Research Article

Integration of Three Vehicle Fleet Types for Delivering Relief Supplies During a Natural Disaster

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Abstract
The combined use of trucks and drones in last-mile delivery offers a more efficient and faster way to make deliveries from an operational standpoint. In this paper, we propose a new routing model that combines different vehicle fleets, including hybrid trucks, traditional trucks, and large drones, to deliver packages from a depot to different destinations cooperatively. This research will give us a better understanding of this drone logistics application, particularly in routing optimization. It can be further implemented to mitigate the impacts of natural disasters, mainly earthquakes, flooding, and landslides. This research aims to study the possibility of using drones to deliver relief supplies such as food, water, and medicine for humanitarian purposes during natural disaster periods to find the best possible route to directly reach the destination and minimize the flying time in the air. We develop a Mixed Integer Programming (MIP) formulation to solve the I-VRPD optimally on a simulated small-scale problem and conduct a case study in one of the most affected regions by natural disasters. The numerical analysis demonstrates an improvement in the delivery time using three experiments that include testing the model on a set of benchmark problems and a case study based on the real scenario. The results show that the delivery time of the proposed model with the integration of three types of vehicle fleets can outperform the operation performed by a single-vehicle fleet by a significant percentage.

Keywords: Drones, Humanitarian, Last-mile delivery, Optimization, Vehicle routing

1 Introduction

In the last half-century, the world has been impacted by natural disasters that have killed and injured countless thousands and economically destroyed residential property and infrastructure. Typical natural disasters in different countries include floods, droughts, tropical storms, tsunamis, forest fires, landslides, earthquakes and hailstorms, etc. Many private and public organizations collaborate in mitigating such threats, monitoring disaster situations, responding and managing the situation, and providing assistance and relief in the immediate aftermath of a disaster. In this modern age, various technologies can help reduce the impact of natural disasters by presenting the opportunity to expedite and magnify the impact of humanitarian relief efforts through greater efficiency and responsiveness, reaching more people sooner, more cost-effectively, and saving more lives.

Traditionally, the supply delivery during the natural disaster period was made by ground networks, massive regional distribution facilities, and fleets of vehicles, which are only suitable for long-distance, intercity shipping [1]. The traditional truck is not well suited to deliver in areas where the road is damaged from natural disasters like flooding, earthquakes, and landslides, etc. Because of this, transportation providers are developing a better solution to last-mile delivery by disrupting their long-standing traditional model and replacing it with a faster, more versatile, and more cost-efficient delivery system. During a pandemic, the last mile is also faced with an ever-increasing parcel ship volume that needs fast, cost-effective and ecologically friendly deliveries. The most prominent approach discussed by practitioners and the academic literature to meet these requests is delivery by autonomous drones, which either depart from a central depot or are launched from a delivery truck. Over the past few years, there has been a recent discussion about using drones, robots, and autonomous vehicles to deliver products to the customer's doorstep in last-mile delivery [2]. Among various types of futuristic vehicles, drones have been recently tested in both academic research and practical aspect to perform such delivery in a specific region permitted by the regulator. Following the announcement of Amazon Prime Air in 2013, many well-known e-commerce companies and traditional logistics couriers like USPS, UPS and FedEx have been testing drone delivery services to deliver various items, including relief supplies, food, and commercial products [3], [4].

Drones have several advantages, including their speed, flexibility, and accessibility to areas where no other modes of transportation can reach. In addition, drones can carry supply kits, such as food, water, and medicine during a natural disaster. A small delivery drone weighs 0.5 to 3 lbs (250–1,300 g) and delivers items between 5 and 30 kg (11–66 lbs). On the contrary, a delivery truck/trailer usually weighs around 6 t and has a payload capacity of around 15 t to 35 t. Therefore, when pairing a drone with a truck that can carry huge loads and travel long-range, this combination can offset the drone's disadvantages, such as its small capacity and short battery duration. The recent research focuses on synchronizing small drones with trucks to improve last-mile delivery performance. One of the very first models to include this function was introduced by Murray and Chu [5] as the “Flying Sidekick Traveling Salesman Problem” (FSTSP) in which a drone initially travels together with a truck, then departs from a truck to make a delivery and returns to a truck for a battery service. Simultaneously, a truck can travel to the following location without waiting for a drone.

In this paper, we propose a new routing model, which includes the synchronization feature between multiple trucks and multiple drones and the capacities of both vehicles that were not previously presented in the FSTSP. We refer to this specific type of truck with the drone equipped on top as a “hybrid truck”. In addition to that, we include two more types of vehicle fleets in the routing operation, including a “large drone” or “cargo drone” and a “traditional truck”. A large drone

(a) (b)

Figure 1: Examples of a hybrid truck with a small drone and a large/cargo drone for delivery purposes. (a) A hybrid truck by Workhorse. (b) A large/cargo drone by Elroy.

is a new “plane-sized” autonomous delivery vehicle that can weigh roughly over 200 lbs and can carry heavy weight items up to hundreds of pounds. They can fly over long distances for hundreds of miles [6]. Large drones offer speed benefits similar to small drones with more endurance and capacity [7]. However, it comes with a high cost and has been recently tested in only a specific region.

Furthermore, unlike a small drone designed to carry a single item one at a time, a large drone can carry many basic disaster supply kits, such as food, water, and medicine. It can stop at multiple locations to deliver the kits before returning to the depot. Lastly, a traditional truck is simply a truck without a small drone and is used in the current delivery. Figure 1(a) and (b) illustrate the hybrid truck with a small drone and the large drone.

To the best of our knowledge, previous studies have yet to integrate and combine different types of vehicle fleets involving drones/large drones. Therefore, we intend to study and investigate the benefits of this approach in comparison with the other existing drone routing models used for last-mile delivery. We name this model “Integrated Vehicle Routing Problem with Drones” (I-VRPD). Figure 2 demonstrates a simple I-VRPD feasible solution in which three different types of vehicles are used in the setting. As illustrated, the solution routes consist of one hybrid truck with two drones, one traditional truck, and one large drone. The solid grey line represents the solution for the traditional truck, and the dashed line represents the solution for a large drone.

The I-VRPD solution contains a mix of different routes, which can be categorized into three types: a hybrid truck route, a traditional truck route and a large

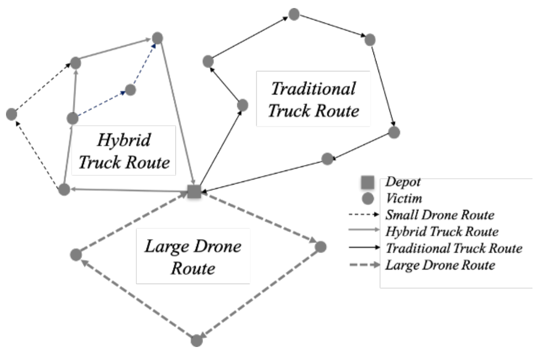


Figure 2: Illustration of the Integrated Vehicle Routing Problem with Drones (I-VRPD).

drone route. The objective of the proposed model is to find a combination of solution routes from different fleets of vehicles that gives the minimum total delivery time while satisfying all demands from diaster victims. We believe that the successful integration of drones combining with other vehicle types could result in cost efficiency and reduce the delivery time performed by the operators. In this study, we formulate a new mathematical model to solve the Integrated Vehicle Routing Problem with Drones (I-VRPD). The main contributions of this work are presented as follows. Firstly. a Mixed Integer Program (MIP) formulation for the I-VRPD was proposed. The MIP formulation can be solved for the solutions for small-size problems by any commercial MILP solver, e.g., CPLEX and GAM. We transform the conceptual idea of integrating different vehicle fleets to transport supply kits to the people in the affected area of natural disaster. We must develop a mathematical model to validate our proposed concept. Secondly, a case study and numerical experiments on different problem sets solved by the MIP model. We use a MIP solver to solve the solutions in the case study and the small-size problems and verify the model using a case study. These experiments are conducted to test if the model can return optimal solutions on different problem sets using a short amount of computational time. The case study can be used to verify if the route solution makes sense from a practical standpoint. Thirdly, the results of the I-VRPD with the classical VRP optimal solutions and other VRP with Drone (VRPD) routing models on various benchmark problems were compared. The results give us an insight into the delivery time savings achieved by implementing mixed vehicle fleets compared to a single vehicle fleet.

2 Materials and Methods

2.1 *Related literature*

The academic routing community has acknowledged the potential application of drones in industrial and commercial operations. There has been an increase in related literatures in drone routing optimization problems over the past few years, which includes different classifications, such as the objectives optimized, solution methods, applications, constraints, and practical use from the industry perspective. Several recent survey articles on drone routing for last-mile delivery provide insights into general and emerging modeling approaches and outline trends and future research directions [8]–[10]. Most of the papers focus on the vehicle-drone integration routing for delivery, which incorporates the use of truck and drone as a combined working unit. The Integrated Vehicle Routing Problem with Drones (I-VRPD) can be considered a variant of the classical Vehicle Routing Problem (VRP) with the implementation of small drones and large drones combined with other fleet types of vehicles. The Vehicle Routing Problem (VRP) is a well-known combinatorial optimization problem in the operation research field to minimize the travel cost of vehicles [11]–[14]. We provide relevant papers on our work in this drone routing optimization area.

Initially, FSTSP by Murray and Chu [5] highlighted the idea of synchronizing between a single truck and a single drone. The authors proposed a mathematical formulation and provided a simple heuristic to solve the solutions. Ponza [15] examined the FSTSP in detail and proposed a metaheuristic based on the simulated annealing technique to find reasonable solutions. Ha *et al.* [16] modified the FSTSP objective to minimize the total cost of transportation and applied TSP-LS and a Greedy Randomized Adaptive Search Procedure (GRASP) to search for reasonable solutions. Jeong *et al.*, [17] studied how the payload affected drone battery consumption and considered the operation in a prohibited area. In a recent study, Murray and Raj [18] introduced the "Multiple Flying Sidekicks Traveling Salesman Problem" (mFSTSP) by considering heterogeneous drones deployed from the truck or the depot. Kitjacharoenchai *et al.*, [19] proposed the “Multiple Traveling Salesman Problem with Drones” (mTSPD), which has the same feature as FSTSP but considers multiple trucks and drones as well as allows drones to land at any available truck.

Agatz *et al.*, [20] proposed a similar problem to FSTSP called the "Traveling Salesman Problem with Drone" (TSP-D), which can be solved by the MIP model, the heuristics based on local search and dynamic programming. Bouman *et al.*, [21] solved the TSP-D exactly using dynamic programming, while Yurek and Ozmutlu [22] solved the same problem with an iterative optimization algorithm. The TSP-D was further extended by Marinelli *et al.*, [23] so that drones can be launched or land at any location in the network. Other drone routing problems based on TSP include the "Heterogeneous Delivery Problem" (HDP) by Mathew *et al.*, [24], the "Traveling Salesman Problem with multiple Drones" (TSP-mD) by Tu *et al.*, [25], the "TSP with a drone station" (TSP-DS) by Kim and Moon [26] and the "Truck-drone in Tandem Delivery Network" by Ferrandez *et al.*, [27].

As for the drone routing problem extended from the VRP, we found many papers on the "Vehicle Routing Problem with Drones" (VRPD) in which the worst-case analyses and the upper bounds on the cost of deployment were developed [28], [29]. At the same time, others examined the VRPD by implementing "Continuous Approximation" (CA) models to determine the optimal sets of parameters, such as the number of vehicles, the total cost of operation, and the minimum completion time [30], [31]. Hong *et al.*, [32] developed a heuristic to determine the optimal network of recharging locations of drones. Schermer *et al.*, [33] also solved the VRPD with the MILP and the heuristic based on the "Variable Neighborhood Search" (VNS). Similarly, Dorling *et al.*, [34] proposed the "Vehicle Routing Problems for Drone Delivery" with two objective functions: delivery costs and delivery time. Ham [35] additionally extended the dropping and pickup operations for drones in the "Parallel Drone Scheduling Traveling Salesman Problem" (PDSTSP) introduced by Murray and Chu [5]. Other drone routing problems based on VRP include "Same-Day Delivery Routing Problems with Heterogeneous Fleets" (SDDPHF) by Ulmer and Thomas [36]. "Multi-Trip Drone Routing Problem" (MTDRP) by Cheng *et al.*, [37]. "Vehicle Routing Problem with Drones and Time Windows" (VRPDTW) by Pugliese and Guerriero [38] and "Vehicle Routing Problem with Drone Resupply" (VRPDR) by Dayarian *et al.* [39].

Considering problems in which drones are allowed to carry many packages and stop at multiple locations per launch, we found the following papers, including the "Two-Echelon cooperated Routing Problem for the Ground Vehicle (GV) and its carried unmanned aerial vehicle (UAV)" (2E-GU-RP) by Luo *et al.*, [40]. the "Hybrid Vehicle-Drone Routing Problem" (HVDRP) by Karak and Abdelghany [41], the "Vehicle Routing Problem with Drones" (VRPD) by Wang and Sheu [42], the "k-Multi-visit Drone Routing Problem" (k-MVDRP) by Poikonen and Golden [43], [44], and lastly the "Two Echelon Vehicle Routing Problem with Drones" (2EVRPD) by Kitjacharoenchai *et al.*, [45].

In the recent VRPD research, Zhu [46] investigated collaborative multi-truck–multi-drone delivery based on local takeoff and landing modes. Trucks were not involved in the problem of distribution by drones (DDP) and the carrier problem of drones (CVP-D). Salama and Srinivas [47] first relaxed the common assumption of restricting drone operations to customer locations by allowing the truck to stop at non-customer locations (referred to as flexible sites for drone) LRO.

2.2 *Mathematical formulation*

In general, the humanitarian supplies delivery problem focuses on making relief goods distribution operations such that supplies can be efficiently and quickly transported from distributing points to affected areas. The delivery problem is considered a critical operation in the Response phase as part of the Disaster Management Cycle diagram, as shown in Figure 3, which aims to save lives and minimize the immediate impacts of the disasters. Many studies have examined this problem by treating it as a vehicle routing problem with different objectives. Time is the most common objective in disaster relief, including the sum of travel times, the total delay cost, and the total response time.

The I-VRPD is a combinatorial optimization problem that can be formulated by Mixed Integer Programming (MIP). The problem can be defined on a directed graph G = (V,E) in which V represents a set of n destination nodes with one depot and E represents the set of arcs in the graph. The new integrated system provides flexibility and options for clients to receive items from any vehicle fleet in which each type of fleet has its advantage. For example, while a traditional truck delivers packages with large volumes or loads

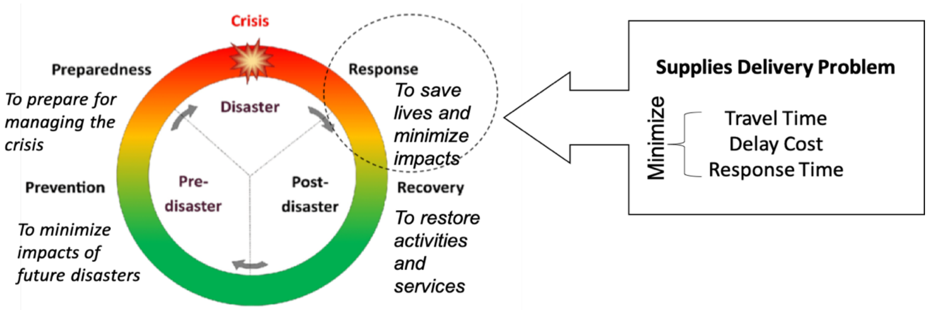


Figure 3: Supplies delivery problem as part of the response phase in the disaster management cycle diagram.

to natural disaster victims who might be located far from the depot, the hybrid truck with small drones can deliver items with small volumes or light loads to the victims who are located close to the depot. In addition, a large drone can carry multiple heavy items with more extended battery capacity than small drones, ideally an excellent fit for the disaster period, which requires faster delivery for large items. The benefits of this configuration could potentially reduce operational costs, improve overall delivery speed, and reduce the waiting times of the victims in the affected zones.

It is important to note that each vehicle fleet is operated independently, and all vehicle units are assumed to be homogenous. Each hybrid truck can only carry a limited amount of small drones. A small drone has a single unit capacity while a large drone has its certain capacity. Both hybrid truck and traditional truck have the same capacity and unlimited endurance. All small drones in the fleet have the same battery capacity and so do the large drones. The battery capacity will determine how long it can fly before receiving a service. We assume that small drones can only land at the destination locations (nodes) on the graph. This assumption applies to all other vehicle fleets as well. In addition, a small drone and a hybrid truck must wait for each other if one happens to arrive at the node first. Finally, whenever a small drone is launched from a hybrid truck, it must return to the same hybrid truck after finishing the delivery.

2.2.1 Notation

Three vehicle fleet types are defined as a set of $K = \{1, 2, 3,\ldots,k\}$, $VT = \{1,2,3,\ldots,vt\}$ and $VD = \{1,2,3,\ldots,vd\}$, which represent a hybrid truck fleet, a traditional truck fleet, and a large drone fleet accordingly. They must carry a load less than their capacities (Q for a hybrid truck, QVT for a traditional truck, and QVD for a large drone). Each fleet type consists of a certain number of homogeneous vehicle units. Each unit of a hybrid truck is attached with a set of small drones, $KD = \{1, 2, 3,\ldots,kd\}$, each can handle a load up to QD. The amount of load is measured by weight unit for all vehicles. In addition, the drone's travel capability is restricted by its battery limitation, defined as B for a small drone and BVD for a large drone. Let D_i be a demand for each destination node i from $1,2,3,\ldots,n$.

Let $\tau^T_{i,j}$ be a truck travel time between node i and node j and similarly let $\tau^D_{i,j}$ be a drone travel time between node i and node j. The I-VRPD is said to be symmetric if $\tau^T_{i,j} = \tau^T_{j,i}$ and $\tau^D_{i,j} = \tau^D_{j,i}$ and asymmetric otherwise. Based on the triangle inequality, the travel time for both truck and drone must satisfy $\tau^T_{i,k} + \tau^T_{k,j} \geq \tau^T_{i,j}$, $\tau^D_{i,k} + \tau^D_{k,j} \geq \tau^D_{i,j}$.

For readability purposes, we define the set of destination nodes $C = \{1,2,3,\ldots,n\}$ and a set $C_0 = \{0(s),1,2,3,\ldots,n\}$ as the set of destination nodes plus a starting depot, and set $C_+ = \{1,2,3,\ldots,0(r)\}$ as the set of destination nodes plus the returning depot. We define the following decision variables: Let $x^k_{i,j} = 1$ if a hybrid truck k travels from a node i to a node j and 0 otherwise. Similarly, let $xvt^{vt}_{i,j}$ and $xvd^{vd}_{i,j} = 1$ if a traditional truck vt and a large drone vd each from a node i to a node j and 0 otherwise. Let $y^{kd,k}_{i,j,p} = 1$ if a small drone kd of hybrid truck k travels from a node i to a node j and from a node j to a node p and 0 otherwise. Additionally, we use variables yt^k_i, yvt^{vt}_i, yvd^{vd}_i and $yd^{kd,k}_i$ to indicate whether a hybrid truck, a traditional truck, a large drone, and a small drone serve destination node i accordingly or not.

To track operational time, we denote the variable tt_j^k as the arrival time of the hybrid truck k and $dt_j^{kd,k}$ as the arrival time of the small drone kd of the hybrid truck k at node j. tt_j^k and $dt_j^{kd,k}$ are adjusted to be the same in any node j. The variables tvt_j^{vt} and tvt_j^{vd} represent the traditional truck vt and large drone arrival time at node $j \in C_+$ accordingly. Lastly, we define the variables u_i^k u_i^{vt}, u_i^{vd} for the VRP sub-tour elimination constraints and the variable $la_i^{kd,k}$ for the launching and landing status of a small drone.

The notations can be summarized as follows:

Set

$C = \{1,2,3,4,5,6,\ldots,n\}$ represents the set of all customers

$C_0 = \{0(s),1,2,3,4,5,\ldots,n\}$ represents the set of all customers including the depot

$C_+ = \{1,2,3,4,5,\ldots,n,0(r)\}$ represents the set of all customers including the depot

$N = C \cup C_0 \cup C_+$ represents all the nodes in the entire operation

$K = \{1,2,3,\ldots,k\}$ represents the set of all units of hybrid-trucks in the operation.

$KD = \{1,2,3,\ldots,kd\}$ represents the set of all units of small drones in each truck.

$VT = \{1,2,3,\ldots,vt\}$ represents the set of traditional trucks in the operation

$VD = \{1,2,3,\ldots,vd\}$ represents the set of large drones in the operation

Parameters

$\tau_{i,j}^T$ = Duration of time for a truck to travel from node i to node j

$\tau_{i,j}^D$ = Duration of time for a drone to travel from node i to node j

Q = Hybrid-trucks capacity (Same for all hybrid-trucks)

Qd = Small drone capacity (Same for all small drones)

Qvt = Traditional truck capacity (Same for all tradtional trucks)

Qvd = Large drone capacity (Same for all large drones)

B = Battery limit for small drones (Small drone' s battery life)

BVD = Battery limit for large drones (Large drone' s battery life)

Di = Customer demand at each node i

Main Variables

$x_{i,j}^k = \{0,1\}$ indicates whether a hybrid-truck k travels from node i to node j or not

$xvt_{i,j}^{vt} = \{0,1\}$ indicates whether a traditional truck vt travels from node i to node j or not

$xvd_{i,j}^{vd} = \{0,1\}$ indicates whether a large drone vd travels from node i to node j or not

$y_{i,j,p}^{kd,k} = \{0,1\}$ indicates whether a drone kd of truck k travels from node i to node j and return to node p or not

Tt_i^k = The time that a hybrid truck k arrives at node i

$Dt_i^{kd,k}$ = The time that a small drone kd of truck k arrives at node i

Tvt_i^{vt} = The time that a traditional truck vt arrives at node i

Tvd_i^{vd} = The time that a large drone vd arrives at node i

$u_i^k, u_i^{vt}, u_i^{vd}$ = Auxiliary variables for subtour elimination

$la_i^{kd,k} = \{0,1\}$ indicates the state of node i which can launch a drone (0 means launchable state, 1 means unlaunchable state)

Bc_i^{vd} = The amount of battery consumption at node i of a large drone vd

2.2.2 The key part of the model

The optimization is separated into three parts: 1) Decision variables, 2) Objective function, and 3) Sets of constraints. All variables used in this model are defined and described in Section 2.2.1 in detail. As for the objective function, we want to minimize the total delivery time of all vehicle fleets, so the objective function's components include the delivery time of the traditional truck fleet, the delivery time of the hybrid truck fleet, and the delivery time of the large drone fleet. As the total delivery time decreases, it will benefit natural disaster victims. They would be able to receive the supply kits such as food, water, and medicine at a faster speed which is part of the immediate actions to save lives and minimize impacts in the Response Phase of the Disaster Management Cycle diagram. Lastly, there are several sets of constraints that can be divided into different groups as follows:

- The set of constraints ensures that every customer is guaranteed to receive a package.
- Flow conservation and continuity for all

trucks/large drones.

- Flow conservation and continuity for small drones in Hybrid trucks.
- Capacity constraints to ensure that each vehicle must be able to carry items within its capacity.
- Battery consumption constraints to make sure that drones must operate within their battery limit.
- Time adjustment constraints to keep track of the delivery time of all vehicles.

2.2.3 Mathematical Formulation

We present the MIP formulation for I-VRPD as follows:

Objective

$$\text{minimize} \sum_{k \in K} tt_{0(r)}^{k} + \sum_{vt \in VT} tvt_{0(r)}^{vt} + \sum_{vd \in VD} tvd_{0(r)}^{vd} \quad (1)$$

The objective function (1) minimizes the total arrival time of all vehicle units across different fleets at the depot.

Subject to

$$\sum_{k \in K} \sum_{kd \in KD} yd_i^{kd,k} + \sum_{k \in K} yt_i^k + \sum_{vt \in VT} yvt_i^{vt} + \sum_{vd \in VD} yvd_i^{vd} = 1; \forall i \in C \quad (2)$$

Constraints (2) ensure that each destination is guaranteed to receive the package from one of the following vehicles: a hybrid truck, a small drone, a traditional truck, and a large drone exactly once.

$$\sum_{i \in C_+} x_{0(s),i}^{k} = 1; \ \forall k \in K \quad (3)$$

$$\sum_{i \in C_0} x_{i,0(r)}^{k} = 1; \ \forall k \in K \quad (4)$$

$$\sum_{j \in C_+} x_{i,j}^{k} = \sum_{j \in C_0} x_{j,i}^{k} = yt_i^k; \ \forall i \in C, \ \ \forall k \in K \quad (5)$$

Constraints (3)–(5) maintain the flow conservation of the hybrid truck at the depot, constraints (3) and (4), and each destination node *i* constraint (5) by enforcing that the hybrid truck *k* must leave the node whenever it enters the node.

$$\sum_{i \in C_+} xvt_{0(s),i}^{vt} = 1; \ \forall vt \in VT \quad (6)$$

$$\sum_{i \in C_0} xvt_{i,0(r)}^{vt} = 1; \ \forall vt \in VT \quad (7)$$

$$\sum_{j \in C_+} xvt_{i,j}^{vt} = \sum_{j \in C_0} xvt_{j,i}^{vt} = yvt_i^{vt}; \ \forall i \in C, \ \forall vt \in VT \quad (8)$$

$$\sum_{i \in C_+} xvd_{0(s),i}^{vd} = 1; \ \forall vd \in VD \quad (9)$$

$$\sum_{i \in C_0} xvd_{i,0(r)}^{vd} = 1; \ \forall vd \in VD \quad (10)$$

$$\sum_{j \in C_+} xvd_{i,j}^{vd} = \sum_{j \in C_0} xvd_{j,i}^{vd} = yvd_i^{vd}; \ \forall i \in C, \forall vd \in VD \quad (11)$$

Similarly, the sets of constraints (6) to (8) and (9) to (11) impose the same restriction for a traditional truck and a large drone which ensures the flow conservation and guarantees the departure and arrival to the depot.

$$\sum_{i \in C} \sum_{p \in C} y_{i,j,p}^{kd,k} = yd_j^{kd,k}; \forall j \in C, \forall k \in K, \forall kd \in KD \quad (12)$$

Constraints (12) ensure that whenever a small drone travels from node *i* to node *j* and from node *j* to node *p*, it will reach a destination at node *j*.

$$\sum_{kd \in KD} \sum_{k \in K} \sum_{j \in C} \sum_{p \in C} y_{i,j,p}^{kd,k} \le 1; \forall i \in C \quad (13)$$

$$\sum_{kd \in KD} \sum_{k \in K} \sum_{p \in C} \sum_{j \in C} y_{p,j,i}^{kd,k} \le 1; \forall i \in C \quad (14)$$

Constraints (13) and (14) enforce that, at most, one small drone must depart from and arrive at a hybrid truck at each stop.

$$2y_{i,j,p}^{kd,k} \le \sum_{\substack{h \in C_0 \\ h \neq i}} x_{h,i}^{k} + \sum_{\substack{l \in C \\ l \neq p}} x_{l,p}^{k}; \ \forall i,j,p \in C, \forall k \in K, \forall kd \in KD \quad (15)$$

Constraints (15) state that if a small drone departs from node *i*, delivers a package at node *j*, and lands at node *p*, then it is guaranteed that a hybrid truck would stop by at node *i* and node *p*.

$$\sum_{kd \in KD} \sum_{k \in K} \sum_{i \in C} \sum_{p \in C} y_{i,j,p}^{kd,k} \le 1 - \sum_{kd \in KD} \sum_{k \in K} \sum_{a \in C} \sum_{b \in C} y_{j,a,b}^{kd,k} \ ; \forall j \in C \quad (16)$$

$$\sum_{kd \in KD} \sum_{k \in K} \sum_{i \in C} \sum_{p \in C} y_{i,j,p}^{kd,k} \le 1 - \sum_{kd \in KD} \sum_{k \in K} \sum_{a \in C} \sum_{b \in C} y_{a,b,j}^{kd,k} \ ; \forall j \in C \quad (17)$$

Constraints (16) and (17) ensure that no flow enters or leaves node j when a small drone makes a delivery at node j accordingly.

The sets of constraints (18) to (25) consider the correctness of a small drone's launching and landing operation. They track whether a particular drone has already been launched and ensure that it can never be relaunched before returning to the truck.

$$la_i^{kd,k}\left(\sum_{j\in C}\sum_{p\in C}y_{p,j,i}^{kd,k}\right)=0;\ \forall i\in N,\ \forall k\in K,\ \forall kd\in KD \tag{18}$$

$$la_i^{kd,k}\left(\sum_{j\in C}\sum_{p\in C}y_{i,j,p}^{kd,k}\right)=0;\ \forall i\in N,\ \forall k\in K,\ \forall kd\in KD \tag{19}$$

Constraints (18) and (19) enforce that when $la_i^{kd,k}=1$, a small drone can not enter or leave node i and vice versa.

$$la_j^{kd,k}\geq 1-M\left(2-x_{i,j}^k-\sum_{q\in C}\sum_{p\in C}y_{i,q,p}^{kd,k}+la_i^{kd,k}+\sum_{a\in C}\sum_{b\in C}y_{a,b,j}^{kd,k}\right);\ \forall i,\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{20}$$

$$la_j^{kd,k}\leq 1+M\left(2-x_{i,j}^k-\sum_{q\in C}\sum_{p\in C}y_{i,q,p}^{kd,k}+la_i^{kd,k}+\sum_{a\in C}\sum_{b\in C}y_{a,b,j}^{kd,k}\right);\ \forall i,\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{21}$$

Constraints (20) and (21) state that as a truck travels from node i to node j, if a small drone is launched from node i and has not returned to node j then $la_j^{kd,k}$ must equal 1.

$$la_j^{kd,k}\geq 1-M\left(2-x_{i,j}^k-la_i^{kd,k}+\sum_{a\in C}\sum_{b\in C}y_{a,b,j}^{kd,k}\right);\ \forall i,\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{22}$$

$$la_j^{kd,k}\leq 1+M\left(2-x_{i,j}^k-la_i^{kd,k}+\sum_{a\in C}\sum_{b\in C}y_{a,b,j}^{kd,k}\right);\ \forall i,\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{23}$$

Similarly, constraints (22) and (23) state the situation where a small drone was previously launched ($la_i^{kd,k}=1$) and has not arrived at node j where the hybrid truck is scheduled to visit. If this is the case, then $la_j^{kd,k}$ must equal to 1.

$$la_j^{kd,k}\geq -M\left(2-x_{i,j}^k-\sum_{a\in C}\sum_{b\in C}y_{a,b,j}^{kd,k}\right);\ \forall i,\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{24}$$

$$la_j^{kd,k}\leq +M\left(2-x_{i,j}^k-\sum_{a\in C}\sum_{b\in C}y_{a,b,j}^{kd,k}\right);\ \forall i,\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{25}$$

Constraints (24) to (25) state that if a small drone returns to node j where a hybrid truck k is scheduled to visit, then $la_j^{kd,k}$ must equal 0.

$$D_j\leq Qd+M\left(1-\sum_{i\in C}\sum_{p\in C}y_{i,j,p}^{kd,k}\right);\ \forall j\in C,\ \forall k\in K,\ \forall kd\in KD \tag{26}$$

Constraints (26) ensure that a small drone must always carry a load less than its capacity (QD).

$$\sum_{i\in C}D_i(yt_i^k)+\sum_{i\in C}\sum_{kd\in KD}D_i(yd_i^{kd,k})\leq Q;\ \forall k\in K \tag{27}$$

Constraints (27) restrict that a hybrid truck must always carry the combined loads of both hybrid truck and small drone less than its capacity at any given time.

$$\sum_{i\in C}D_i(yvt_i^{vt})\leq QVT;\ \forall vt\in VT \tag{28}$$

$$\sum_{i\in C}D_i(yvd_i^{vd})\leq QVD;\ \forall vd\in VD \tag{29}$$

Constraints (28) and (29) address a similar condition as in (27) by ensuring that each traditional truck vt must carry the load less and its capacity, and so does the large drone.

The sets of constraints (30)–(32) deal with the battery consumption of drones.

$$\tau_{i,j}^D+\tau_{j,p}^D\leq B+M\left(1-\sum_{i\in C}\sum_{p\in C}y_{i,j,p}^{kd,k}\right);\ \forall j\in C,\ \forall k\in K,\ \forall kd\in K \tag{30}$$

Constraints (30) address that when a small drone departs from node i, visit node j and return to node p, it must have enough battery to cover the entire flight which must be less its battery capacity B.

$$bc_j^{vd} \geq bc_i^{vd} + \tau_{i,j}^{D} - M\left(1 - xvd_{i,j}^{vd}\right);$$
$$\forall i \in C_0,\ \forall j \in C_+,\ \forall vd \in VD \quad (31)$$

$$bc_i^{vd} \leq BVD \quad (32)$$

Similarly, constraints (31) and (32) ensure that the large drone must have enough battery at any point by limiting the battery consumption to less than the battery capacity.

$$\sum_{j \in C} y_{i,j}^{kd,k}(tt_i^k - dt_i^{kd,k}) = 0; \forall i \in C_0, \forall k \in K, \forall kd \in KD \quad (33)$$

$$\sum_{j \in C} y_{j,i}^{kd,k}(tt_i^k - dt_i^{kd,k}) = 0; \forall i \in C, \forall k \in K, \forall kd \in KD \quad (34)$$

At node i, where both vehicles merge, constraints (33) enforce the departure time of both small drone and hybrid truck to be the same, while constraints (34) enforce the arrival time to be the same for both vehicles.

$$tt_j^k \geq tt_i^k + \tau_{i,j}^{T} - M(1 - x_{i,j}^k); \forall i \in C_0, \forall j \in C_+, \forall k \in K \quad (35)$$

$$tvt_j^{vt} \geq tvt_i^{vt} + \tau_{i,j}^{T} - M(1 - xvt_{i,j}^{vt});$$
$$\forall i \in C_0,\ \forall j \in C_+,\ \forall vt \in VT \quad (36)$$

$$dt_p^{kd,k} \geq dt_i^{kd,k} + \tau_{i,j}^{D} + \tau_{j,p}^{D} - M(1 - y_{i,j,p}^{kd,k});$$
$$\forall i,\ \forall j,\ \forall p \in C,\ \forall k \in K,\ \forall kd \in KD \quad (37)$$

$$tvd_j^{vd} \geq tvd_i^{vd} + \tau_{i,j}^{D} - M(1 - xvd_{i,j}^{vd});$$
$$\forall i \in C_0,\ \forall j \in C_+,\ \forall vd \in VD \quad (38)$$

Constraints (35)–(38) update the arrival time of the hybrid truck, traditional truck, small drone, and large drone accordingly whenever the vehicles travel from one node to another node.

$$u_i^k - u_j^k + Q(x_{i,j}^k) \leq D_j; \forall i,\ \forall j \in C \cup C_0 \cup C_+,\ \forall k \in K \quad (39)$$

$$D_i \leq u_i^k \leq Q; \forall i, \forall j \in C \cup C_0 \cup C_+,\ \forall k \in K \quad (40)$$

$$u_i^{vt} - u_j^{vt} + Qvt(xvt_{i,j}^{vt}) \leq Qvt - D_j;$$
$$\forall i \in N,\ \forall j \in N,\ \forall vt \in VT \quad (41)$$

$$D_i \leq u_i^{vt} \leq Qvt; \forall i \in N,\ \forall j \in N,\ \forall vt \in V \quad (42)$$

$$u_i^{vd} - u_j^{vd} + Qvd(xvd_{i,j}^{vd}) \leq Qvd - D_j;$$
$$\forall i \in N,\ \forall j \in N,\ \forall vd \in VD \quad (43)$$

$$D_i \leq u_i^{vd} \leq Qvd\ ; \forall i \in N,\ \forall j \in N,\ \forall vd \in VD \quad (44)$$

Pairs of constraints (39)–(44) ensure that there is no sub-tour in all tours of the hybrid truck fleet, traditional truck fleet, and large drone fleet accordingly [48].

$$x_{i,j}^k,\ y_{i,j,p}^{kd,k},\ xvt_{i,j}^{vt},\ xvd_{i,j}^{vd},\ yt_i^k,\ yd_i^{kd,k},\ yvt_i^{vt},\ yvd_i^{vd},$$
$$la_i^{kd,k} \in \{0,1\},$$
$$tt_j^k,\ dt_j^{kd,k},\ bc_i^{vd},\ tvt_j^{vt},\ tvd_j^{vd} \geq 0,\ \forall i,\ \forall j,\ \forall p \in C,$$
$$\forall k \in K,\ \forall kd \in KD,\ \forall vt \in VT,\ \forall vd \in VD \quad (45)$$

Lastly, we specify the types and ranges of the variables in constraints (45). The M value must be large enough, and we can use the delivery time of the traditional trucks by solving the CVRP.

Since the I-VRPD is considered a generalization of the classical VRP, which is proven to be an NP-hard problem, the I-VRPD is, by nature, an NP-hard problem. Therefore, to test the proposed model's performance as part of the strategic operation in disaster response, we have designed a different set of experiments to verify the model and correspondingly compare its solution with different routing models from the previous studies.

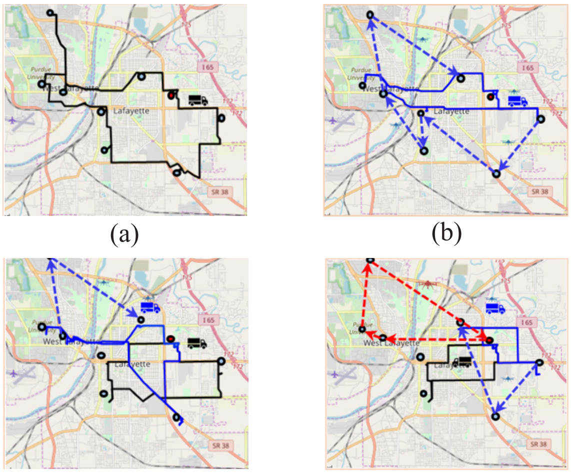
3 Results and Discussion

In this section, we ran different experiments to find out the solution of the I-VRPD on various sets of instances. Beginning with a case study conducted in Lafayette Indiana, we want to get the visualization of the solution routes when integrating different fleet types of vehicles. This experiment would give us a much clearer picture of how this work can benefit the last-mile delivery service in a real-world setting. In the second and third experiments, we solved the small-size benchmark problems with the MIP formation from Section 2 and observe the delivery time among different sets of vehicle fleets. We additionally compare the results of the I-VRPD with other results of the relevant routing models from the literature. These experiments demonstrate the potential gain from implementing combined fleets vs. a single fleet type. For all experiments, we assume $\tau_{j,i}^{T} = 1.5\ \tau_{i,j}^{D}$ based on Brar *et al.*, [49]. Other assumptions still hold valid from Sections 1–2. All experiments were conducted, and the MIP formulation was solved by CPLEX on GAMS 23.51.

3.1 *A case study*

In this section, we conduct a case study using the real world scenario to investigate the usefulness of the I-VRPD model in the practical aspect and compare different solution routes under various settings. First, we randomly select eight destination nodes and one depot node in Lafayette/West Lafayette area. For this particular experiment, all trucks are assumed to travel in the road network while the drones travel in the air space in Euclidean space. Other assumptions are still the same as we indicated earlier in the paper. Finally, we ran the MIP from Section 2 in the solver and generated different solution routes, as shown in Figure 4.

Figure 4(a) represents the solution route using a traditional truck alone, which is the typical way of delivery, and Figure 4(b) represents the solution route using a hybrid truck with one small drone. The gain from using a drone in the model accounts for a 33% improvement in delivery time. If one traditional truck is added to the operation, as shown in Figure 4(c), it will reduce the delivery time by 21.8%. Lastly, combining a large drone, a hybrid truck, and a traditional truck in operation [Figure 4(d)] shows a significant reduction in delivery time by 67% from the traditional truck alone. The case study demonstrates the potential benefit of integrating different types of vehicles in last-mile delivery and illustrates the feasible solution route from the real-world scenario.



(a) (b) (c) (d)

Figure 4: Result of the case study. (a) Single Traditional truck (Delivery time: 2046 S.). (b) Single Hybrid truck (Delivery time: 1369 S.). (c) One Hybrid truck & One Traditional truck (Delivery time: 1070 S.). (d) One Hybrid truck, One Traditional truck & One Large (Delivery time: 671 S.).

3.2 *Experiment with VRP benchmark*

In this experiment, we tested our proposed I-VRPD model with the modified CVRP benchmark instances [50], [51]. We used samples of the classical A, B, and P CVRP sets. The complete sets have 27, 23, and 23 instances, accordingly, ranging from 31 to 100 customers. The problem sizes and demand distributions are similar, but the customers in sets A, and P are uniformly distributed and in B clustered. For each instance, we ran the model by adjusting the type and the number of vehicles starting from a traditional truck to a whole combination of a hybrid truck, a traditional truck, and a large drone. For simplicity, we assume that all vehicles travel in Euclidean space. All experiment runs use the same set of settings and assumptions, as stated in Section 2. Finally, we set the objective as the makespan of delivery time and showed the results of the experiment in Figures 5 and 6.

The results suggest combining different vehicle types can significantly reduce the total delivery time in all tested instances. It can be seen from the chart that using the regular truck or traditional truck returns the longest delivery time among different types of vehicle operations. On the contrary, combining all types of vehicles to make delivery returns the shortest delivery time suitably works best when time is the most critical factor, like during the disaster relief period. Looking at the line graph in Figure 6, we can see that the slope is steep at the beginning and begins to stay flat as more resources are added to the operation. This finding shows that adding a hybrid truck equipped with a drone can make a substantial impact while adding a large drone might be less effective in this small-size problem. One explanation is that only a few customers are located on the map and can be served simply with one or two vehicles. Thus, adding a large vehicle may not improve solution performance significantly.

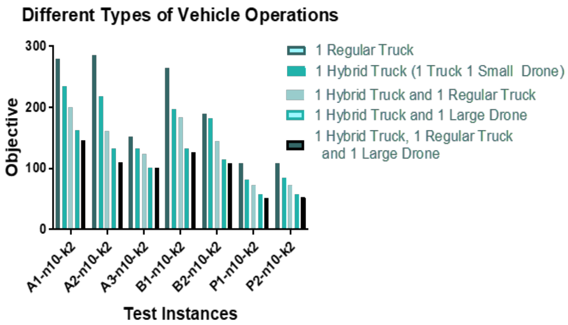


Figure 5: Result of testing the model with the benchmark using different combinations of vehicles.

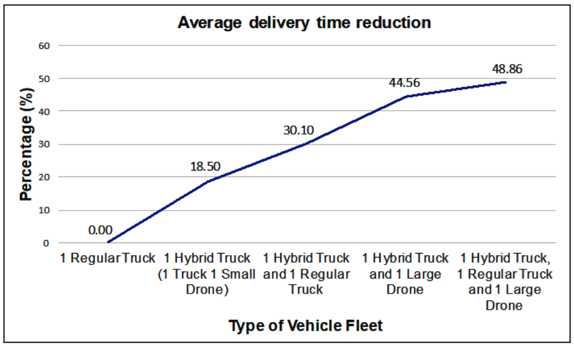


Figure 6: Average delivery time reduction among various settings.

3.3 *Comparison of I-VRPD MIP and other MIP routing models*

This section compares the solution between the proposed I-VRPD and other routing models, including VRPD, which utilizes small drones in a hybrid truck, and CVRP on different small-size benchmark instances. We obtained the exact solutions for both I-VRPD and CVRP using the CPLEX. This experiment aims to evaluate the cost (time) saving when combining different fleets of vehicles to make delivery. We also want to get an estimation of how long the solver would take to return an optimal solution for I-VRPD. For each instance, we set the number of destination nodes to eight and the maximum number of vehicles to two. The CVRP model consists of only traditional trucks, while the VRPD model consists of the only hybrid truck in which each unit is equipped with one small drone [52]. Exactly one hybrid truck with a small drone and one large drone is used in the I-VRPD. The results are shown in Table 1.

When comparing I-VRPD to VRPD in column “I-VRPD v.s. VRPD,” the results show an improvement in objective value approximately by 12.98% (9.76% (min) to 18.95% (max)) depending on the instance. The objective improvement is much more significant when compared to CVRP in the column “I-VRPD v.s. CVRP,” with an average improvement of 23.76% (20.24% (min) to 28.52% (max)). The results from this experiment demonstrate the gain from implementing the new routing model when using all heterogeneous fleet vehicles in the setting. In addition, the MIP takes significant time to generate the optimal solutions even for the small-size problem (451.26 seconds for I-VRPD, 1859.41 for VRPD, and 68.33 for CVRP). Numerical analysis shows that substantial savings in delivery completion time (13% on average in v.s. VRPD case and 25% on average instances in v.s. CVRP case) can be achieved by using a large drone together with a hybrid truck-drone vehicle for all

Table 1: Comparison of the results between MIP IVRP-D, VRPD, and MIP CVRP on a small-size instance

Instance	MIP CPLEX						Improvement (%)	
	I-VRPD		VRPD		CVRP		I-VRPD v.s. VRPD	I-VRPD v.s. CVRP
	Objective	Runtime (Second)	Objective	Runtime (Second)	Objective	Runtime (Second)		
A1-n8-k2	253	623.13	300	2196.09	338	88.72	15.67	25.15
A2-n8-k2	218	455.85	248	2788.66	305	75.30	12.10	28.52
A3-n8-k2	159	382.53	185	1471.09	204	95.86	14.05	22.06
B1-n8-k2	259	653.64	287	2231.58	340	76.11	9.76	23.82
B2-n8-k2	201	609.42	248	1964.14	252	64.66	18.95	20.24
P1-n8-k2	108	256.87	120	1038.87	140	40.86	10.00	22.86
P2-n8-k2	113	177.37	126	1325.49	148	36.83	10.32	23.65
Average		451.26		1859.42		68.33	**12.98**	**23.76**

instances. Our findings also led to several practical insights into using combinations of different types of delivery vehicles.

Based on the experiments, the small-size instances can be optimally solved by the MIP formulation run on CPLEX shown in Section 3.1. Then, we present different routing scenarios in the case study to visually demonstrate the implementation of the I-VRPD in the real-world aspect. Section 3.2 tests our proposed MIP model with some well-known VRP benchmark instances and compares the delivery time using different vehicle type combinations. The result shows that the scenario combining three different delivery vehicles returns the shortest delivery time. Lastly, we compare the I-VRPD and other routing models using the same amount of resources in Section 3.3, which shows significant savings in delivery time.

4 Conclusions

In this study, we present a new routing model, the Integrated Vehicle Routing Problems with Drones (I-VRPD), combining three routing operations: Traditional truck routing, Hybrid truck routing, and Large drone routing for humanitarian relief delivery. The I-VRPD is considered an extension of the traditional VRP with heterogeneous trucks and drones in which the hybrid truck is equipped with small drones. The study results have shown the benefit of integrating different vehicle fleet types as the delivery time can be reduced significantly, which is quite an essential part of the response phase in disaster management. The limitations of this work include 1) the restriction of a drone with just a payload limit of one parcel per sortie and 2) the longer computational time of the proposed model as the number of destination nodes as well as the number of delivery vehicles increase. The latter problem can be resolved by developing an efficient heuristic polynomial time algorithm. For future work, we can consider different fleets of vehicles or various modes of operation, including electric bikes, scooters, and droids. We can also reformulate the MIP formulation to strengthen the computational performance of the mathematical models using valid inequalities. From an algorithmic perspective, designing other metaheuristic algorithms could effectively solve the I-VRPD problem with a better objective value and lower computational time.

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Author Contributions

P.S.: Conceptualization, Resources, Supervision. P.K.: Investigation, Methodology, Writing an original draft, Writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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