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# A Hybrid Truck-Drone Routing Problem Considering Deprivation Cost in the Post-Disaster Situation

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***Abstract*** *– Natural disasters and their destructive effects on life and property are the most important issues these days. Implementation time of the relief operation and limitations associated with the ground infrastructure in disaster situations is the main priority of humanitarian logistics. So the necessity of using Unmanned Aerial Vehicles (UAVs) to reduce the service time is evident. On the Other hand, considering the deprivation cost function as an appropriate objective function can improve existing problems in disaster situations. This paper proposes a hybrid vehicle-drone routing model in the post-disaster phase. Multi trucks and multi drones with complementary capabilities are applied. Trucks are restricted to travel to the nodes with undamaged road networks, known as LD nodes. Drones can fly from the trucks to the nodes with damaged roads, known as DN nodes. They are used multiple times from each truck at LD nodes. The objective is to minimize the deprivation cost as a function of the deprivation time of both types of nodes. So by minimizing the deprivation cost, the vehicles' arrival times are minimized, and better routes are selected for vehicles. The effect of the population rate of the affected area on the route determination also is considered by the deprivation cost function. Finally, the validation of the proposed model is tested by solving it in GAMS software. Some examples are solved to show how applying the deprivation cost can improve the selecting routes by this model.*

***Keywords****– Deprivation Cost, Disaster Response, Humanitarian Logistics, Hybrid Truck–Drone Routing Problem, Unmanned Aerial Vehicles (UAVs).*

## I. INTRODUCTION

The devastating consequences of natural disasters such as casualties, destruction of infrastructure, and destruction of natural and vital resources in communities not only are unavoidable but also need more attention from managers and researchers. Some catastrophic events such as earthquakes and storms that humans are not involved in, and the time of their occurrence is unpredictable. After a disaster, the rapid and effective distribution of goods and relief forces to the affected areas is a top priority. In this situation, the existence of humanitarian aid is very effective (Dascioglu et al., 2019).

Disaster management is a dynamic, sustainable, and integrated process to improve the effectiveness and efficiency of activities related to all four stages in the disaster management cycle, including prevention and mitigation, preparedness, response, and recovery. The first two are implemented before a disaster, known as pre-disaster activities, to reduce the potentially destructive impact of an event. Quickly after a disaster, responders start the response phase,

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and after that recovery phase starts, which is known as post-disaster activities. After happening a disaster, the transportation of humanitarian goods must be adequately managed so that the goods arrive in the affected areas at the appropriate time and according to the type of required demand (Al Theeb & Murray, 2017). After a disaster, there is much demand for relief and pharmaceutical goods. Rapid distribution of these goods to affected areas acts as a critical role in the effectiveness of disaster management. It has an essential role in improving critical conditions and serving people in the region.

The humanitarian supply chain is another form of the supply chain. It is responsible for supplying, producing, and delivering goods to customers. Its primary purpose is to serve people in the affected areas in the shortest possible time. The required time to carry out relief operations and save people's lives is a critical priority of the humanitarian supply chain. Therefore, supplying the basic needs of people in affected areas is one of the main goals of the humanitarian supply chain. Its effort is to minimize the number of humans suffering in critical situations. Considering the psychological effect of humans suffering from shortage or lack of access to relief goods and services, in recent years, has been identified as the deprivation cost as one of the main goals of the humanitarian supply chain and other logistics costs (Holguín-Veras et al., 2013).

Holguin Veras et al. (2013) proposed deprivation cost as an appropriate objective function for humanitarian logistics and calculated using a direct criterion for quantifying suffering. According to their definition, the economic value of human suffering due to shortage or lack of access to relief goods or services is introduced as deprivation cost in humanitarian logistics. Deprivation cost is a widely recognized problem in the Humanitarian Logistics Organization that is considered an effective and efficient concept for solving the inappropriate objective functions for humanitarian logistics.

On the other hand, to deal with complex problems in disaster situations, there is a need for extensive and precise coordination of different vehicles to transport goods, victims, and volunteers through the communication network. After a disaster, an efficient distribution system of goods through the land communication network is essential. It cannot alone cover the various dimensions of the destructive effects of such catastrophic events. Therefore, aerial vehicles, especially UAVs (i.e., drones), also should be used.

Recently, applying Unmanned Aerial Vehicles (UAVs) or drones has been overgrown. Drones' various applications are, 1. inspection of disaster areas in a shorter time, 2. the ability to supply the demands without needing ground infrastructure, 3. remote control sensors, 4. search and inspection operations as well as delivering goods (Otto et al., 2018).

Amazon, a big commercial company, introduced a new intention of meeting customers by offering drone delivery services. According to the company's announcement, the proposed drones could meet customers within 30 minutes through its PrimeAir transportation scheduling (Meola, 2017). After their statement, many technology organizations such as Google, Alibaba, and JD have experimented the delivery services with drones. Flirtey, a drone delivery company, accomplished the drone delivery with a package for the first time. The package includes bottled water, emergency food, and other essential boxes to people in the affected region where regular communications were impossible (Hern, 2014). Drones have also been applied to deliver foods such as pizza by Flirtey, Chipotle, and Google (Volkman, 2018).

Drones are used as a suitable vehicle for delivery operations. Due to various reasons, including superior speed and the ability to meet demand nodes regardless of road infrastructure. They also apply electric batteries that produce less air pollution. Drones' main weaknesses are their limited payload capacity and short battery durability. It can be counteracted by matching drones with trucks that have a considerable capacity and long durability range to improve delivery operations.

The Academic Routing community has announced that consolidating drones with more oversized vehicles (trucks) leads to increases in the performance of delivery operations. The first hybrid truck-drone model was introduced by Murray and Chu (2015) as the Flying Sidekick Traveling Salesman Problem (FSTSP), derived from the Vehicle Routing Problem (VRP) with coordination limitations (Drexl, 2012). In their model, a drone is placed overhead the delivery truck. It can move simultaneously along with the truck. The drone starts flying from the delivery truck to deliver the goods, and the delivery truck keeps traveling to serve its customers in another location. When the drone accomplishes its services, it must return to the delivery truck at its current nodes or continue its flight to another demand node.

The Multiple Traveling Salesman Problem with Drones (mTSPD) is a development of the Multiple Traveling Salesman (mTSP) problem in which the delivery of goods is achieved using drones. The mTSP model is developed from the FSTSP model introduced by Murray and Chu (2015), plus several further limitations from the mTSP model. In the mTSP model, the *m* salesman must visit *n* locations, which results in forming *m* tours (paths) for each salesman in the problem. The mTSP model has two main constraints. The first constraint states that each salesman must start its trip from the starting node (depot) and return to the same node (starting node or depot), regardless of which tour is selected for the salesman. The second constraint requires each salesman to visit a particular set of demand nodes traveling between the starting node (depot) and the last one. Each demand node must be visited once by truck or drone, except the starting node (depot) (Bektas, 2006).

The general goal of mTSP models is to gain the total shortest route so that the salesman travels from the depot to meet the specified set of customers and eventually returns to the depot. The main objective of the mTSPD model is to reduce the delivery time. The objective of mTSPD problems is more diverse than mTSP problems, which tries to reduce the maximum time of each tour (Kivelevitch et al., 2013, Bertazzi et al., 2015). By solving the mTSPD problem, strictly *m* tours are required, equal to the number of salesmen.

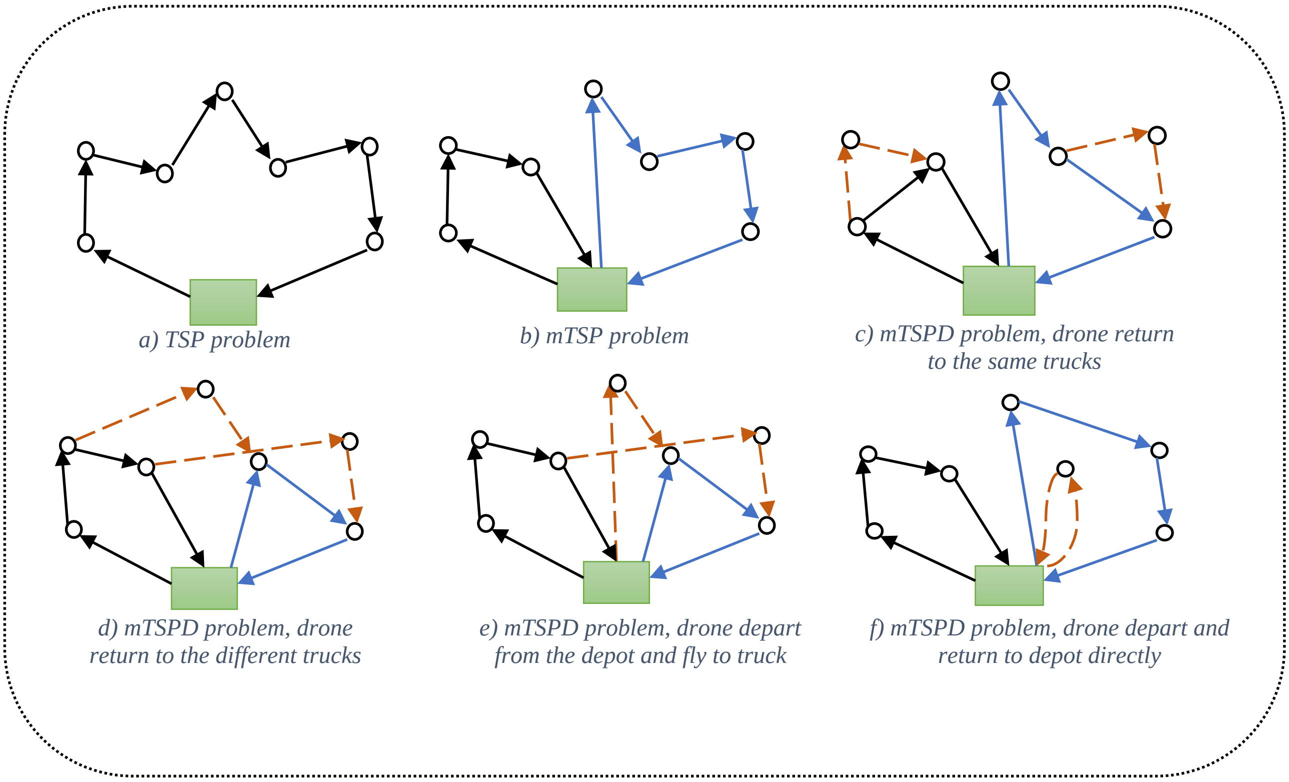


**Fig. 1. Schematic representation of feasible solutions for TSP, mTSP, and mTSPD problems**

Hybrid drone-truck routing problems, as a developed variant of the TSP models, each truck acts as a salesman. Because the capacity of the trucks and the amount of customers' demand is neglected. Each truck is assumed to have an unlimited capacity for carrying packages and drones throughout the total operation. The departure time of all trucks in the depot is zero. All trucks must start their travel from the depot and go back to it after visiting all their assigned customers. In this case, each customer must be visited only once and by one vehicle.

The mTSPD model, which has a real operation like the hybrid drone-truck model, was implemented by UPS in February 2017. A drone started its trip from one of the UPS delivery trucks automatically and flew back to the trucks after delivering a package to the customer. This delivery operation by drone happens simultaneously when the truck continues to drive along a route to complete the delivery operation (Hughes, 2017). Fig. 1 shows an illustration of the feasible solutions from TSP, TSPD, mTSP, and mTSPD. The solid lines in all sub Fig.1 (a)-(f) show the truck routes, and the dot lines show the drone routes.

If customer demand and truck capacity is considered in a hybrid drone-truck routing problem, it will transform from the Traveling Salesman Problem with Drone to the Vehicle Routing Problem with Drone (VRPD). Hybrid drone-truck routing problem as a VRPD problem, the trucks have a specific capacity for delivering packages, which their routes are determined according to these capacities.

In recent years, special consideration has been given to the utilization of drones in commercial logistics, whereas, in humanitarian logistics, they are less noticeable. Therefore, adopting the hybrid truck-drone routing models with disaster situations is one of the most challenging issues for researchers. Delivery operations coordinated differently between vehicles followed by the specific circumstances of the crisis. In humanitarian logistics, the kind of service is not merely commercial costs. The psychological effects caused by the disaster also must be considered, which in most cases are ignored. On the other hand, applying the appropriate objective function for the models in humanitarian logistics is another challenging issue in this field. Therefore, the importance of using concepts such as the deprivation cost is essential in this area.

The necessity of using the hybrid model of the vehicle-drone problems synchronized with the real-world situations and reducing the execution time with the appropriate objective function is an incentive to present this paper. In this research, we presented a different mathematical formulation. A hybrid vehicle-drone routing problem is proposed in the post-disaster phase. Multi trucks and multi drones with complementary capabilities are applied. The coordination between the vehicles and the drones depends on the status of the communication road. Trucks can travel to the nodes with undamaged road networks, known as Local Depot (LD) nodes. Drones can fly from the trucks to the nodes with damaged roads, known as Damaged Nodes (DN), and can be used multiple times from each truck at LD nodes. The main contribution of this study is using an appropriate objective function known as deprivation cost for humanitarian logistics. The objective is to minimize the deprivation cost as a function of the deprivation time of both types of nodes. By minimizing The deprivation time, the arrival time of both vehicles is reduced.

In the remainder of this paper, Section 2 reviews the literature on the hybrid drone-truck routing problems and discusses the concept of deprivation cost in humanitarian logistics. Section 3 deals with the problem definition and details about the proposed model. In section 4, the validation of the current model is tested by solving the problem in GAMS software, and some examples are solved. Also, sensitivity analysis is done for some parameters. In section 5. conclusions and some future research are presented.

# I. LETERATURE REVIEW

## *A. Hybrid vehicle routing problem*

Vehicle Routing Problem is one of the most critical and practical issues in humanitarian logistics that are used combined with unmanned aerial vehicles such as drones. Such practical applications that have been used to improve the disaster conditions can be referred to as transporting relief goods and services in post-disaster situations. There are two general models for classical routing problems: 1) The Vehicle Routing Problem (VRP) with multiple trucks, and 2) The Traveling Salesman Problem (TSP) with only one truck. The use of drones in each section has its position and literature, which we will introduce in the following sections.

### *Drone-Truck routing as* **the development** *of TSP models*

In recent years, coordinated delivery operations between trucks and drones have attracted the attention of many researchers in logistics, especially humanitarian logistics. Murray and Chu (2015) proposed such a coordination system by presenting the FSTSP model. They solved the problem with a simple heuristic approach and coordinated the delivery operations between a truck and a drone. Murray and Chu (2015) presented another model introduced as the Parallel Drone Scheduling Traveling Salesman Problem (PDSTSP) in another study. In their model, trucks, and drones are operated separately to meet all demand nodes. Ferrandez et al. (2016) developed Murray and Chu(2015)'s FSTSP by considering several drones and examined the effectiveness of the hybrid drone-truck delivery model. They used the k-means clustering algorithm alongside the GA algorithm to find optimal locations for drones to fly and land. Ponza (2015) presented a detailed FSTSP and employed the Simulated Annealing approaches to find better answers. By modifying the FSTSP, Jeong et al. (2019) examined the effect of drone payload on the drone power using and limited flying ranges. Sacramento et al. (2019) proposed an FSTSP model intending to reduce the operational cost. They solved their model with a meta-heuristic algorithm, ALNS.

Agatz et al. (2018) studied a problem like Murray and Chu (2015)'s model and introduced it as the Traveling Salesman Problem with a Drone (TSP-D). They solved their new MIP model with competent heuristic methods using Local Search and Dynamic Planning.

Ha, et al. (2018) presented the min-cost TSP-D problem to reduce the total transportation costs applying two approaches: TSP-LS using Local Search and Greedy Randomized Adaptive Search Procedure (GRASP). Yurek and Ozmultu (2018) developed an iterative optimization algorithm for the TSP-D problem by decomposing the problem into two sections: the first part is finding a route for the truck, and the second part is finding optimal drone routes along the truck route.

Bouman et al. (2018) solved their "TSP-D" model with an exact solution using Dynamic Programming. Marinelli et al. (2018) developed the TSP-D so that any drone is allowed to launch and back to a truck route at any location. Matthew et al. (2015) introduced a new model of hybrid truck-drone problems introduced as the Heterogeneous Delivery Problem (HDP), with similar features to the TSP-D and FSTSP. Kim and Moon (2019) proposed the TSP with a Drone Station (TSP-DS) which shares alike attribute to the "PDSTSP" problem, except that is considered a drone station for storing and charging drones. Tu et al. (2018) presented the new problem by developing the TSP-D, introduced as the TSP-mD. In their model, a truck can travel with several drones that,

Kitjacharoen et al. (2019) proposed an mTSPD problem with similar features to the FSTSP model. Multiple trucks and drones are used in which, contrary to the previous assumption that each drone must return only to the same truck, it can return to the nearest available truck.

Murray and Raj (2019) introduced the Multiple Flying Sidekick Traveling Salesman Problem (mFDTSP), as the development of their previous study of FSTSP which the desired number of different drones is considered in their model, which starts drones' flight either from trucks or from stations. The authors provided a Mixed Integer Linear

Programming (MILP) formulation and used a three-part heuristic algorithm to solve the problem. de Freitas & Penna (2020) developed a Flying Sidekick Traveling Salesman Problem (FSTSP) with a truck and a drone that meet all customers together. Additionally, they used several new limitations related to the drone, such as endurance and payload capacity. They solved the problem with a hybrid heuristic. The initial solution is generated from the optimal TSP solution obtained from a Mixed-Integer Programming (MIP) solver. Then, the General Variable Neighborhood Search generates the delivery routes of trucks and drones. Gonz´alez-R et al. (2020) developed an FSTSP that the truck must wait for the drone at a specific location. Also, the drone can meet several customers on its tour. However, they announced that a truck sometimes could not wait for a drone at the same location where it was launched. Dell'Amico et al. (2020) considered a TSP-D problem and used metaheuristic methods for solving the problem. AlMuhaideb et al. (2021) introduced a different type of Traveling Salesman Problem in hybrid delivery systems called the TSP-D. Their hybrid delivery problems include a truck and a drone. The truck and the drone cooperate to deliver packages to customers. The objective is to reduce the total delivery time. They applied metaheuristics to solve the problem. Roberti and Ruthmair (2021) developed a new Traveling Salesman Problem with the Drone (TSP-D). A truck and a drone cooperated to meet a set of customers. They solved the problem with an exact solution approach.

***Drone-Truck routing* the development *of VRP models***

Wang et al. (2016) applied the worst-case analysis for the Vehicle Routing Problem with Drones (VRP-D) problem and examined the effect of two parameters - the number of drones in each truck and the drones' speed on the maximum savings from using drones. Poikonen et al. (2017) developed the VRP-D problem. They tried to get upper bounds for the saved time that is gained from using drones. They also modeled the problem using multiple factors such as drones' battery charge, cost criteria, and fixed cost of using drones. Schermer et al. (2018) proposed a Mixed-Integer Linear Program for the VRP-D problem. They solved the problem using the famous Variable Neighborhood Search (VNS) algorithm. Pugliese and Guerriero (2017) presented the Vehicle Routing Problem with Drone and Time Windows (VRPDTW) that applies time window limitations.

Campbell et al. (2017) used the Continuous Approximation method to find the optimal number of trucks and drones for delivery operations per route, the optimal number of drones per truck, and the optimal total cost of operations in the hybrid truck-drone delivery problem. Similarly, Carlsson and Song (2017) accomplished a CA method to ascertain the appropriate set of parameters that minimize the delivery time in hybrid drone-truck delivery operations in the Euclidean plane. Dorling et al. (2017) studied VRP based models from another perspective. The first problem is based on total delivery costs to reduce delivery time, and the second problem is based on the total delivery time to observe budget constraints.

Ulmer and Thomas (2017) presented the Same-Day Delivery Problem with Heterogeneous Fleets (SDDPHF) and formulated it using the Markov decision process. Cheng et al. (2018) developed a Multi-Tour Drone Routing Problem (mTDRP) by only considering drones in the transportation system. In this problem, each drone can visit several demand nodes on each tour. Dayarian et al. (2018) proposed a Vehicle Routing Problem with Demand Resupply (VRPDR) with multiple drones and multiple vehicles that jointly deliver online orders from supply centers. Ham (2018) developed the PDSTSP by considering two different types of drone duties, including pickup and delivery. Hong et al. (2017) proposed a heuristic model for finding optimal locations for drone recharging stations that linked drone recharging stations and delivery locations based on the continuous space shortest path. Luo et al. (2017) developed a Two-Echelon Cooperated Routing Problem for the Ground Vehicle (GV) and its carried unmanned aerial vehicle (2E-GU-RP). Their problem is similar to the VRPD problem presented by Schermer et al. (2018). Drones are allowed to perform several delivery operations on their tour and visit multiple customers.

Karak and Abdelghany (2019) introduced the Hybrid Vehicle-Drone Routing Problem (HVDRP) for pickup and delivery services which different drones can dispatch from the same vehicle to carry out pickup and delivery operations concurrently. Wang and Sheu (2019) introduced the Vehicle Routing Problem with Drones (VRPD), considering distinguished features that allow drones to perform multiple deliveries per tour. The authors recommended a Mixed-

**Table I. Overview of the hybrid truck-drone routing problem**

| *Type of Hybrid Problem* | | *Author* | *year* | *Time limit* | *Number of vehicles* | | *Objective Function* | *Solution Approach* |
|---|---|---|---|---|---|---|---|---|
| | | | | | *Truck* | *Drone* | | |
| FSTSP | | Murray & Chu | 2015 | No | Single | Single | Minimize delivery time | Heuristic |
| | mFSTSP | Ferrandez et al. | 2016 | No | Single | Multiple | Minimize delivery time<br>Minimize drone's energy consumption | Meta- Heuristic |
| | | Ponza | 2016 | No | Single | Single | Minimize Maximum delivery time | Meta- Heuristic |
| | | Marinelli et al. | 2018 | No | Single | Single | Minimizes operational cost | Heuristic |
| | | Sacramento et al. | 2019 | Yes | Multiple | Multiple | Minimizes operational cost | Meta- Heuristic |
| | mFSTSP | Murray, Raj | 2019 | No | Single | Single | Minimize delivery time | Heuristic |
| | | Gonz´alez-R et al. | 2020 | No | Single | Single | Minimize earliest departure time | Heuristic |
| TSPD | | Agatz et al. | 2018 | No | Single | Single | Minimize delivery time | Heuristic |
| | | Bouman et al. | 2018 | No | Single | Single | Minimize cost | Exact |
| | | Ha et al. | 2019 | No | Single | Single | Minimize cost<br>Minimize trucks' waiting time | Heuristic |
| | | Kim, Moon | 2019 | No | Single | Multiple | Minimize delivery time | Heuristic |
| | mTSPD | Kitjacharoenchai | 2019 | | Multiple | Multiple | Minimize delivery time | Meta- Heuristic |
| | PDTSP | de Freitas & Penna | 2020 | No | Single | Single | Minimize cost route | Heuristic |
| | | Dell'Amico et al. | 2020 | No | Single | Single | Minimize delivery time | Meta- Heuristic |
| | | AlMuhaideb et al. | 2021 | No | Single | Single | Minimize delivery time | Meta- Heuristic |
| | | Roberti and Ruthmair | 2021 | | Single | Single | Minimize delivery time | Exact |
| VRPD | | Wang et al. | 2016 | No | Multiple | Multiple | Minimize delivery time | Heuristic |
| | | Pikonen et al. | 2017 | No | Multiple | Multiple | Minimize delivery time<br>Minimize cost | Heuristic |
| | VRPDR | Dayarian et al. | 2017 | No | Multiple | Multiple | Minimize delivery time | Heuristic |
| | VRPDTW | Pugliese, Guerriero | 2017 | No | Multiple | Multiple | Minimize cost | CPLEX software[1] |
| | | Schermer et al. | 2018 | No | Multiple | Multiple | Minimize delivery time | Meta- Heuristic |
| | HVRPD | Karak, Abdelghany | 2019 | No | Single | Multiple | Minimize cost | Heuristic |
| | | Wang, Shew | 2019 | No | Multiple | Multiple | Minimize cost | Exact |
| | K-mVRPD | Pikonen, Golden | 2020 | No | Single | Multiple | Minimize delivery time | Heuristic |
| VRPD | | Our study | | Yes | Multiple | Multiple | Minimizing deprivation cost | GAMS software[2] |

1 . CPLEX 12.5.1 library
2 . GAMS studio 25.1.2

Integer Programming model and developed a Branch-and-Price algorithm as an exact solution for solving the "VRPD". Poikonen and Golden (2020) newly presented a k-Multi-visit Drone Routing Problem (k-MVDRP) with a pair of truck and k drones, and the drones can deliver several packages to customers. Table I introduces some papers about the hybrid truck-drone routing problems, including the objective function, the number of trucks and drones, time limitations, and the solution approach.

### *B. Deprivation cost in humanitarian logistics*

One of the main goals of humanitarian logistics is to supply people's basic needs in the affected areas by disaster, and it seeks to minimize human suffering during the disaster. According to Van Wassenhove (2006), humanitarian logistics is everything that regards the processes and systems involved in the transportation of resources, people, abilities, and knowledge to aid helpless people in affected areas. However, in existing humanitarian logistics research, human suffering is often ignored, or the concept of suffering is illustrated only through indirect measurements, which in practice are difficult to apply for humanitarian logistics problems. Numerous articles have explicitly addressed the phrase defining an appropriate objective function for calculating the degree of human suffering as the main priority of delivery operations in humanitarian logistics to achieve an appropriate function (Gutjahr & Fischer, 2018). The aim of an objective function in humanitarian logistics should thus be to gain the optimal equilibrium among the logistics cost acquired by the responders and the suffering of the survivors. Therefore, finding a suitable method for quantifying human suffering in affected areas has become challenging for many researchers in humanitarian logistics.

Holguin-Veras et al. (2013) applied the economic valuation techniques for quantifying human suffering. This method uses an exponential equation to determine deprivation costs in the model. The estimated economic valuation of human suffering due to lack of access to relief goods or services is defined as deprivation cost. It is widely recognized by humanitarian logistics organizations and is considered a new concept to solve the challenge of inappropriate objective functions for humanitarian logistics.

Holguin-Veras et al. (2013) presented a new function to calculate human suffering as deprivation cost. The function $\gamma$ calculates deprivation cost over deprivation time. $\delta$ is the time people have been living without receiving relief goods during the disaster. $\gamma$ is an exponential function (Fig. 2) so that deprivation cost increases exponentially as the deprivation time of relief goods increases.

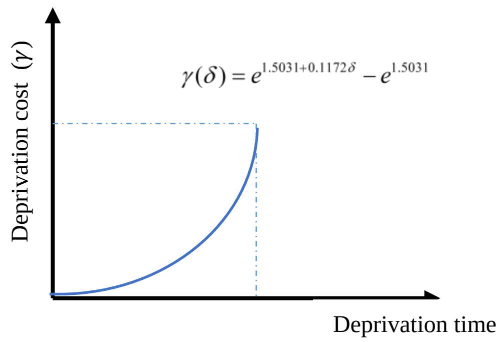


**Fig. 2. The exponential deprivation cost function**

Studies carried out by Holguin-Veras et al. (2016) have been the foundation of applying deprivation cost function for humanitarian logistics. Equation 1 shows the deprivation cost function. $\gamma(\delta_{it})$ is the deprivation cost function based on deprivation time. $\delta_{it}$ is deprivation time of people in the affected area *i* in the period *t*.

$$\gamma(\delta_{it}) = e^{1.5031+0.1172\delta_{it}} - e^{1.5031} \tag{1}$$

Therefore, it is clear that the deprivation cost plays an essential role in decision-making in humanitarian logistics. Deprivation cost that is not economically visible but psychologically affects the human's souls, which inadvertently, like other economic costs caused by the disaster, deteriorates the disaster's condition. So it is best to consider deprivation cost as the main objective for humanitarian logistics.

## III. DESCRIPTION OF THE PROPOSED PROBLEM NETWORK

Our assumed problem network includes a central depot. It can be considered as a place to store trucks, drones, and relief packages. It is assumed that people waiting for relief goods are not evenly distributed throughout the affected area. Access to some areas is geographically more difficult due to the destruction of the roads; in contrast, access to some areas is possible. Therefore, the whole area should be divided into sections; ground vehicles such as trucks can travel to some nodes which their roads are not ruined. There is a fixed part in the trucks to carry drones. Disaster areas that can be reached by ground vehicles such as trucks are introduced as Local Depot (LD) nodes. In addition, there are nodes in this area that are not accessible by ground vehicles, and unmanned aerial vehicles or drones must be applied. These nodes are introduced as Damaged Nodes (DN), which must be assigned to the LDs. Therefore, trucks must supply the demands of LDs and DNs allocated to the LDs. Drones deliver relief packages to the DNs.

Due to the importance of time to implement relief operations, one of the crucial goals of humanitarian logistics is to reduce the service time to the affected areas. On the other hand, in recent years, special attention has been paid to applying deprivation costs, as an appropriate objective function, by researchers interested in humanitarian logistics. Therefore, we intend to reduce the vehicle arrival time by reducing deprivation cost, which is a function of deprivation time.

The main assumptions of the problem are based on some of the real-world in post-disaster situations:

1. The location of the central depot is known, which is a place to store all relief goods and vehicles, including trucks and drones.
2. Multiple trucks, a single depot, and multiple drones are considered.
3. All points of this assumed network include the central depot, LDs, and DNs.
4. Each LD must be visited only by one truck.
5. Fixed places are embedded in trucks to transport drones. Each truck carries multiple drones per tour. When the trucks reach the LD nodes, the drones launch to the DNs assigned to these LD nodes and supply their demands.
6. LDs are the nodes to which trucks travel, and if DNs are assigned to them, the trucks stop, and drones launch to deliver relief packages to the DNs that have inaccessible roads via land vehicles.
7. It is assumed that the locations of LDs and DNs are known and that DNs are previously assigned to LD nodes.
8. Due to the limited flight range and battery charge, each drone has a round-trip, and each drone may have multiple tours throughout its mission.
9. The maximum flying time of the drones is restricted.
10. Multiple drones can be dispatched from the truck concurrently.
11. The flight range of drones is limited, and each truck carries several specific types of drones.
12. The truck must wait until the drones finish their mission in the LD nodes.
13. Travel time between each pair of customer (or depot) locations is symmetric
14. The objective is to reduce the deprivation time of people requesting relief goods at LDs and DNs. The time that people spend without relief goods is defined as Deprivation time. It is equal to the vehicle arrival times to LDs and DNs.

Fig.3 shows a schematic view of the proposed problem. A central depot is considered for the storage of relief packages and vehicles. The solid lines show the trucks' routes, and the dot lines show the round-trip route of the drone. Drones may have multiple round trips.

### *A. Problem modeling*

The problem is modeled according to the main assumptions outlined in the previous section. Details of the sets, parameters, and decision variables are described in Table II.

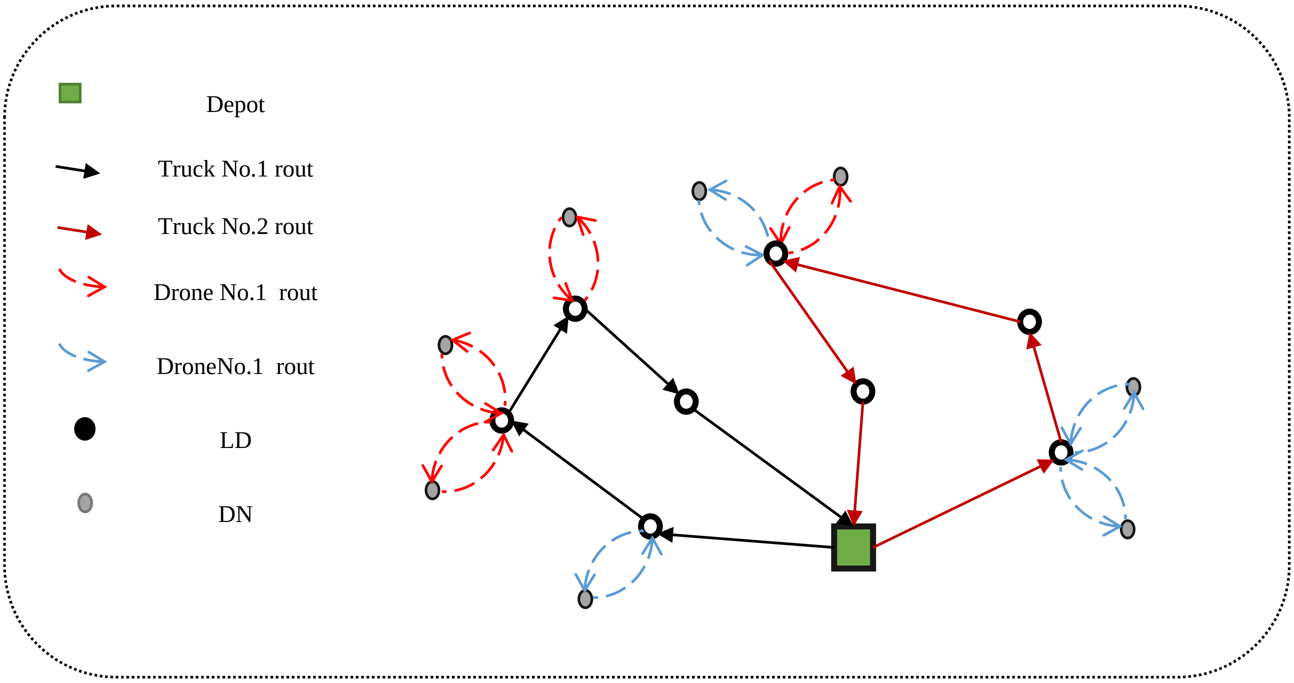


**Fig.3. Schematic view of the hybrid truck-drone routing problem network**

**Table II. Sets, parameters, and decision variables**

| ***Sets*** | | ***Parameters*** | |
|---|---|---|---|
| $V$ | Set of all trucks indexed by v | $t_{ij}$ | Travel time between node i and j by truck ($i, j \in OLD$) |
| $D$ | Set of all drones indexed by d | $t'_{ik}$ | Travel time between node i and k by drone ($i \in LD, k \in DN_i$) |
| $O$ | Central depot node | $L$ | Flight range limit of UAVs |
| $LD$ | Set of local depot nodes indexed by i and j | $c_{ij}^{v}$ | Travel cost between node i and j by truck v ($i, j \in OLD$) |
| $DN_i$ | Set of damaged nodes assigned to LD nodes indexed by k ($i \in LD$) | $c'^{v}$ | Travel cost of using truck v |
| $OLD$ | Set of local depot nodes and central depot node ($OLD \in LD \cup O$) | $T$ | The maximum time that all vehicle's missions have to be completed |
| $R$ | Set of the number of allowable tours for drones indexed by r | | |

**Continue Table II. Sets, parameters, and decision variables**

| ***Sets*** | ***Parameters*** |
| --- | --- |
| ***Decision variables*** | |
| $x_{ij}^{v} \in \{0,1\}$ | If $v^{th}$ truck travels from node i to node j ( $i, j \in OLD$ ) |
| $x'^{v} \in \{0,1\}$ | If $v^{th}$ truck is used for delivery operation |
| $y_{d}^{v} \in \{0,1\}$ | If $d^{th}$ drone is allocated to the $v^{th}$ truck |
| $z_{ik}^{dr} \in \{0,1\}$ | If $d^{th}$ drone in its $r^{th}$ trip travels from node i to node k ( $i \in LD, k \in DN_i$ ) |
| $M_{id}^{v} \in \{0,1\}$ | If $d^{th}$ drone from $v^{th}$ truck is selected to launch to damaged nodes ( $i \in LD$ ) |
| $w_i$ | Waiting time of trucks at node i ( $i \in LD$ ) |
| $T_k'^{d}$ | Drone arrival time to $k^{th}$ damaged nodes ( $k \in DN_i$ ) |
| $T_i^{v}$ | Truck arrival time to $i^{th}$ local depots ( $i \in LD$ ) |

$$\min z = \sum_{i \in LD} \Gamma_i + \sum_{k \in DN_i} \Gamma_k + \sum_{v \in V} \sum_{i,j \in OLD} c_{ij}^{v}.x_{ij}^{v} + \sum_{v \in V} c'^{v}.x'^{v} \tag{2}$$

In this model, Eq. (2) represents the objective function. The first and second parts minimize the sum of deprivation cost as a function of the deprivation time in LD points and DN points. The third and fourth parts minimize the cost of using trucks and travel costs on existing routes. The deprivation cost function is given by Eq. (3) introduced by Holguin-Veras et al. (2013) in which $T_i^{v}$ and $T_k'^{d}$ is considered as deprivation time of affected areas' people.

$$\Gamma_i = \sum_{v \in V} e^{(1.5+0.12(T_i^{v}))} - e^{1.5} \tag{3}$$

$$\sum_{v \in V} \sum_{j \in OLD} x_{ji}^{v} = 1 \qquad \forall i \in LD \tag{4}$$

$$\sum_{j \in LD} x_{oj}^{v} \le 1 \qquad \forall v \in V \tag{5}$$

$$\sum_{i \in OLD} x_{ij}^{v} = \sum_{i \in OLD} x_{ji}^{v} \qquad \forall j \in OLD, \forall v \in V, i \ne j \tag{6}$$

$$x'^{v} = \sum_{i \in LD} x_{oi}^{v} \qquad \forall v \in V \tag{7}$$

$$\sum_{d \in D} \sum_{r \in R} \sum_{i \in LD} z_{ik}^{dr} = 1 \qquad \forall k \in DN_i \tag{8}$$

$$\sum_{k \in DN_i} z_{ik}^{dr} \le 1 \qquad \forall i \in LD, \forall d \in D, \forall r \in R, \tag{9}$$

$$\sum_{r \in R} z_{ik}^{dr} \le \sum_{v \in V} M_{id}^{v} \qquad \forall i \in LD, \forall d \in D, \forall k \in DN_i \tag{10}$$

$$\sum_{v \in V} y_d^{v} \le 1 \qquad \forall d \in D \tag{11}$$

$$y_d^{v} + \sum_{j \in OLD} x_{ji}^{v} \le 1 + M_{id}^{v} \qquad \forall i \in LD, \forall d \in D, \forall v \in V \tag{12}$$

$$M_{id}^{v} \le y_d^{v} \qquad \forall i \in LD, \forall d \in D, \forall v \in V \tag{13}$$

$$M_{id}^{v} \le \sum_{j \in OLD} x_{ji}^{v} \qquad \forall i \in LD, \forall d \in D, \forall v \in V \tag{14}$$

$$(t'_{ik} + t'_{ki}) z_{ik}^{dr} \le L \qquad \forall i \in LD, \forall k \in DN_i, \forall d \in D, \forall r \in R \tag{15}$$

$$\sum_{k \in DN_i} z_{ik}^{dr} \ge \sum_{k \in DN_i} z_{ik}^{d(r+1)} \qquad \forall i \in LD, \forall d \in D, \forall r \in R \tag{16}$$

$$\sum_{r \in R} \sum_{k \in DN_i} (t'_{ik} + t'_{ki}) z_{ik}^{dr} \le w_i \qquad \forall i \in LD, \forall d \in D \tag{17}$$

$$T_i^v \geq t_{oi}.x_{oi}^v - M(1 - x_{oi}^v) \qquad \forall i \in LD, \forall v \in V \tag{18}$$

$$T_j^v \geq T_i^v + t_{ij} + w_i - M(1 - x_{ij}^v) \qquad \forall i \in LD, \forall j \in OLD, \forall v \in V \tag{19}$$

$$T_j^v \leq |T| * \sum_{i \in OLD} x_{ji}^v \qquad \forall v \in V, \forall j \in OLD \tag{20}$$

$$T_k'^d \geq T_i^v + t_{ik}'.z_{ik}^{dr} + \sum_{r' \prec r} \sum_{k \in DN_i} (t_{ik}' + t_{ki}') z_{ik}^{dr'} - M(1 - M_{id}^v)$$
$$\forall i \in LD, \forall k \in DN_i, \forall v \in V, \forall d \in D, \forall r \in R \tag{21}$$

$$T_k'^d \leq M * \sum_{r \in R} \sum_{i \in LD} z_{ik}^{dr} \qquad \forall k \in DN_i, \forall d \in D \tag{22}$$

$$x'^v \in \{0,1\}, y_d^v \in \{0,1\}, x_{ij}^v \in \{0,1\}, z_{ik}^{dr} \in \{0,1\}, M_{id}^v \in \{0,1\}, w_i \geq 0, T_k'^d \geq 0, T_i^v \geq 0 \tag{23}$$

Constraint (4) guarantee that each LD node is visited only by a truck. Constraint (5) indicates that some trucks are selected. They do relief operations for LD nodes. Constraint (6) guarantee the sequence of flow for the truck. Constraint (7) shows the number and type of trucks that left the depot for doing relief operations, in other words, which trucks are used. Constraint (8) indicates that a drone must service any DN on a single trip, and or DNs must be visited only by one drone and in on tour. Constraint (9) indicates that each drone can be used at most once. Constraint (10) shows the relationship between the two decision variables. One related to selecting the drone for each truck and the second to serve the damaged DNs. A drone that is sent to the DN, must have already been selected and carried by truck to the LD. Constraint (11) indicates that each drone must be assigned to only one truck. Constraint (12) states that for serving a DN, a truck must first select the drone and travel to the LD node. Constraints (13) and (14) show the logical relationship between the decision variables. Constraint (15) guarantees the length of each drone trip cannot surpass the drone flight time limit. Constraint (16) shows the correct sequence of trip assignments to drones. Constraint (17) calculates the waiting time of the truck for all drones in LD nodes. It is equivalent to the largest sum of all trips by each drone launched at node i. Constraints (18) and (19) calculate the vehicle arriving time to the LD and DN nodes. When the truck first moves from the depot to the desired LD node, the arrival time is equal to the travel time between the depot and the desired LD nodes. If it goes from another LD node to the desired node, the truck's waiting time at the previous node must also be added. Constraint (20) guarantees the overall time needed for doing the relief operations cannot exceed the specified time limit. Constraints (21) and (22) compute the drone arrival time to DNs. Finally, constraint (23) specifies the type of the decision variables.

### *B. Computational results*

To solve The proposed problem in this paper, we needed to solve it using the exact solution method of GAMS (General Algebraic Modeling System) software. So we solved the model using GAMS software version 25.1.2 on a personal computer with a 2.53 GHz CPU and 4 GB of RAM.

Solving the proposed model is divided into three sections: 1. at the first section, the objective function is to minimize the vehicles' arrival, 2. at the second section, the objective function is to minimize deprivation cost, and 3. n the third section, the objective function is to minimize deprivation cost, considering the population of the disaster nodes.

#### *Minimizing the vehicles' arrival time*

Before considering the deprivation cost, we suppose that the problem's objective function is to minimize the arrival time of vehicles to the LDs and DNs (Eq. 24). As previously mentioned, access to the LD nodes is possible through ground vehicles such as trucks, while visiting DNs will be possible only through the travel of drones to these nodes. A simple example is considered according to the assumptions, and the proposed model and its computational results obtained from GAMS software are presented below.

$$\min z = \sum_{v \in V} \sum_{i \in LD} T_i^v + \sum_{d \in D} \sum_{k \in k_i, i \in LD} T_k'^d \sum_{i,j \in OLD} c_{ij}^v . x_{ij}^v + \sum_{v \in V} c'^v . x'^v \tag{24}$$

According to the problem assumptions, the central depot in a specific place is considered as a place for storing relief goods and vehicles. The affected area by disaster is divided into five sections for sending trucks by land road, introduced as LD nodes in the proposed problem. Each of these five sections has its sub-sections (i.e. DNs) that are not accessible by land road; drones should be used to supply DN's relief packages. There are ten trucks and five drones in the central depot, and each truck can carry multiple types of drones on its trip. The travel time between the central depot and the LDs and from LDs to the DNs is already known. According to the problem definition, Fig.4 shows a schematic view of a solved example of the problem. Points 6, 7, and 8 are DNs assigned to the first local depot (LD 1). Similarly, several DNs are assigned to each LD node. The solid lines are the trucks' tours, and the dotted lines are the drone flight paths. According to the information from the problem solution, trucks No.1 and No.5 have been selected for relief operations. Truck No.1 initially travels to LD No.2, then moves to visit LD No.1, and then returns to the central depot. Fig.5 shows the drone route in detail. At LD No.1, drone No.3 and drone No.5 are selected to deliver relief packages to the 10th and 9th DN nodes, respectively. Also, only drone No.3 is used to complete the relief operation at

LD No.1. As we have already assumed, each truck carries multiple drones, and each drone can have multiple tours.

Drone No.3, in its first, second, and third tours, visit the DNs No.6, No.8, and No.7, respectively (Fig.5).

#### *Minimizing deprivation cost*

ow, we solve the same example in the previous section with the objective function of deprivation cost (Eq. 2). It has different results. As shown in Fig. 6, trucks No.8 and No.1 are selected. Truck No.8 first visits LD No.2 and return to the depot after traveling to LD No.1. The reason for choosing this route is precise because of applying the deprivation cost function .The number of DNs that are allocated to the LD No.1 is more than those allocated to LD No.2. If truck No.8 visits LD No.2 drones' arrival times to DNs, allocated to LD No.1, will increase more than the previous example. Because the deprivation cost increases exponentially. Therefore the truck No.8, unlike the previous example, first visit LD No.1. for the same reasons. Truck No.1 first visit LD No.5 then travel to LD No.4 and after visiting LD No.3 return to the depot (Fig. 6). In the previous example, arrival time to the disaster nodes increases linearly in the main objective function of the problem, so drones can be used multiple times. Meanwhile, in the second part, considering that cost increases exponentially with increasing time, the maximum number of drones must be used to reduce the vehicles' arrival time.

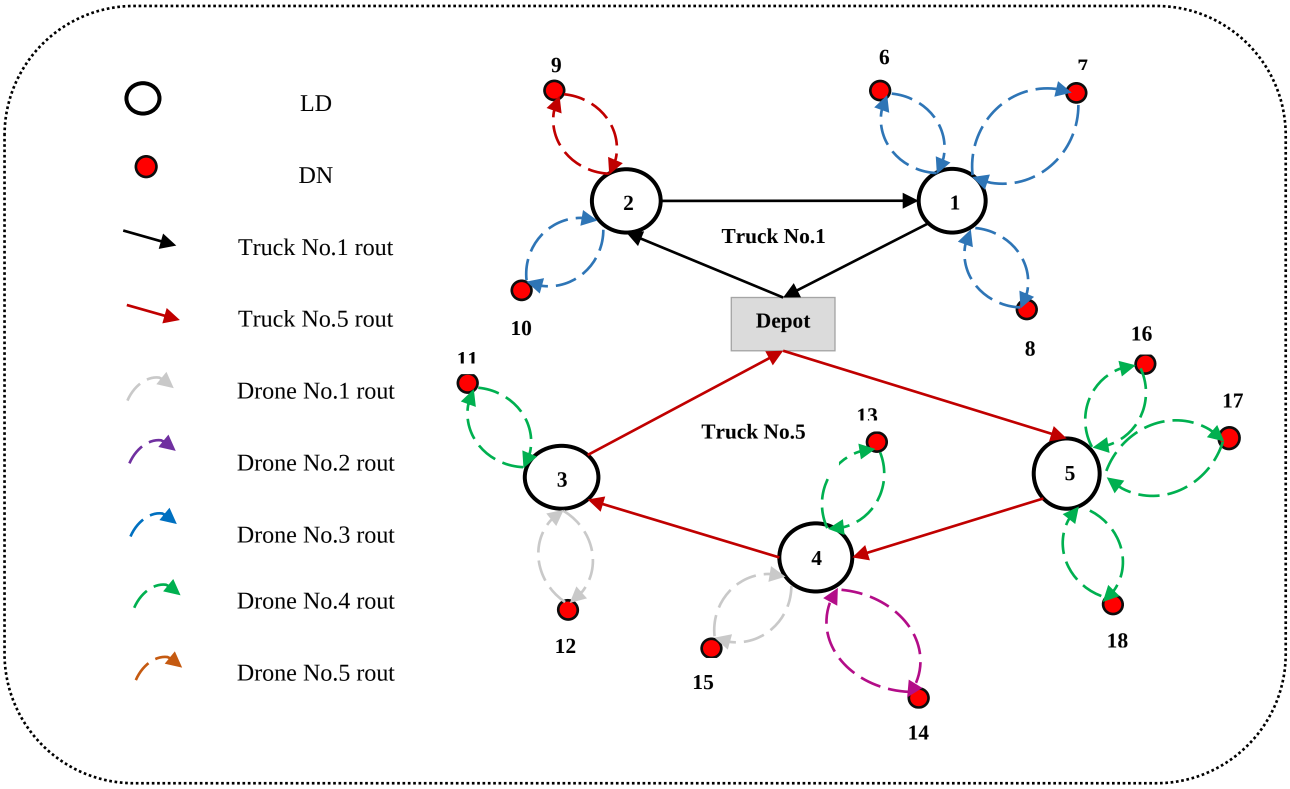


**Fig. 4. Schematic view of problem-solving with the objective function of vehicle arrival time**

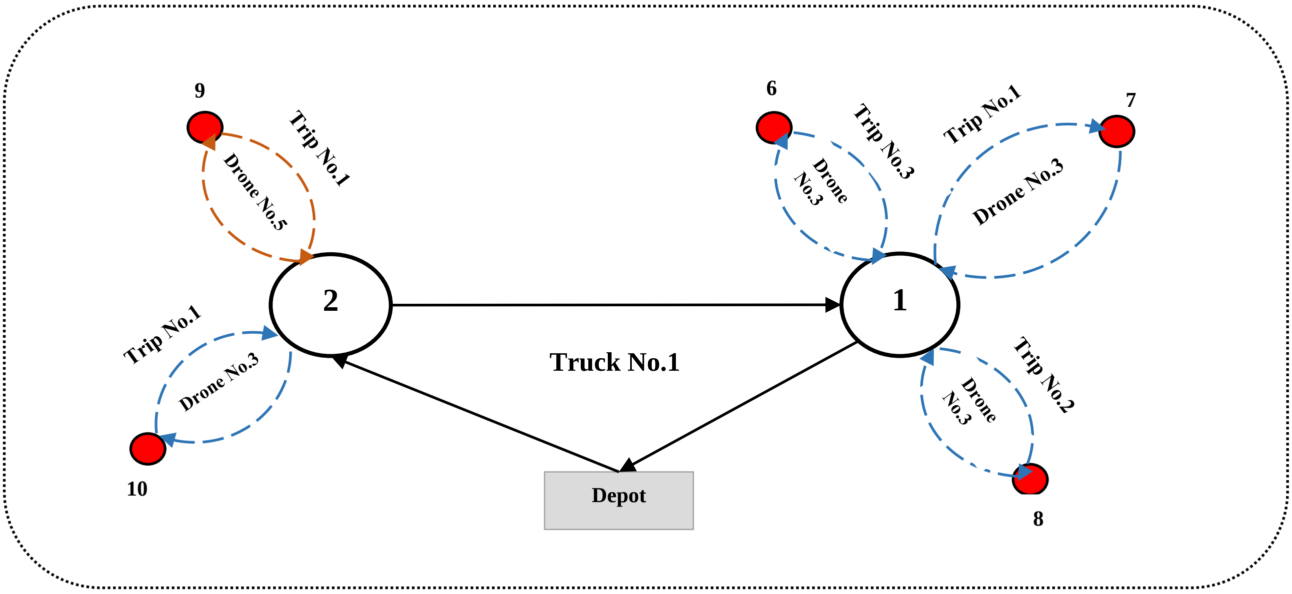


**Fig. 5. Flight paths of truck No.1 in details**

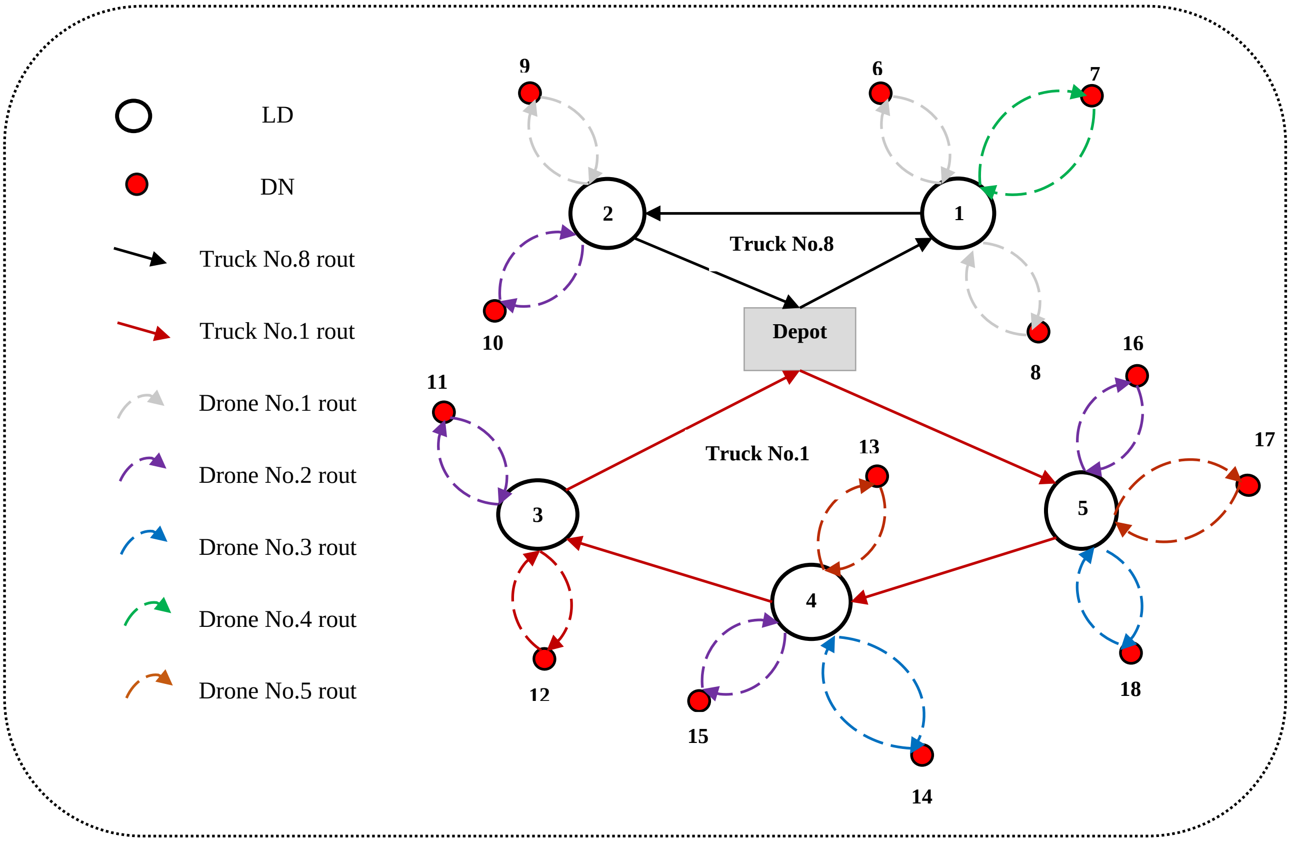


**Fig. 6. Schematic view of problem-solving with the objective function of deprivation cost**

### *Minimizing deprivation cost, considering the population of the affected areas*

Considering the population of DNs according to Table III and solve the previous example using the following objective function (Eq. 25) leads to an answer similar to Fig 7.

$$z = \sum_{i\in LD} \Gamma_i * p(i) + \sum_{k\in k_i, i\in LD} \Gamma_k * p(k) + \sum_{i,j\in OLD} c_{ij}^v . x_{ij}^v + \sum_{v\in V} c'^v . x'^v \tag{25}$$

**Table III. The population of different disaster areas, including LDs and DNs**

| *DNs* | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $p(k)$ | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| | 50 | 100 | 80 | 100 | 80 | 150 | 150 | 60 | 70 | 50 | 50 | 80 | 40 |
| *LDs* | | | | | | | | | | | | | |
| $p(i)$ | 1 | 2 | 3 | 4 | 5 | | | | | | | | |
| | 200 | 400 | 250 | 200 | 450 | | | | | | | | |

As shown in Fig. 7, trucks No.4 and No.10 have been selected for doing relief operations. Truck No.10 first visits LD No.1 and after visiting LD No.5 returns to the depot. Truck No.4 visits LD No.2, LD No.3, and LD No.4, respectively.

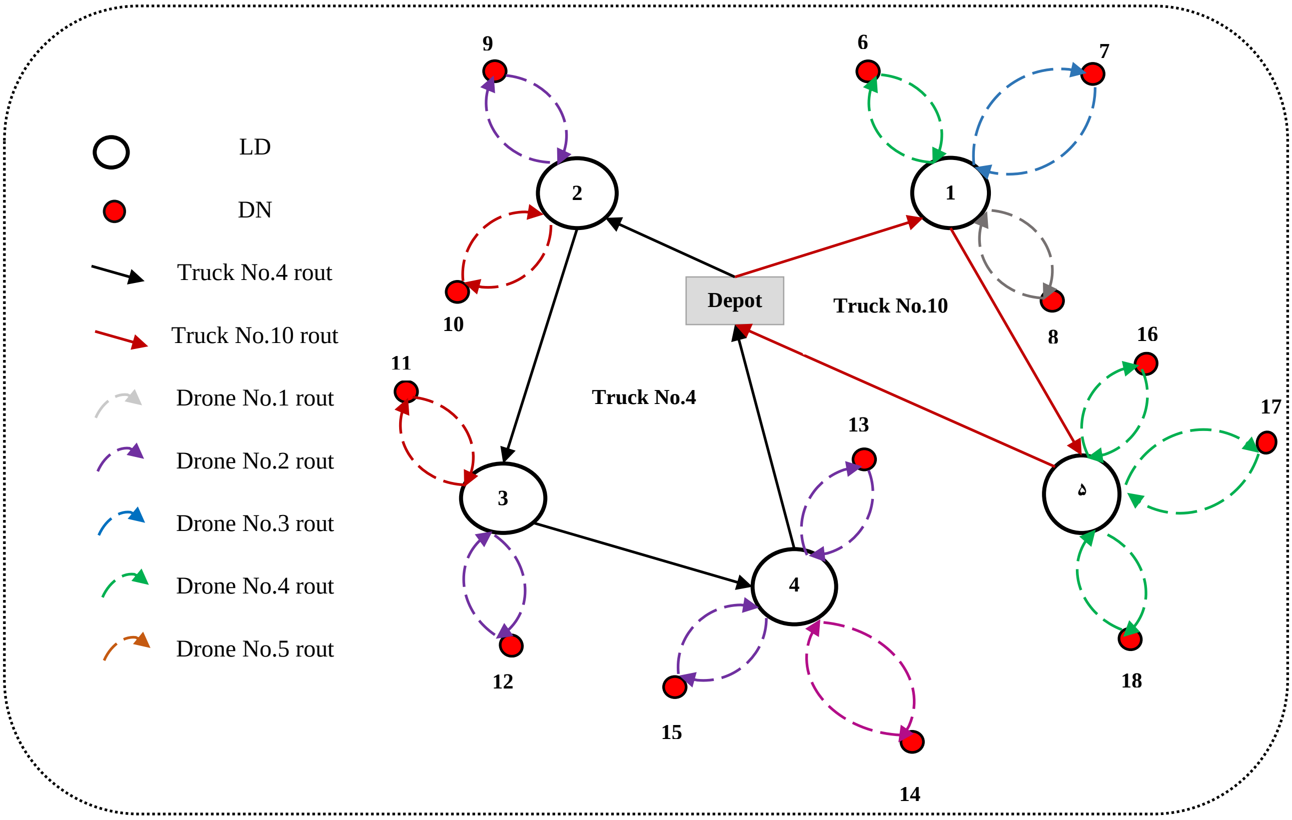


**Fig 7. Schematic view of problem-solving using the deprivation cost considering the population of the affected areas**

**Table IV. Information of examples**

| *Example #* | *LDs* | *DNs* | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1-5 | 1 | 2 | 3 | 4 | 5 | | | | | | | |
| | | 6,7,8 | 9,10 | 11,12 | 13,14,15 | 16,17,18 | | | | | | | |
| 2 | 1-6 | 1 | 2 | 3 | 4 | 5 | 6 | | | | | | |
| | | 7,8,9 | 10,11 | 12,13,14 | 15,16 | 17,18,19, 20 | 21,22,23 | | | | | | |
| 3 | 1-8 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | | | | |
| | | 9,10,11 | 12,13 | 14,15 | 16,17,18, 19,20 | 21 | 22,23,24 | 25,26,27 | 28,29,30 | | | | |
| 4 | 1-10 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | | |
| | | 11 | 12,13 | 14,15 | 16,17,18, 19,20 | 21 | 22,23,24 | 25,26,27 | 28,29,30 | 31,32,33 | 34,35,36 | | |
| 5 | 1-12 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| | | 13 | 14,15 | 16,17 | 18,19,20 | 21 | 22,23,24 | 25,26,27 | 28,29,30 | 31,32,33 | 34,35,36, 37 | 38,39,40 | 41,42,43, 44,45 |

### *Sensitivity analysis*

Since it is surmised that some parameters affect the amount of objective function and the quality of implementation of relief operations, so the effect of these parameters on the objective function is investigated: 1. The number of allowable tours for drones (R), and 2. the maximum duration for completing all relief operations (T). Examples are designed according to Table IV. Several levels of these parameters are considered.

**Table V. Sensitivity analysis of the objective function to the number of drones' allowable tours**

| *Example* | *Objective Value: Deprivation cost +other costs* | | | *Solution time(GAMS)* |
|---|---|---|---|---|
| 1 | $T_1 = 150\,\text{min}$ | $R_1 = 2$ | $z = 58880555.9$ | 0.110s |
| | | $R_2 = 3$ | $z = 57536412.3$ | 0.234s |
| 2 | $T_1 = 150\,\text{min}$ | $R_1 = 2$ | $z = 94631130.9$ | 0.203s |
| | | $R_2 = 3$ | $z = 98680324.0$ | 0.391s |
| | | $R_3 = 4$ | $z = 59536484.0$ | 0.672s |
| 3 | $T_1 = 210\,\text{min}$ | $R_1 = 2$ | $z = 478248571.3$ | 0.391s |
| | | $R_2 = 3$ | $z = 174465274.3$ | 0.938s |
| | | $R_3 = 4$ | $z = 353668440.8$ | 1.859m |
| 4 | $T_1 = 270\,\text{min}$ | $R_1 = 2$ | $z = 637789019.0$ | 2.062m |
| | | $R_2 = 3$ | $z = 336598867.3$ | 2.80m |
| | | $R_3 = 4$ | $z = 509563487.2$ | 3.516m |
| 5 | $T_1 = 400\,\text{min}$ | $R_1 = 2$ | $z = 1267845527.7$ | 5.265m |
| | | $R_2 = 3$ | $z = 876826065.2$ | 5.515m |
| | | $R_3 = 4$ | $z = 1106497748.0$ | 5.718m |

**Table 6. Sensitivity analysis of the objective function to the completion time of all relief operations**

| *Example* | *Objective Value: Deprivation cost +other costs* | | | *Solution time(GAMS)* |
|---|---|---|---|---|
| 1 | $R_2 = 3$ | $T_1 = 150\,\text{min}$ | $z = 58880555.9$ | 0.234s |
| | | $T_2 = 210\,\text{min}$ | $z = 63486908.6$ | 0.219s |
| 2 | $R_3 = 4$ | $T_1 = 150\,\text{min}$ | $z = 59536484.0$ | 0.672s |
| | | $T_2 = 210\,\text{min}$ | $z = 83561102.3$ | 0.750s |
| | | $T_3 = 270\,\text{min}$ | $z = 151323053.1$ | 0.780s |

**Continue Table 6. Sensitivity analysis of the objective function to the completion time of all relief operations**

| *Example* | *Objective Value: Deprivation cost +other costs* | | | *Solution time(GAMS)* |
|---|---|---|---|---|
| 3 | $R_2 = 3$ | $T_1 = 150\,\text{min}$ | $z = 159679694.7$ | 0.812s |
| | | $T_2 = 210\,\text{min}$ | $z = 174465274.3$ | 0.938s |
| | | $T_3 = 270\,\text{min}$ | $z = 240723579.8$ | 0.980s |
| 4 | $R_2 = 3$ | $T_3 = 250\,\text{min}$ | $z = 311971600.7$ | 2.90m |
| | | $T_3 = 270\,\text{min}$ | $z = 336598867.3$ | 2.80m |
| | | $T_3 = 350\,\text{min}$ | $z = 283374657.1$ | 2.83m |
| 5 | $R_2 = 3$ | $T_3 = 400\,\text{min}$ | $z = 876826065.2$ | 5.515m |
| | | $T_3 = 450\,\text{min}$ | $z = 1793142506.1$ | 6.617m |
| | | $T_3 = 500\,\text{min}$ | $z = 1898068932.8$ | 6.801m |

The effect of deprivation time on the value of the objective function is greater than other costs, so the reduction of vehicles arrival time will cause a more reduction in total cost. According to the results of solving examples (Table V), it is observed that the increase in the number of allowable tours for drones can decrease the cost of vehicle utilization and reduce the arrival time of vehicles to the affected area. In example 3 (Table V), by Increasing the number of drones to 3 and 4 ($R_2 = 3$ , $R_3 = 4$) the objective function value is reduced, the increase in the number of the allowable tour to 3 ($R_2 = 3$) results in a better reduction of the objective function value.

On the other hand, considering shorter completion time causes the vehicle arrival time to the affected areas to be reduced. More vehicles have to be utilized to complete the operation. However, the objective value decreases due to the effect of deprivation time reduction when reducing the amount of objective value is high. In Table VI, the objective value is increased by increasing the allowed time to complete the relief operation. When completion time increases, deprivation time also increases. By increasing the deprivation time, the costs increase exponentially.

We also investigate the impact of the number of vehicles on the problem solution. Increasing the number of both vehicles can improve the problem. Since the number of trucks in the objective function is controlled, increasing these numbers will not significantly affect the objective value. While increasing the number of drones can reduce the deprivation cost in the damaged nodes and reduce the overall costs. So trucks can carry more drones with them to serve damaged nodes. We have analyzed the examples' objective value (Table VII) by increasing the number of drones. According to the results of Table 6, the increase in the number of drones can cause reduce total costs. However, in some examples, the increase is more effective in reducing costs. The number of drones' allowable tours also must be considered. Therefore, it can be concluded that the increase in the number of drones can reduce total costs.

**Table VII. Sensitivity analysis of the drones' number**

| *Example #* | *Drone's numbers* | *Objective value* |
|---|---|---|
| 1 | 3 | $z = 114070332.1$ |
| | 4 | $z = 85384301.8$ |
| | 5 | $z = 57536412.3$ |
| 2 | 3 | $z = 198090386.6$ |
| | 4 | $z = 132343761.5$ |
| | 5 | $z = 151323053.1$ |
| 3 | 5 | $z = 359172781.5$ |
| | 6 | $z = 238152593.9$ |
| | 7 | $z = 347919922.0$ |
| 4 | 6 | $z = 556716406.9$ |
| | 7 | $z = 336598867.3$ |
| | 8 | $z = 250713833.0$ |
| 5 | 6 | $z = 1792179936.0$ |
| | 7 | $z = 987330099.3$ |
| | 8 | $z = 531172953.2$ |

## IV. CONCLUSION AND SUGGESTIONS FOR FUTURE RESEARCH

In this paper, we developed a hybrid vehicle routing model with the objective function of deprivation cost, which uses multiple drones in combination with multiple trucks to deliver emergency packages to people in affected areas with disaster. The main goal of using the deprivation cost function is to minimize people's waiting time for emergency packages. The affected area is divided into two sections. Demand nodes with undamaged roads are visited by trucks, known as LD nodes, and demand nodes with destroyed roads are supplied with drones, known as DN nodes. Drones can launch multiple times from each truck to deliver packages. To show how the deprivation cost function acts in our proposed model, some examples are solved, and their results are compared with each other. for this purpose, the original model with three objective functions is solved separately: 1. at the first section, the objective function is to minimize the vehicles' arrival, 2. at the second section, the objective function is to minimize deprivation cost, and 3. In the third section, the objective function is to minimize deprivation cost with the population of the disaster nodes. Experimental results show that using deprivation cost function as a function of vehicle arrival time can cause better results than using current objective functions for problems in humanitarian logistics. Better routes are selected so that people in affected areas wait for less, as the most important goal in humanitarian logistics. Also, the impact of the demand points' population on selecting the vehicles' paths is investigated. Computational results show that with increasing the demand nodes' population, regardless of the state of communication roads and other transportation costs, these points are considered as the priority to serve. The basis of applying the deprivation cost is based on reducing the deprivation time. As the time of deprivation time increases, the total costs will be increased exponentially. So demand points with a high population are in priority. Therefore, by considering the specific features of the disaster situations, the objective function of minimizing the deprivation cost with the population of demand points acts better than other objective functions

Some suggestions for future research are mooted here:

- Charging stations for drones
- By considering charging stations, drones are not required to travel back and forth to the local depot and visit multiple customers on their trip.
- Considering the separate routes for drones independently of the trucks routes allows drones to travel directly from the depot and not be forced to get packages from trucks.
- Considering the periodic time for calculating deprivation cost after happening the disaster to improve the performance of the deprivation cost function.

Of course, there are also opportunities to develop efficient solution methods to solve the problem in larger sizes.

## REFERENCES

Agatz, N., Bouman, P., & Schmidt, M. (2018). Optimization Approaches for the Traveling Salesman Problem with Drone. *Transportation Science*, 52(4):965-981.

AlMuhaideb, S., Alhussan, T., Alamri, S., Altwaijry, Y., Aljarbou, L., and Alrayes, H. (2021). Optimization of Truck-Drone Parcel Delivery Using Metaheuristics. *Applied sciences*, *11*(14), 6443.

Al Theeb, N., & Murray, C. (2017). Vehicle routing and resource distribution in post-disaster humanitarian relief operations. *International Transactions in Operational Research*, 24(6), 1253-1284

Bektas, T. (2006). The multiple traveling salesman problem: An overview of formulations and solution procedures. *Omega*, 34(3), 209–219

Bertazzi, L., Golden, B., & Wang, X. (2015). Min-max vs. min-sum vehicle routing: A worst-case analysis. *European Journal of Operational Research*, 240(2), 372–381.

Bouman, P., Agatz, N., & Schmidt, M. (2018). Dynamic Programming Approaches for the Traveling Salesman Problem with Drone. *Networks*, 72(4), 528-542.

Campbell, J., Sweeney, D., & Zhang, J. (2017). Strategic Design for Delivery with Trucks and Drones(Tech.).

Carlsson, J. & Song, S. (2017). Coordinated logistics with a truck and a drone *Management Science*, 64(9), 3971-4470.

Cantillo V., Serrano I., Macea L.F., Holguín-Veras J. (2018). Discrete choice approach for assessing deprivation cost in humanitarian relief operations, *Soc. Econ. Plan. Sci*. 63

Cheng, C., Adulyasak, Y., & Rousseau, L. M. (2018). Formulations and Exact Algorithms for Drone Routing Problem. Working Paper.

Dascioglu, B. G., Vayvay, O., & Kalender, Z. T. (2019). Humanitarian Supply Chain Management: Extended Literature Review *Industrial Engineering in the Big Data Era* (pp. 443-459): Springer.

Dayarian, I., Savelsbergh, M., & Clarke, J. P. (2018). Same-Day Delivery with Drone Resupply. Technical Report. 2018. *Available a*t: http://www. optimization-online. org/DB_FILE/2017/09/6206. pdf.

Dorling, K., Heinrichs, J., Messier, G. G., & Magierowski, S. (2017). Vehicle Routing Problems for Drone Delivery. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(1), 70-85.

Dell'Amico, M., Montemanni, R., & Novellani, S. (2020). Metaheuristic algorithms for the parallel drone scheduling traveling salesman problem. Annals of Operations Research, 289, 211-226.

Drexl, M. (2012). Synchronization in Vehicle Routing—A Survey of VRPs with Multiple Synchronization Constraints. *Transportation Science*, 46(3), 297-316.

de Freitas, J. C., & Penna, P. H. V. (2020). A variable neighborhood search for flying sidekick traveling salesman problem. International *Transactions in Operational Research*, 27, 267-290.

Gonz´ alez-R, L., Canca, D., Andrade-Pineda, J.L., Calle, M., (2020). Truck-drone team logistics: A heuristic approach to multi-drop route planning. *Transport. Res. Part C: Emerg. Technol*. 114, 657–680.

Gutjahr W.J., Fischer S., Equity and deprivation costs in humanitarian logistics, (2018). *Eur. J. Oper. Res*. 270 ,185–197

Hern, A. (2014). DHL launches first commercial drone 'parcelcopter' delivery service, https://www.theguardian.com/technology/2014/sep/25/german-dhl-launches-first commercial drone-delivery-service

Ha, Q., Deville, Y., Pham, Q., & Hà, M. (2018). On the min-cost Traveling Salesman Problem with Drone. *Transportation Research Part C*, 86, 597-621.

Ham, A. M. (2018). Integrated scheduling of m-truck, m-drone, and m-depot constrained by time window, drop-pickup, and m-visit using constraint programming. *Transportation Research Part C: Emerging Technologies*, 91, 1-14.

Holguín-Veras J., Perez N., Jaller M., Van Wassenhove L.N., Aros-Vera F., (2013). On the appropriate objective function for post-disaster humanitarian logistics models, *J. Oper. Manag.* 31, 262–280

Hong, I., Kuby, M., & Murray, A. (2017). A Deviation Flow Refueling Location Model for Continuous Space: A Commercial Drone Delivery System for Urban Areas. *Advances in Geocomputation Advances in Geographic Information Science*, 125-132.

Hughes, M. (2017). UPS successfully delivered a package with a drone. https://thenextweb.com/insider/2017/02/21/ups-successfully-delivered-package-drone/.

Jeong, H.Y., Lee, S., & Song, B.D. (2019) Truck-drone hybrid delivery routing: Payload-energy dependency and no-fly zones. *International Journal of Production Economics*.

Karak, A., & Abdelghany, K. (2019). The hybrid vehicle-drone routing problem for pickup and delivery services. *Transportation Research Part C: Emerging Technologies*, 102, 427-449.

Kim, S., & Moon, I. (2019). Traveling salesman problem with a drone station. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 49(1), 42-52.

Kitjacharoenchai, P., Ventresca, M., Moshref-Javadi, M., Lee, S., Tanchoco, J. M., & Brunese, P. A. (2019). Multiple traveling salesman problem with drones: Mathematical model and heuristic approach. *Computers & Industrial Engineering*, 129, 14-30.

Kivelevitch, E. H., Cohen, K., & Kumar, M. (2013). A binary programming solution to the min-max multiple-depots, multiple traveling salesman problem. *AIAA Infotech@Aerospace (I@A) conference*

Luo, Z., Liu, Z., & Shi, J. (2017). A two-echelon cooperated routing problem for a ground vehicle and its carried unmanned aerial vehicle. *Sensors*, 17(5), 1144.

Marinelli, M., Caggiani, L., Ottomanelli, M., & Dellorco, M. (2018). En route truck–drone parcel delivery for optimal vehicle routing strategies. *IET Intelligent Transport Systems*, 12(4), 253- 261.

Meola, A. (2017). Shop online and get your items delivery by a drone delivery service: The future Amazon and Domino's have envisioned for us. Retrieved from https://www.businessinsider.com/delivery-drones-market-service-2017-7

Murray, C. C., & Chu, A. G. (2015). The flying sidekick traveling salesman problem: Optimization of drone-assisted parcel delivery. *Transportation Research Part C: Emerging Technologies*, 54, 86-109.

Murray, C. & Raj, R. (2019) The Multiple Flying Sidekicks Traveling Salesman Problem: Parcel Delivery with Multiple Drones. Available at SSRN: https://ssrn.com/abstract=3338436 or http://dx.doi.org/10.2139/ssrn.3338436

Otto, A., Agatz, N., Campbell, J., Golden, B., & Pesch, E. (2018). Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: A survey. *Networks*, 72(4), 411-458

Ponza, A. (2015) Optimization of Drone-Assisted Parcel Delivery. http://tesi.cab.unipd.it/51947/1/Andrea_Ponza_Analisi_e_ottimizzazione_nell%27uso_di_droni _ per_la_consegna_di_prodotti.pdf

Poikonen, S., & Golden, B. (2020). Multi-visit drone routing problem. *Computers & Operations Research*, 113, 104802.

Poikonen, S., Wang, X., & Golden, B. (2017). The vehicle routing problem with drones: Extended models and connections. *Networks*, 70(1), 34-43.

Pugliese, L. D. P., & Guerriero, F. (2017). Last-Mile Deliveries by Using Drones and Classical Vehicles. *In International Conference on Optimization and Decision Science* (pp. 557-565). Springer, Cham.

Roberti, R., Ruthmair, M. (2021). Exact Methods for the Traveling Salesman Problem with Drone. *Transportation Science*, 55(2): 315-335.

Schermer, Daniel & Moeini, Mahdi & Wendt, Oliver. (2018). A Variable Neighborhood Search Algorithm for Solving the Vehicle Routing Problem with Drones.

Tu, P., Dat, N., & Dung, P. (2018). Traveling salesman problem with multiple drones. *In Proceedings of the Ninth International Symposium on Information and Communication Technology*, 46-53. ACM.

Ulmer, M. W., & Thomas, B. W. (2017). Same-day delivery with a heterogeneous fleet of drones and vehicles (pp. 1-30). *Technical report*.

Van Wassenhove, L.N., (2006). Humanitarian aid logistics: supply chain management in high gear. *J. Operat. Res. Soc.* 57 (5), 475–489.

Volkman, E. (2018, June 21). 8 Things That Can Be Delivered By Drone. Retrieved from https://tech.co/8-things-can-delivered-drone-2017-12.

Wang, X., Poikonen, S., & Golden, B. (2016). The vehicle routing problem with drones: Several worst-case results. Optimization Letters, 11(4), 679-697.

Wang, Z., & Sheu, J. B. (2019). Vehicle routing problem with drones. *Transportation research part B: methodological*, 122, 350-364.

Yurek, E. E., & Ozmutlu, H. C. (2018). A decomposition-based iterative optimization algorithm for traveling salesman problem with drone. Transportation Research Part C: Emerging Technologies, 91, 249-262.