_{Batt})} - \frac{I_{Batt} \times \Delta t}{C_{nom}} \tag{8}$$

where $C(I_{Batt})$ is the relationship between capacity and battery current that can be derived from the datasheet as described in [20] and C_{nom} is the nominal capacity. The effect of the discharge variation is not an instantaneous quantity; therefore, the model uses the Short Time Fourier Transform (STFT) to compute load frequency components in each time interval window. $V_{lost}(f_{load})$ is obtained by evaluating (9) at each Δt.

$$\Delta SOC(f_{load}) = \sum_{i=1}^{N_{FFT}} \left(\frac{I_{Batt}(i) \times \Delta t}{C(f_{load})} - \frac{I_{Batt}(i) \times \Delta t}{C_{nom}}\right) \tag{9}$$

where N_{FFT} is length of timing window in STFT; $I_{Batt}(i), i = 1, \ldots, N_{FFT}$ is a string of current values within a timing window; $C(f_{load})$ is the relation between capacity and load frequency. The method proposed in [20] shows that using the information in the datasheet can derive the relation between discharge energy and current and the relation between discharge time and current. Then the relation between discharge power and current is computed based on the previous two relations. The power and current relation and the energy and current relation are used to draw a *Ragone plot*. The diagonals in the *Ragone plane* indicate the discharge time; the inverse of each discharge time represents a frequency. Thus the relation between energy and frequency is extracted; after converting energy to capacity, $C(f_{load})$ is computed.

We assume that all the cells behave identically within the battery pack. Therefore, we built the pack model for the electric van and drone by ideally scaling all electrical parameters according to the serial and parallel connectivity of the battery cells within the pack. This accelerates simulation, and as it is not necessary to simulate individual cells, the fast simulation speed can effectively support the delivery scheduling exploration.

D. Cost Function

1) Weighted-sum between energy and time: The weighted-sum cost function is used to find energy- and time-efficient delivery routes. A weight parameter, W_α, reflects the individual's preference or priority of the delivery between the energy and the time as follows:

$$C_{sum}(n_1, n_2) = W_\alpha T(n_1, n_2) + (1 - W_\alpha) E(n_1, n_2) \tag{10}$$

where a function $T()$ outputs time for the delivery from node n_1 to n_2; a function $E()$ outputs the sum of energy consumption of the EV and drone from n_1 to n_2. The functions $T()$ and $E()$ are described as follows:

$$\begin{aligned} t_{EV}(n_{EV} - 1, n_{(EV,D)}) &= \frac{d_{EV}}{v_{EV}}, \\ t_D(n_D - 1, n_{(EV,D)}) &= \frac{d_D}{v_D} + 2\frac{h_{ver.}}{v_{ver.}}, \\ T(n_1, n_2) &= \max(t_{EV}(n_1, n_2), t_D(n_1, n_2)), \\ E(n_1, n_2) &= P_{EV} t_{EV} + P_D t_D \end{aligned} \tag{11}$$

d_{EV}, v_{EV}, and t_{EV} are the distance, velocity, and travel time of the EV and d_D and v_D, $h_{ver.}$ and $v_{ver.}$, and t_D are the straight distance and the velocity from n_1 to n_2, vertical distance and vertical drone speed for take-off and landing, and travel time of the drone. P_{EV} and P_D are related power consumption of the EV and drone, which are described in eqs. (2) and (6). When estimating $T_{(n1,n2)}$, it takes a longer delivery time between EV and drone, which applies a waiting time for the slower vehicle to arrive.

2) Economic Model: The weighted sum as a cost function is a reasonable metric for individuals. However, in the delivery industry, the most important preference is the economic income of the delivery. It is not easy to find the optimal W_α maximizing the economic delivery income. The delivery company may lose a chance to earn more economic benefits by delaying packages to save energy consumption. The delivery company should know i) how much economic benefit we can make in a given delivery time and ii) how much economic benefit we may lose with a given amount of energy consumption.

We convert energy and time for the delivery from n_1 to n_2 into a single cost parameter $C_{economic}$ as follow:

$$\begin{aligned} C_{economic}(n_1, n_2) &= C_{time}(n_1, n_2) + C_{energy}(n_1, n_2) \\ C_{time}(n_1, n_2) &= I_{time} \times T(n_1, n_2) \\ C_{energy}(n_1, n_2) &= C_{elec} \times E(n_1, n_2) \end{aligned} \tag{12}$$

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where $C_{time}()$ and $C_{energy}()$ mean costs of delivery time spent from n_1 to n_2 and the consumed electricity for this delivery. $C_{energy}()$ is simply obtained from the product of electricity fee C_{elec} and $E()$. Estimation of $C_{time}()$, on the other hand, is based on the expected delivery income per hour I_{time}. If we waste more time on the delivery, we lose expected future income obtained through the next delivery under the fixed daily operating hour. Equation (13) shows the derivation of expected income per time unit.

$$I_{time} = \frac{I_{del} \times D_{driver}}{T_{work}} \tag{13}$$

$$I_{del} = \frac{I_{net}}{365 \times D_{com}} \tag{14}$$

where I_{del} is an expected average income by a delivery; D_{driver} is the amount of daily deliveries handled by one driver; T_{work} presents a daily working hours of a delivery driver; I_{net} is an annual net income of a company; D_{com} is the average amount of daily deliveries in a company.

IV. Energy and Time Efficient Coordinated Scheduling

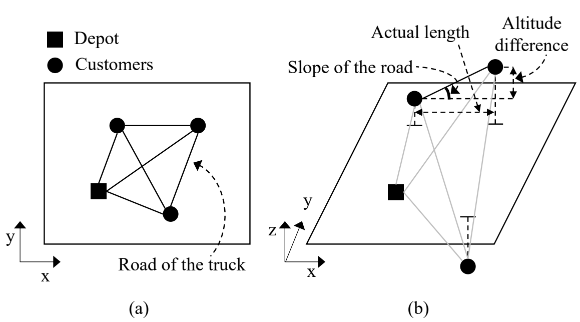


Figure 7. Problem definition for coordinated EV-drone delivery.

Figure 7(a) shows an instance of the problem with three locations on the plane, and Figure 7(b) in its 3D view represents a proposed delivery task, including the corresponding topographic information. This example has one depot node, three customer nodes, and an EV. All nodes are fully connected with vehicle roads, including Euclidean distance on the plane. Each node has a different altitude and a coordinate location on the plane. Each road of the vehicle has an actual length, including bends, and the slope of the road is derived from the length and altitude difference between the two nodes as indicated in Figure 7(b).

A. Scenario Definition

We adopt the following delivery scenario: an EV is equipped with one drone and supposed to deliver n of packages to a set of n destinations. The EV starts from a depot node; it visits all customers once and returns to the depot node when the delivery is complete. The overall delivery task is denoted by $\mathbf{Q} = \{q_1, \ldots, q_n\}$ and is defined upfront. Each delivery task q_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., a route exists between any two locations, including the depot. The distance between each node pair corresponds to the actual driving distance.

Concerning the EV and drone movements and considering the drone's payload capacity, the drone carries one or more packages on each flight. Moreover, there is no drone battery replacement, and the drone is used until it is totally depleted. The EV must follow a given speed on each road and can not make temporary stops on the road; it can only stop at the depot or customer locations for delivery. Our objective is to maximize drone delivery utilization and deplete its battery pack capacity as much as possible.

B. Algorithm

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

Algorithm 1 sketches our coordinated EV-drone delivery algorithm. Its objective is to find the optimal sequence of delivery tasks for the EV and drone, minimizing both *time* and *energy consumption* of the EV under a given drone battery size. It takes as inputs the set $\mathbf{Q}$ of n delivery tasks, the distance matrix $\mathbf{D}$ between any of the $n+1$ vertices (including the depot), including slope information, and the drone battery capacity E_D; it outputs the list of deliveries carried out by each vehicle (S_V for the EV and S_D for the drone).

Algorithm 1 Proposed coordinated EV-drone delivery

1: **Input**: Q = $\{q_1,...,q_n\}$, D = $\{d_{ij}\}$, E_D
2: **Output**: Delivery task sequences by S_V and S_D
3: $P = (p_0 \rightarrow \ldots \rightarrow p_{n+1}) = TSP(D)$
4: S_D = {}; S_V = Q
5: **while** $E_D > 0$ **do**
6: Extract $\Delta E_V = [\Delta E_{V,1}, \ldots, \Delta E_{V,n+1}]$, $\Delta T_V = [\Delta T_{V,1}, \ldots, \Delta T_{V,n+1}]$ and $\Delta E_D = [\Delta E_{D,1}, \ldots, \Delta E_{D,n+1}]$ based on the schedule P
7: Calculate $\Delta C_V = [\Delta C_1, \ldots, \Delta C_{n+1}]$ from ΔE_V and ΔT_V
8: $p_m \leftarrow$ pick the edge with the largest ΔC_V that is compatible with drone constraints
9: **if** (no edge is compatible) **break**
10: E_D = $E_D - \Delta E_{D,m}$
11: add q_k to S_D and remove q_k from S_V
12: update P removing the edges corresponding p_m
13: **endwhile**

As the proposed method is based on the selective replacement of some vehicle 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 3). 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 [21]. 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 4) the two delivery lists by assuming the EV serves all deliveries.

Given the initial schedule, we calculate (Line 6) the required time and energy consumption for each delivery according to the order defined by P for both the EV (ΔT_V and ΔE_V) and the drone (ΔE_D). ΔT_V and ΔE_V are used to calculate (Line 7) cost function ΔC_V, which is the cost for each delivery with the EV described in Section III-D. ΔE_D is used to estimate the SOC of the drone battery when the delivery is done by the drone. More precisely, for edges $p_i \rightarrow p_{i+1} \rightarrow p_{i+2}$, the required time and energy to visit p_{i+1} by the EV are compared with the travel without visiting p_{i+1} ($p_i \rightarrow p_{i+2}$ directly), and the differences (ΔE_V and ΔT_V) are extracted.

It is essential to observe it for the EV, and this calculation must *account for its current weight*: at step i, the EV delivers the remaining packages, so the energy consumption depends on the "state" of the delivery sequence. Conversely, the drone only carries packages supposed to be delivered. So only the energy for single delivery (flight) is considered.

This generates two lists of delivery cost and drone battery energy ΔC_V, ΔE_D with one entry for each of the $n+1$ edges. We then pick from ΔC_V the edge p_m that incurs the most massive cost demand for the EV, and that is *compatible* with a drone delivery (Line 8). This represents a delivery that a drone carries out, and that relieves the EV maximally in terms of energy and time consumption. Compatibility with the drone delivery consists of two conditions: (1) the corresponding package should not exceed the drone's maximum payload capacity, and (2) The current remaining capacity of the drone battery meets the requested energy for delivery.

If one such edge exists, the corresponding drone energy ΔE_D is subtracted from the drone battery capacity. Let the two nodes connected by p_m be i and j, with j 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 EV, the actual energy drawn to serve j implies flying back and forth. As the exact take-off/landing time and location of the drone depend on the remaining route, we approximate this by assuming that the drone departs when the EV leaves i and returns before the EV 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 10). We then add the corresponding delivery task q_k to the set S_D and subtract it from EV delivery set S_V.

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 now includes a new edge (i,k) that was not initially there. Therefore we need to update the route (Line 12). 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_V, ΔT_V and ΔE_D are recomputed for all the edges of the new P. Clearly, as a drone serves the removed edges, the newly added edge (i,k) also can be served by the drone. In this case, the drone carries two packages for j and k at once when it leaves i. Then, the drone visits j and k sequentially. After the deliveries ((i,j) and (j,k)) by the drone, the drone returns to the EV located in l, the node after k. The process is repeated until there is residual energy in the drone.

V. Simulation Results

A. Simulation Setup

1) Vehicle Powertrain Model: Major delivery service companies have been using electric vans for environmental reasons such as zero-emission. We chose the Nissan e-NV200 (hereafter 'electric van') as the EV, as FedEx adopts it, and it is one of the electric vans launched for the small-medium size parcel delivery purpose [22]. We implement powertrain and battery pack models based on the released information [23]: a powertrain system consists of an 80 kW AC synchronous motor and a 40 kWh lithium-ion battery pack with 360 V of nominal voltage. The curb weight of e-NV200 is 1,515 kg, and its maximum payload is 705 kg. The modeling result shows driving range errors within ±5% in the new European driving cycle and world harmonized light-duty vehicles test procedure. The coefficients for the Nissan e-NV200 electric van powertrain model are obtained as Table I.

Table I
Power model coefficients of Nissan e-NV200.

α	0.0686	β	10.3969	γ	1.0465
δ	0.000374	C_0	500	C_1	24.8904
C_2	5	C_3	0.000106	ϵ	0.6341
ζ	2875.7				

2) Drone Powertrain Model: We selected a quad-copter DJI Matrice 100 [24] as a delivery drone. The maximum weight to take off is 3.4 kg and the longest flight time is 16 minutes with a 1 kg payload. The maximum speed is 79 km/h without a payload. We obtained measurement data from [25], which includes the required angular speed of the rotors by thrust and related battery voltage and current consumption. Figure 8 shows the relation between battery power versus angular speed. We implement the drone powertrain model as a function of drone speed and weight [16].

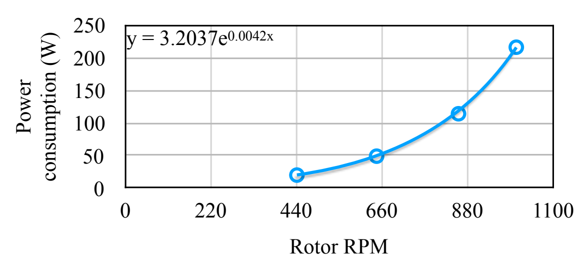


Figure 8. Drone battery power versus motor angular speed [25].

3) Battery Pack Model: An accurate battery pack model of the drone is mandatory to estimate a drone flight time and manage the utilization of the drone delivery. We chose a DJI TB48D LiPO battery pack, in which six battery cells are connected in series. The nominal battery capacity is 5,700 mAh, and the nominal voltage is 22.8 V. We use the physical parameters of a 5,700 mAh LiPO single-cell from [26], then build the battery pack model described in section III-C.

4) Delivery Task Model: In this work, we evaluate the delivery cost saving with respect to battery size for a set of explorative parameters in Table II. Sets of 30 to 150 locations are uniformly distributed within a 10 km by 10 km area where the altitude of each location is from -200 m to +200 m.

Table II
VARIOUS SIMULATION CONDITIONS.

Weight W_α	1 to 0
Area (km×km)	10×10
Altitude (m)	-200 to +200
Payload (kg)	Random from 0.1 to 0.3
The number of locations	30, 60, 90, 120, 150
Drone battery capacity (Wh)	42.18, 84.36, 168.72

Most delivery vans spend about 70% of their driving time at velocities less than 35 mph (nearly 56 km/h), including slowing down for parking, and average driving velocity is 20 km/h to 35 km/h [27] [28]. We choose 50 km/h as the velocity of the electric van for the travel. We assume that the drone flight speed is 40 km/h, half of the maximum speed of the DJI Matrice 100. Alternatively, we can adapt energy-optimal speed as done in [11]. We choose the drone's height during horizontal flight at 40 m above 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) [29].

5) Cost Function: For the weighted-sum cost function, the required information is energy and time consumption for each delivery provided by the EV and drone powertrain models. For the economic model, equation 12 in Section III-D is populated with the coefficients in Table III.

Table III
PARAMETERS FOR THE CONVERSION TO THE ECONOMIC MODEL.

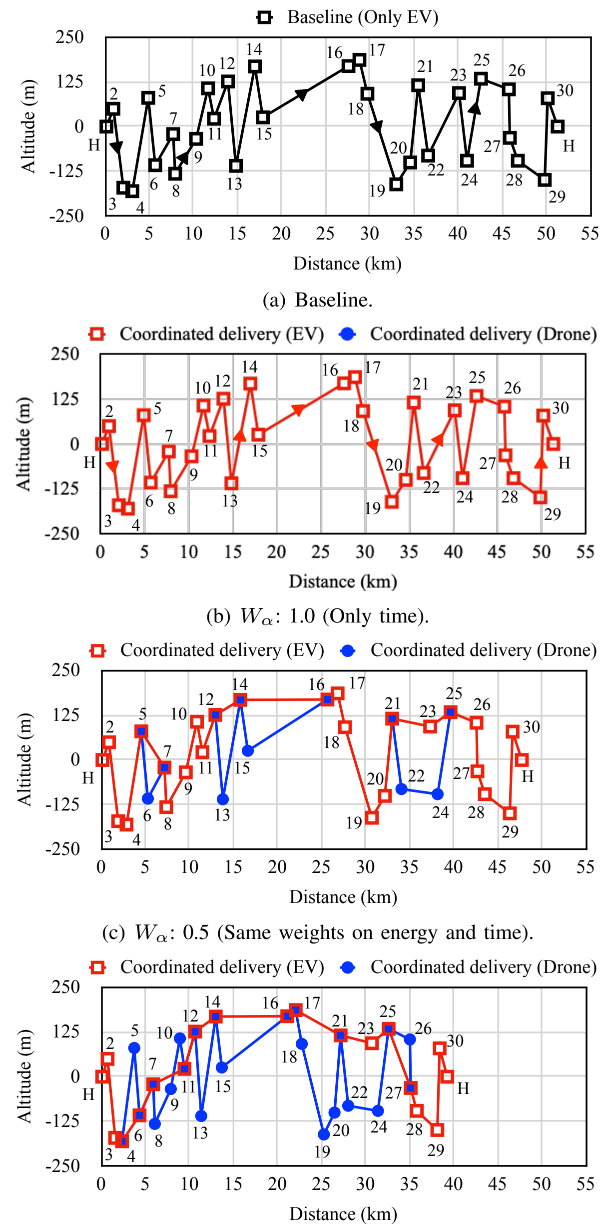
Electricity	C_{elec} (\$/kWh) [30]	0.36
Time	D_{driver} (pacakages/day) [31] [32]	150
	T_{work} (hours)[a] [33]	10
	I_{net} (\$) [34]	1.34 B
	D_{com} (packages/day) [35]	21.1 M
	I_{time} (\$/hours)	2.61

[a] A delivery driver works six days a week.

B. Simulation Result

1) Weighted Sum of Energy and Time as a Cost Function: As mentioned in Section III-D, the time and energy priority, and preference are different for each individual. Figure 9 shows the results of baseline and coordinated delivery planning for 30 locations. Squares mean target locations for the delivery, and black lines mean a baseline route that delivers with only an electric van. Red lines and blue lines present, respectively, a route for the electric vehicle and the drone in the coordinated delivery method. The X-axis is the distance following the road, and Y-axis is the altitude of locations. The slope of each black and red lines means the road slope of the electric van if it drives along the road.

Figure 9(b) presents a route with only red lines when it cares only time, meaning that all the locations are visited by only the electric van only and no drone, to deliver as fast as it can. Figure 9(c) shows a coordinated delivery plan when considering both time and energy. Figure 9(d) shows properly distributed delivery plans for the electric van and drone to save only energy consumption. If the slope to the next delivery is high, the delivery is assigned to the drone. So, the slope of the red line, the average road slope of the electric van, becomes smooth. Also, Figure 9 shows that, as the drone delivers more locations, the total distance of the EV decreases.



(a) Baseline.

(b) W_α: 1.0 (Only time).

(c) W_α: 0.5 (Same weights on energy and time).

(d) W_α: 0.0 (Only energy).

Figure 9. EV-drone coordinated delivery route according to W_α.

As W_a becomes higher (Figure 9(d) to 9(b)), the electric van visits more locations to save time, which means that delivery with the electric van is faster than the drone. This is true under two assumptions: 1) the drone's velocity is slower than the electric van, 2) the number of drones is only one, and the electric van should wait for the drone at the following location. Of course, delivery with multiple drones can save the overall delivery time. This is out of scope with respect to the paper, and we will work on it in future work.

Figure 10 shows energy and time consumption of the coordinated delivery by W_α. Blue circles mean simulation results by the given W_α. Blue circles show a Pareto curve between energy and time. The coordinated delivery with bigger W_α means that the delivery time is more concerned than energy consumption.

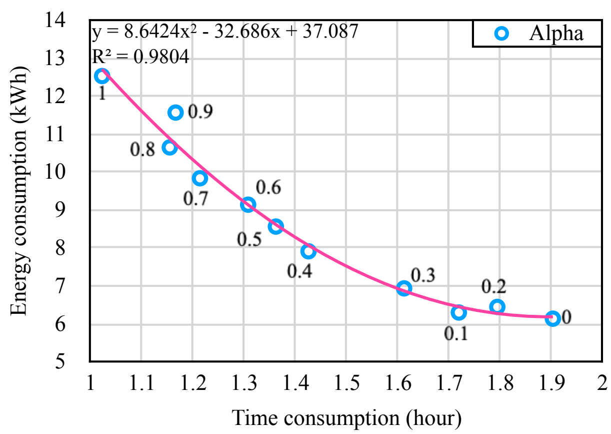


Figure 10. Energy and time consumption by the EV-drone coordinated delivery with various W_α.

2) Economic Model as Cost Function: Figure 11 shows C_{time} and C_{energy} in different velocity of the electric van. The x-axis is the velocity of the electric van, and the y-axis is the cost breakdown by the coordinated delivery. The total cost decreases with the velocity of the electric van becoming faster. Specifically, C_{energy} increases slightly while C_{time} significantly decreases, which decreases the total cost. This figure shows that focusing only on energy saving and reducing vehicle velocity causes an overall cost increase. In the future, the energy cost will increase more and more because many countries are moving toward eco-friendly power generation, so delivery considering energy will become more important. For example, electricity price in Germany increases every year [36]. Therefore, the proposed coordinated delivery with the economic model will give more weight to energy consumption than time.

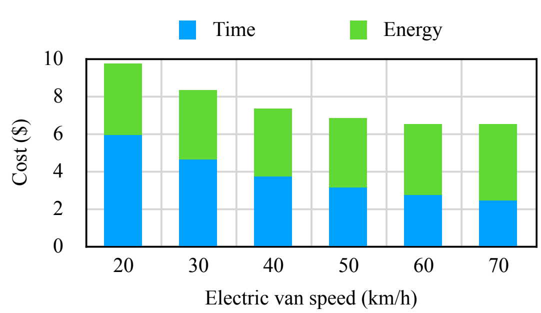


Figure 11. The overall delivery cost of various electric van velocities.

Figure 12 shows cost improvement compared with the baseline method (electric-van-only delivery) according to different electric van velocities. The y-axis 'improvement' means how much total cost is reduced compared with the baseline result. The improvement has decreased to the increase in the electric van velocity. In this example, the maximum cost improvement is 15.5% at 20 km/h van velocity, while the minimum percentage is 5.7%. The average improvement percentage is 9.1%. As the velocity increases, coordinated delivery cannot save C_{time} enough compared with the baseline because the electric van should wait for the returning drone after delivery. However, suppose C_{energy} increases with the rise of electricity cost in the future. In that case, the saving of C_{energy} by the coordinated delivery will increase more and, therefore, overall improvement will be better.

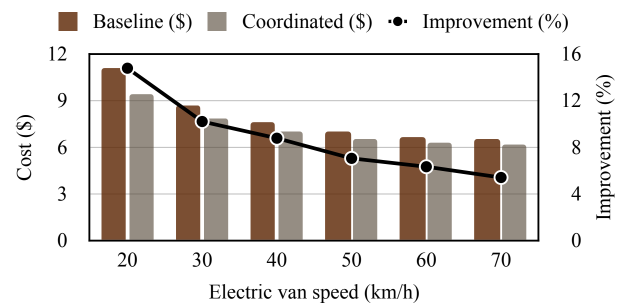


Figure 12. Delivery cost ($) and improvement (%) of the proposed method compared with the baseline.

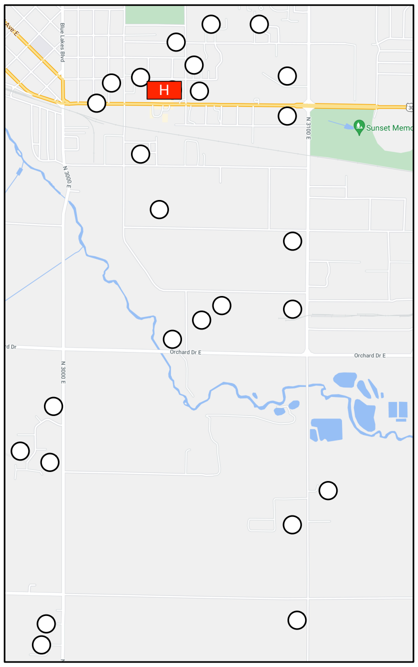
C. Case Study for the Real Road

Coordinated delivery planning on real road cases has two different issues from the simulation above: One is that the drone and EV have different delivery distances for the same delivery from one node to another node. A drone flies a straight path, the shortest distance between two nodes, while an EV should follow a given road, mostly winding on hills. The other is that sometimes there is no direct connection between two locations due to geographical obstacles, such as a river or a mountain. The EV should detour the obstacles to reach the location. For the real-world application, we choose two different cases: one with a small altitude difference and the other with a relatively large altitude difference among delivery locations. Information on road distance, altitude, latitude, longitude, and navigation are obtained from Google Map and Google Earth Pro. Table IV shows environmental information for two test cases.

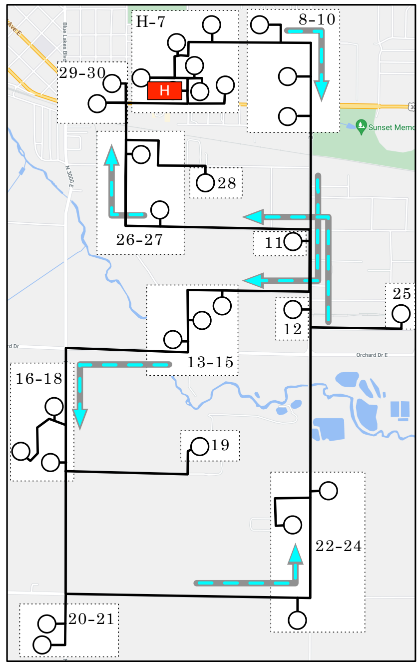
Table IV
ENVIRONMENTAL INFORMATION FOR THE CASE STUDIES.

Description	Case 1	Case 2
City	Twin Falls, ID, USA	San Diego, CA, USA
Max. altitude difference (m)	51	376
Average slope (Up/Down) (%)	1.2 / -1.2	6.7 / -8.9
Maximum slope (Up/Down) (%)	7.7 / -9.3	24.2 / -33.9
The number of locations	30	13

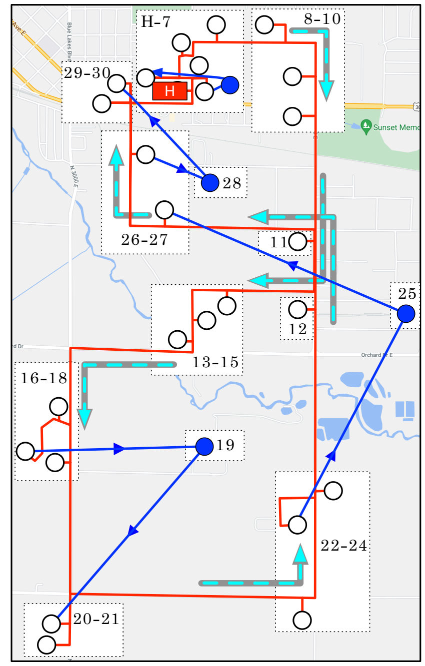
1) Case 1: Real Road with Small Altitude Difference: We choose a city named Twin Falls, ID, USA, for a real road example with a small altitude difference and pick 30 random delivery locations shown in Figure 13(a). Some delivery locations are densely close to each other in a small area to reflect the real-world environment. Figure 13 shows the results of the EV-drone coordinated delivery plan on the actual road example. 'H' in a red box in the figures means the hub where the electric van starts and comes back, and the numbers present the delivery sequence. We first obtain the shortest paths of the electric van among delivery locations under the given road environment. Then, we extract the delivery task sequences for the electric van S_V using the algorithm 1. When



(a) Delivery locations.

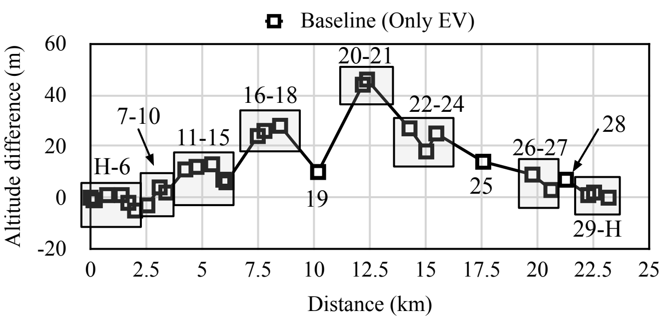


(b) Baseline: delivery route of EV only.

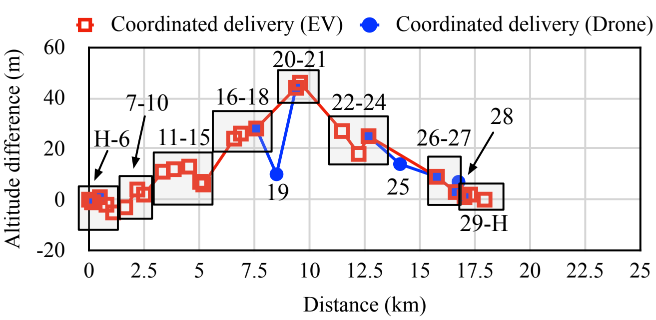


(c) Coordinated: delivery route of the EV and the drone.

Figure 13. Delivery routes of the baseline method and the coordinated delivery method for Case 1.

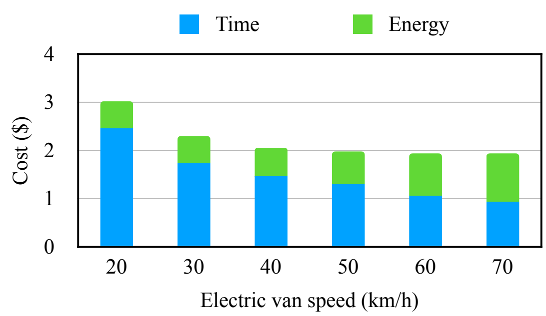


(a) Baseline.

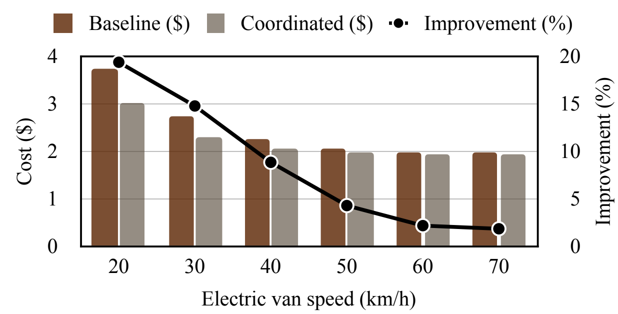


(b) Coordinated delivery.

Figure 14. Altitude vs. distance for Case 1 delivery.



(a) Delivery cost by various electric van velocity.

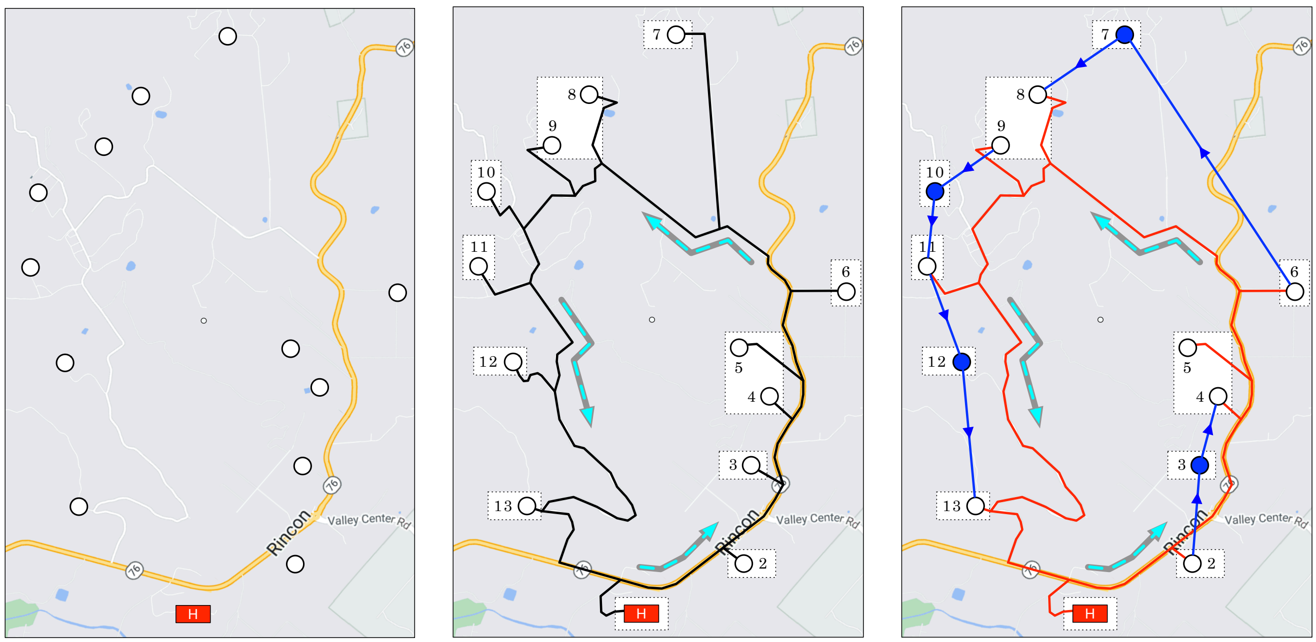


(b) Delivery cost ($) and cost improvement (%) comparison between the proposed coordinated delivery and baseline delivery.

Figure 15. Result of the proposed coordinated delivery on Twin Falls city.

delivering with only an electric van called 'baseline', the paths for the electric van are shown as black lines in Figure 13(b). The delivery task sequences for the drone and electric van are obtained based on cost function as the economic model. The red line presents the electric van delivery route in the coordinated delivery with the drone. The blue line means the drone flight path, which is straight, and the blue circles mean the delivery locations served by the drone delivery in Figure 13(c). Saved routes due to the drone delivery are the routes that don't exist in Figure 13(c), but exist in Figure 13(b). These routes can be found by checking the deleted black lines that are originally connected to drone delivery locations.

Figure 14 represents altitudes of delivery locations for the travel distance of the electric van of the baseline and the co-ordinated delivery methods. The saved distance of the electric



(a) Delivery locations. (b) Baseline: delivery route of EV only. (c) Coordinated: delivery route of the EV and the drone.

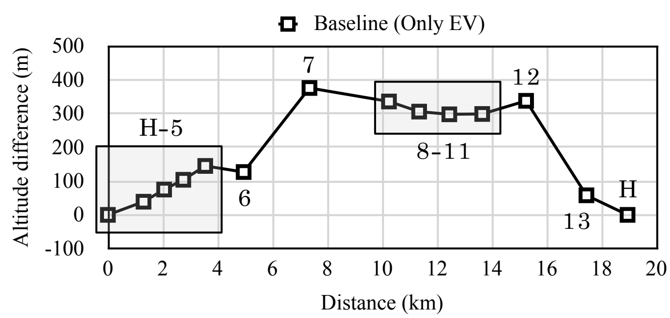
Figure 16. Delivery routes of the baseline method and the coordinated delivery method for Case 2.

van is 5.25 km, which can be seen by comparing the travel distance of Figure 14(a) with Figure 14(b). The coordinated delivery method reduces the travel distance between nodes, resulting in decreasing the total distance referring to the figures. The drone delivers to 4th, 19th, 25th, and 28th destinations. Especially delivering to the 19th with the drone can save energy significantly because the altitude differences of the 19th location are relatively large. The drone doesn't deliver to some delivery locations because the proposed method calculates the best combination of drone delivery locations that can be delivered with the given battery capacity to save costs.

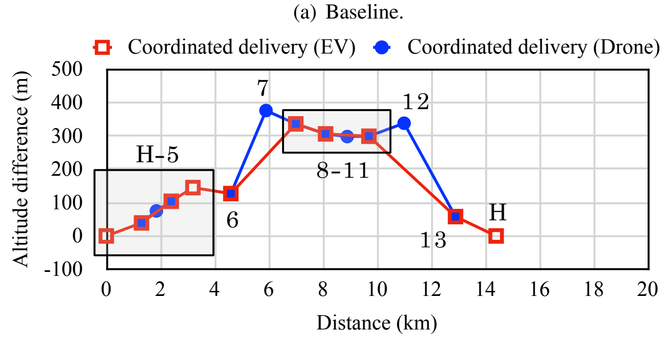
Figure 15(a) shows the cost breakdown into time and energy by the velocity of the electric van. Energy becomes more important as the electric van velocity increases. Higher than 70 km/h of electric van velocity, C_{energy} becomes higher than C_{time}. Unlike the scenario described in Section V-B where, in Figure 9(d), the electric van drives on a flat road from 14th location to 16th location under the drone goes to 15th location. Nevertheless, in the real case, the roads connecting the 14th and 16th locations are not always at the same altitude due to the terrain. Therefore, the electric van is still necessary to drive uphill and downhill roads even in coordinated delivery.

Figure 15(b) shows the cost improvement up to 19.4% with an average percentage of 8.6%. As mentioned in Section V-B1, the average velocity of a typical delivery van is from 20 km/h to 35 km/h [27] [28], the average cost improvement percentage is 14.36%.

2) Case 2: Real Road with Large Altitude Difference: We choose a city named San Diego, CA, USA, for a real road example with a significant altitude difference and pick 12 random delivery locations, as in Figure 16(a). Figure 16 shows the EV-drone coordinated delivery plan results. Figure 16(b) shows the baseline paths with only an electric vehicle with a black line. The same cost function as case 1 is applied. The result of the coordinated delivery method is shown in Figure 16(c).



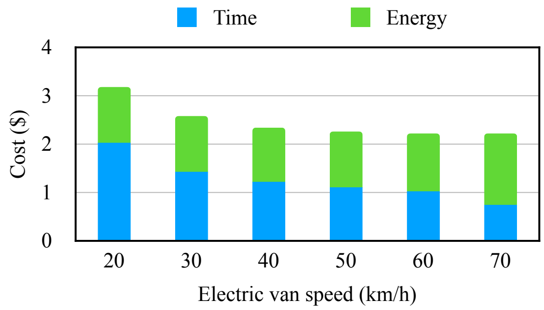
(a) Baseline.



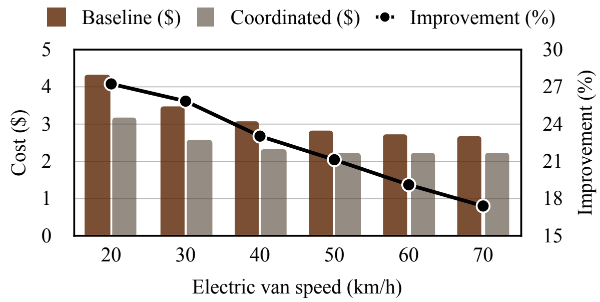
(b) Coordinated delivery.

Figure 17. Altitude vs. distance for Case 2 delivery.

Figure 17 represents the altitudes of delivery locations for the travel distance of the electric van of the baseline and the coordinated delivery methods. The saved distance of the electric van is 4.5 km in comparison to the travel distance of Figure 17(a) with Figure 17(b). Also, coordinated delivery re-



(a) Delivery cost by various electric van velocities.



(b) Delivery cost ($) and cost improvement (%) comparison between the proposed coordinated delivery and baseline delivery.

Figure 18. Result of the proposed coordinated delivery on Case 2.

duces travel distances of the electric van. The drone delivers to the 3rd, 7th, 10th, and 12th destinations. Especially delivering to 7th and 12th with the drone can save energy significantly because of the large altitude differences and the travel distance compared to other locations.

Figure 18(a) shows the cost breakdown into time and energy by the velocity of the electric van. Energy in case 2 takes much more portion than that in case 1 because much more dynamic altitude difference among delivery locations cause the electric vehicle to spend much more energy in case 2. Figure 18(b) shows the cost improvement up to 27.25% with an average percentage of 22.3%. The average cost improvement percentage when the electric van speed is from 20 km/h to 40 km/h is 25.38%. Comparison improvement according to all the electric van speeds in case 2 to those in case 1 shows that the coordinated delivery method has a stronger advantage on delivery in an area with a large altitude difference in such as case 2 than case 1.

VI. Conclusions

The delivery industry grows fast every year, and companies in this industry have started to use electric vans. Some delivery service destinations are much out of town and cause a long round trip just for one or a few deliveries resulting in substantial inefficient energy and time consumption. This paper proposes a scheduling framework using a heuristic algorithm for energy-efficient, time-efficient, and cost-saving delivery sequences with an electric van and a drone. The scheduling framework considers altitude, which causes significant energy draw from the van, and road conditions, such as the presence of many curves instead of just a straight road. Time and energy consumption are considered as a cost, and we convert time and energy to the economic model. It shows up to 15.5% achievement in fully connected delivery problems as straight roads. The achievement becomes better as up to 27.25% in the real-world application where locations are not fully connected and roads are winding. The multiple drones with one van scenarios will be considered in future work. Coordinated delivery with multiple drones can save overall delivery time because others can share the flying and waiting time for drones.

Acknowledgment

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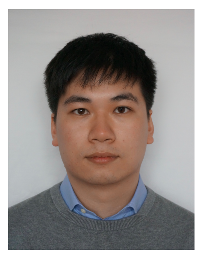
Young Hoo Cho (Student Member, IEEE) received a B.S. degree from the Department of Mechanical Engineering, Purdue University, West-Lafayette, IN, USA, in 2013 and an M.S. degree from the Department of Electrical Engineering, Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2019. He is working toward a Ph.D. in Electrical Engineering at the Korea Advanced Institute of Science and Technology, Daejeon, South Korea.

Donkyu Baek (Member, IEEE) is currently an Assistant Professor at the School of Electronics Engineering, Chungbuk National University, South Korea. He received a Ph.D. degree in Electrical Engineering from the Korea Advanced Institute of Science and Technology, South Korea, in 2017. From 2018 to 2019, he was a Postdoc researcher at the Department of Control and Computer Engineering at Politecnico di Torino. His current research interests include the optimization framework of electric vehicles and drones and IoT digital system design.



Yukai Chen (Member, IEEE) received the M.Sc. and Ph.D. degrees in Computer Engineering from Politecnico di Torino, Turin, Italy, in 2014 and 2018, respectively. He is currently a Postdoc researcher at IMEC, focusing on system-level power and thermal management for High-Performance Computing Architecture. His research interest includes design automation for non-functional properties modelling, simulation, and optimization of Cyber-Physical Systems, emphasizing energy-efficient design, low-power design, and design space exploration.

Min Jae Jung (Student Member, IEEE) received a B.S. degree in Electronic Engineering from Hanyang University, Seoul, South Korea, in 2018 and an M.S. degree in Electrical Engineering from Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2020. He is currently pursuing a Ph.D. degree in the School of Electrical Engineering at the Korea Advanced Institute of Science and Technology, South Korea. His research interests include the diagnosis and optimization of battery systems.

Sara Vinco (Senior Member, IEEE) is currently an Associate Professor of Computer Engineering with Politecnico di Torino, Turin, Italy. She received her Ph.D. degree in Computer Science from the University of Verona, Verona, Italy, in 2013. Her current research interests include the digital twin of EVs and the smart manufacture of Industry 4.0, energy-efficient design automation and techniques for the simulation and validation of cyber-physical production systems.

Enrico Macii (Fellow, IEEE) received the Laurea degree in Electrical Engineering from the Politecnico di Torino, Torino, Italy, the Laurea degree in Computer Science from the Università di Torino, Turin, Italy, and the Ph.D. degree in Computer Engineering from the Politecnico di Torino, Torino, Italy. He is a Full Professor of Computer Engineering with the Politecnico di Torino, Torino, Italy. His research interests include the design of digital circuits and systems, with a particular emphasis on low-power and energy-efficiency design, sustainable urban mobility, and clean and intelligent manufacturing. He currently serves as vice president for strategy of the IEEE Council on Electronic Design Automation.

Massimo Poncino (Fellow, IEEE) received the Ph.D. degree in Computer Engineering and the Dr.Eng. degree in Electrical Engineering from Politecnico di Torino, Torino, Italy. He is a Full Professor of Computer Engineering with the Politecnico di Torino, Torino, Italy. His current research interests include various aspects of electronic design automation, emphasizing modelling and optimizing energy-efficient Cyber-Physical Systems. He currently serves as an Associate Editor for the IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems and IEEE Transactions on Computers.