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Resilient Humanitarian Logistics: Planning for Relief Distribution Amidst Damaged Infrastructure

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Planning the distribution system of humanitarian relief efforts following a disaster is a crucial aspect. An optimal distribution system can only function properly in the presence of robust infrastructure networks, such as transportation networks. However, disasters, whether natural or man-made, often cause severe damages or destructions to such infrastructure networks. In this work, we examine the planning of the distribution system, which involves transporting relief materials from storage facilities to distribution centers using trucks, then delivering them to the victims' demand nodes using unmanned aerial vehicles. Accordingly, we develop an optimization model using mathematical programming with the objective of enhancing the resilience of the system. Furthermore, the model takes into account the capacity of the roads within a transportation network that are utilized by trucks, considering their level of damage following the disaster and the time to restore them. We solve the developed optimization model for a transportation network with various scenarios considering different levels of road damages and different restoration durations for such damaged roads. The results show that based on the performance in various restoration time scenarios, planning for the delivery of relief goods does not always have to be done right after a disaster occurs due to the dynamic nature of the disruptions in transit. In addition, based on the travel time of the system, decision makers can decide to implement the most ideal scenario for disaster response in terms of the restoration time for the damaged infrastructure.

Keywords: Optimization, Resilience, Restoration, Relief Distribution, Disaster Management, Transportation, UAV.

1. Introduction

After natural disasters, humanitarian relief is of utmost importance in attending to the suffering of the affected areas. In contrast, damage to infrastructure makes it increasingly difficult to deliver relief to the victims in an effective manner. One of the most pressing challenges in post-disaster relief operations is making certain that aid reaches the afflicted regions; assistance is particularly needed when essential infrastructure, especially roads, is heavily damaged. The capability to redesign infrastructure to cope with these changes is one of the most important aspects of any relief operation. This research discusses the incorporation of optimization models to formulate plans for the relief distribution that is resilient and emphasizes the restoration of transportation networks as a primary element of post-disaster logistics. This research looks deeply into the issue of a limited capacity while trying to find a solution to the shortest path problem. Specifically, this study will focus on the efficient restoration of damaged roads. Restoring the roads is essential to guaranteeing the possibility of using the transportation routes at the proper cost, optimal timing, and most efficient provisioning system. For adequate allocation of resources, there is a need for models that consider both damaged and restored road segments.

The distribution of relief becomes increasingly difficult in a post-disaster setting where road networks are disrupted. The restoration effort has an effect on the state of the road networks and the transportation routes as well. There is a need for models that are able to operate under these restrictions, which include the optimum movement of goods Gupta and Arora (2013). In addition, the location routing problem is also important in disaster response as it deals with the design and the operational planning of the multi-tiered transportation system that integrates ground vehicles with Unmanned Aerial Vehicles (UAVs). The improvement of roads opens the way to new routing options for manned ground vehicles, while UAVs can also provide delivery services to regions that are still inaccessible by road Faiz et al. (2024). There is a definite correlation between the routing and the operating combination of varying types of transportation modes to the road improvements.

The study aims to optimize relief distribution planning in damaged infrastructure by integrating shortest path models with dynamic capacity restrictions and transportation-UAV routing problems. We develop a mathematical model to enhance resilience in humanitarian relief, especially in distribution planning, by accounting for infrastructure restoration. This model minimizes travel times while ensuring the system remains adaptive, allowing rapid recovery of damaged infrastructure. The study enhances resilience planning by providing scenarios for better relief operations planning, coordination, and execution, ensuring resources are delivered efficiently, at the right place and time, while considering the dynamic nature of infrastructure restoration.

2. Related Works

The shortest path problem variants are crucial for optimizing relief goods distribution in post-disaster environments, where damaged infrastructure poses significant challenges. (Himmich et al. (2020) focused on finding the least-cost path between two nodes while adhering to resource limitations, which is essential in scenarios with infrastructure damage, road closures, and capacity limits. Wang et al. (2017) considered expanding edge costs and capacity limits, which are particularly relevant in resource-limited post-disaster recovery. Baouche et al. (2014) used the electric vehicle shortest path problem, incorporating battery capacity and charging stations, which is also applicable for energy-efficient routing in disaster relief. Dondo (2012); Li and Zhu (2013) discussed the models with capacity and time constraints further, ensuring compliance with these limits during routing. The approach for managing the uncertainty and complexity of post-disaster, where exceeding capacity and time-sensitive delivery are critical factors, is discussed by Motameni and Ebrahimnejad (2018).

The transportation problem is crucial in disaster relief operations. Based on Khurana (2015), transshipment problem variants handle multi-tiered transportation systems typical in disaster scenarios. The fractional capacitated transportation problem introduces flow restrictions on certain routes, useful when transport networks are impaired (Gupta and Arora (2013)). Kaur et al. (2017) proposed time minimization problems with restricted flow to optimize resource movement while minimizing delays, essential for timely aid delivery. These studies help develop transportation plans that consider damaged infrastructure and the need for efficient aid delivery. As relief operations often involve multiple conflicting objectives—such as balancing shipping costs and completion dates—goal programming approaches have been used to address such trade-offs Singh and Saxena (1998). These models, which explicitly consider environmental constraints, organizational goals, and decision-making structures, are valuable in humanitarian relief logistics, where diverse objectives need to be balanced. Furthermore, transportation problems with conflicting node categorization and restrictions in specific delivery environments, such as shipyards, have been explored Ficker et al. (2021), further underscoring the complexity of planning relief distribution in challenging, post-disaster conditions.

The UAV routing problem in disaster response coordinates the delivery of emergency aid through two levels of vehicles: first-stage vehicles (trucks) and second-stage vehicles (UAVs). The problem addresses challenges like uncertain demand and infrastructure failures by employing a robust optimization model, which is crucial in areas with severely damaged infrastructure, as seen in Hurricane Maria Faiz et al. (2024). This problem can also be applied in scenarios where ground vehicles are used to transport UAVs to satellite locations, enabling efficient aid delivery to affected populations despite infrastructure disruptions Faiz et al. (2024). This is particularly relevant when considering areas that may have roads blocked or damaged.

Models for optimizing the two-echelon location routing problem combine ground vehicles and UAVs to enhance response efficiency and minimize total response time Perwira Redi et al. (2023) and optimize waste clean-up efforts after a disaster, further contributing to effective disaster management Cheng et al. (2022). Multi-objective models also play a role in balancing cost, time, and risk, as seen in the bi-level model for optimizing the chain Khanchehzarrin et al. (2022). By incorporating advanced technologies such as UAVs and employing scenario-based approaches to account for uncertainty, these models ensure that disaster response systems remain resilient and adaptive to the dynamic challenges posed by damaged infrastructure Chang et al. (2017); Raziei et al. (2018).

3. Proposed Model

In this paper, we propose a two-stage model where the solution of the second stage depends on the solution of the first stage. The objective of this model is to plan distribution strategies to enhance post-disaster resilience.

3.1. *System description*

The system discussed in this paper adapts the shortest path, transportation, and location routing problem as shown in Fig. 1. The system consists of Warehouse Facilities (WFs) that supply relief goods to each Distribution Centers (DCs) using trucks and then deliver the goods to the victim community (VCs) via UAVs afterwards.

This study focuses on the roads used by trucks, which sustain damage post-disaster in stage I, leading to restricted accessibility. Due to these limitations, the location routing model cannot be applied as is since the cost from WF to DC, typically represented by distance or travel time, is always given and known. However, roads are highly susceptible to damage, especially in the event of a disaster. Therefore, this paper addresses the issue by considering road damage, marked by road capacity limitations and restoration time, making the capacity dynamic over time. Moreover, in stage II, the delivery of relief goods is carried out by UAVs due to the difficulty of truck access on damaged roads post-disaster. Each UAV has a durability constraint, indicated by a limited travel time. The objective is to minimize the travel time of all UAVs assigned to deliver relief goods to each VC.

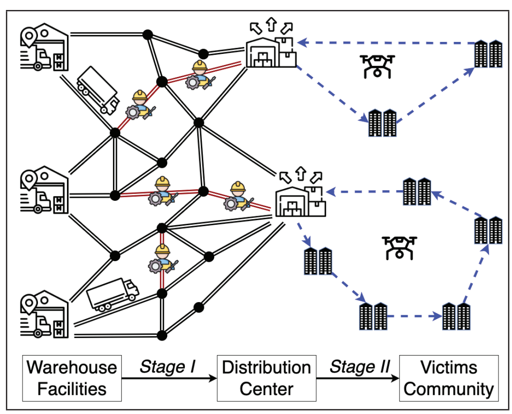

Fig. 1. Schematic description of the system.

3.2. *Mathematical Model*

There are sets of VCs $i \in \mathrm{V}$ that require relief goods. These goods are sent from several WFs $i \in \mathrm{F}$ using trucks $k \in \mathcal{T}$ through DCs $j \in \mathrm{D}$ traversing roads $(i,j) \in \mathcal{A}$ that are damaged or under restoration at time $\tau \in \mathcal{T}$. Assuming trucks cannot deliver relief goods to $i \in \mathrm{V}$ due to unfavorable road conditions, the relief goods are delivered via DCs using UAVs $k \in \mathcal{K}$ which have a maximum flight duration $T_{\max}$. We use the notations as shown in Table 1 to define the sets, parameters, and variables in the model.

Model I: Shortest path model considering dynamic capacity

This is the submodel to find the optimal path from WFs to DCs and optimal execution planning time.

$$\text{Min} \sum_{a\in\mathcal{A}} \sum_{h\in\mathcal{H}} \sum_{\tau\in\mathcal{T}} t_a \cdot s_{ah}^{(\tau)} + \sum_{\tau\in\mathcal{T}} \mathrm{p} \cdot \tau \cdot z^{(\tau)} \tag{1}$$

$$\sum_{\tau\in\mathcal{T}} z^{(\tau)} = 1 \tag{2}$$

$$s_{ah}^{(\tau)} \le z^{(\tau)}, \forall a \in \mathcal{A},\, h \in \mathcal{H},\, \tau \in \mathcal{T} \tag{3}$$

$$\sum_{j\in\mathcal{C}} s_{ijh}^{(\tau)} = z^{(\tau)}, \forall i \in \mathcal{F}, h \in \mathcal{H},\, \tau \in \mathcal{T} \tag{4}$$

$$\sum_{i\in\mathcal{C}} s_{ijh}^{(\tau)} = z^{(\tau)}, \forall j \in \mathcal{D}, h \in \mathcal{H},\, \tau \in \mathcal{T} \tag{5}$$

$$\sum_{h\in\mathcal{H}} s_{ah}^{(\tau)} \le m_{a\tau}, \forall a \in \mathcal{A}, \tau \in \mathcal{T} \tag{6}$$

$$\sum_{i\in\mathcal{F}\cup\mathcal{C}} s_{ijh}^{(\tau)} = \sum_{i\in\mathcal{C}\cup\mathcal{D}} s_{jih}^{(\tau)}, \quad \forall j \in \mathcal{C}, h \in \mathcal{H},\, \tau \in \mathcal{T} \tag{7}$$

$$s_{ah}^{(\tau)} \in \{0,1\}, \forall a \in \mathcal{A}, h \in \mathcal{H}, \tau \in \mathcal{T} \tag{8}$$

$$z^{(\tau)} \in \{0,1\}, \forall \tau \in \mathcal{T} \tag{9}$$

Table 1. Notations of sets, parameters, and variables in the formulation.

Notation	Description
$\mathcal{F}$	Set of warehouse facility
$\mathcal{C}$	Set of connection point/ intermediary
$\mathcal{D}$	Set of distribution center
$\mathcal{V}$	Set of victim point
$\mathcal{H}$	Set of arc $(i,j), \forall i \in \mathrm{F}, j \in \mathrm{D}$
$\mathcal{A}$	Set of road $(i,j) \subset (f,c) \cup (m,n)$, $\forall f \in F, c \in C, m \in C, n \in D$
A	Set of arc $(i,j), \forall i,j \in D+V, i \neq j$
$\mathcal{T}$	Set of restoration period (0, 1, 2, ..., τ)
$\mathcal{K}$	Set of truck
K	Set of UAV
A	Set of all arcs
t_a	Time to travel for arc $a \in \mathcal{A}$
p	Consequence of additional time for each restoration period $\tau \in \mathcal{T}$
$m_{a\tau}$	Maximum capacity of road $a \in \mathcal{A}$ for each restoration period $\tau \in \mathcal{T}$
c_a	Time to travel for arc $a \in \mathrm{A}$
s_h^*	Optimal cost for arc $h \in \mathcal{H}$
d_i	Demand for each $i \in \mathcal{V}$
r	Maximum capacity for $i \in \mathcal{F}$
$\mathbf{q}$	Maximum capacity for $k \in \mathcal{K}$
q	Maximum capacity fot UAV $i \in \mathrm{K}$
$T_{\max}$	Maximum duration for UAV $i \in \mathrm{K}$
$s_{ah}^{(\tau)}$	Binary decision variable indicating whether the path $a \in \mathcal{A}$ for $h \in \mathcal{H}$ in period $\tau \in \mathcal{T}$ is used.
$z^{(\tau)}$	Binary decision variable indicating whether a condition is met during time period τ.
x_{ak}	Binary decision variable indicating wether arc $a \in \mathcal{A} + \mathrm{A}$ is used for $k \in \mathcal{K} + \mathrm{K}$.
y_{ij}	Binary decision variable indicating wether $i \in \mathcal{V}$ is served by $j \in \mathcal{D}$.
l_{ak}	Continues variable indicating the amount of material sent on arc $a \in \mathcal{A}$ by truck $k \in \mathcal{K}$.
u_{ik}	Continues variable indicating the cumulative amount of material delivered by UAV $k \in \mathrm{K}$ to $i \in \mathcal{V}$.

Model II: Transportation-UAV routing problem

This model is to find the optimal routes of UAVs from DCs to VCs.

$$\text{Min} \sum_{h\in\mathcal{H}}\sum_{k\in\mathcal{K}} s_h^* \cdot x_{hk} + \sum_{a\in\mathcal{A}}\sum_{k\in\mathrm{K}} c_a \cdot x_{ak} \tag{10}$$

$$\sum_{i\in\mathcal{F}}\sum_{k\in\mathcal{K}} l_{ijk} = \sum_{i\in V} d_i \cdot y_{ij}, \forall j \in \mathcal{D} \tag{11}$$

$$\sum_{j\in\mathcal{D}}\sum_{k\in\mathcal{K}} l_{ijk} \leq r, \forall i \in \mathcal{F} \tag{12}$$

$$\sum_{a\in\mathcal{H}} x_{ak} \leq 1 \quad \forall k \in \mathcal{K} \tag{13}$$

$$\mathbf{q} \cdot x_{ak} \geq l_{ak} \quad \forall a \in \mathcal{H},\, k \in \mathcal{K} \tag{14}$$

$$\sum_{j\in\mathcal{D}+\mathcal{V},\, j\neq i}\ \sum_{k\in\mathrm{K}} x_{jik} = 1 \quad \forall i \in \mathcal{V} \tag{15}$$

$$\sum_{j\in\mathcal{D}+\mathcal{V}}\ \sum_{i\in\mathcal{V},\, j\neq i} d_i \cdot x_{jik} \leq q, \forall k \in \mathrm{K} \tag{16}$$

$$\sum_{j\in\mathcal{D}+\mathcal{V},\, j\neq i} x_{ijk} = \sum_{j\in\mathcal{D}+\mathcal{V},\, j\neq i} x_{jik}, \quad \forall k \in \mathrm{K},\, i \in \mathcal{D}+\mathcal{V} \tag{17}$$

$$\sum_{j\in\mathcal{D}}\sum_{i\in\mathcal{V}} x_{jik} \leq 1 \quad \forall k \in \mathrm{K} \tag{18}$$

$$u_{ik} + d_v \leq u_{vk} + M \cdot (1 - x_{ivk}), \quad \forall i, v \in \mathcal{V},\, i \neq v,\, k \in \mathrm{K} \tag{19}$$

$$\sum_{v\in\mathcal{V}} x_{jvk} + \sum_{v\in\mathcal{D}+\mathcal{V}} x_{vik} \leq 1 + x_{ij}, \quad \forall i \in \mathcal{V}, v \neq i,\, j \in \mathcal{D},\, k \in \mathrm{K} \tag{20}$$

$$\sum_{j\in D} x_{ij} = 1, \forall i \in \mathcal{V} \tag{21}$$

$$\sum_{a\in\mathrm{A}} c_a \cdot x_{ak} \leq T_{\max}, \forall k \in \mathrm{K} \tag{22}$$

$$l_{ak} \geq 0, \forall a \in \mathcal{A}, k \in \mathcal{K} \tag{23}$$

$$y_{ij} \in \{0,1\}, \forall i \in \mathcal{V}, j \in \mathcal{D} \tag{24}$$

$$x_{ijk} \in \{0,1\}, \forall (i,j) \in \mathrm{A}, k \in \mathrm{K} \tag{25}$$

$$u_{ik} \geq 0, \forall i \in \mathcal{V}, k \in \mathrm{K} \tag{26}$$

The objective function of stage I, represented by Eq. (1) is to minimize the total travel time from each $i \in \mathcal{F}$ to each, $j \in \mathcal{D}$ and the consequence of additional time p depends on the chosen restoration period τ. Eq. (2) ensures only a single restoration period $\tau \in \mathcal{T}$ is chosen. Eq. (3) ensures the activation of arc $s_{ah}^{(\tau)}$. The path should start from $i \in \mathcal{F}$ and end to $j \in \mathcal{D}$ represented by Eqs. (4) and (5) where Eq. (6) ensures the flow of arcs $s_{ah}^{(\tau)}$ does not violate the limitations of the roads. Eq. (7) is flow conservation at $i \in \mathcal{C}$. Eqs. (8) and (9) are the binary decision variables. The objective function at stage II is Eq. (10) which minimizes the total travel time from both stages. Eq. (11) shows the balance of supply and demand. Eq. (12) ensures the total supply of $i \in \mathcal{F}$ is not exceed it's capacity. Eq. (13) ensures each truck $k \in \mathcal{K}$ can use at most one, where Eq. (14) avoids exceeding the capacity of the truck. All $i \in \mathcal{V}$ are served exactly once by UAV, $k \in \mathrm{K}$ guaranteed by Eq. (15) where Eq. (16) ensures the capacity of UAV is not exceeded. Flow conservation in stage II is shown in Eq. (17) and Eq. (18) shows that UAVs are used only in one route. Eq. (19) prevents the subtour. Eqs. (20) and (21) ensure the compatibility of UAV $k \in \mathrm{K}$, $i \in \mathcal{V}$ and $j \in \mathcal{D}$. Eq. (22) ensures the durability of UAVs, and Eqs. (23) – (26) are binary and continuous decision variables.

4. Illustrative Example and Discussion

We generated an example to represent the problem under discussion. In this example, as shown in Fig. 2, there are six $h \in \mathcal{F}$, five $i \in \mathcal{C}$, two $d \in \mathcal{D}$, and eight $j \in \mathcal{V}$. For arcs $(i,j), \forall i \in \mathcal{F}, \forall j \in \mathcal{C}$ and $(i,j), \forall i \in \mathcal{C}, \forall j \in \mathcal{D}$ one-way arcs, apply, whereas for arcs $(i,j), \forall i \in \mathcal{D}+\mathcal{V}, \forall j \in \mathcal{D}+\mathcal{V}, i \neq j$ two-way arcs are applied. To reduce the number of possible arcs, we use Algorithm 1, ensuring that the resulting arcs are consistent with the data. For instance, if there is no path

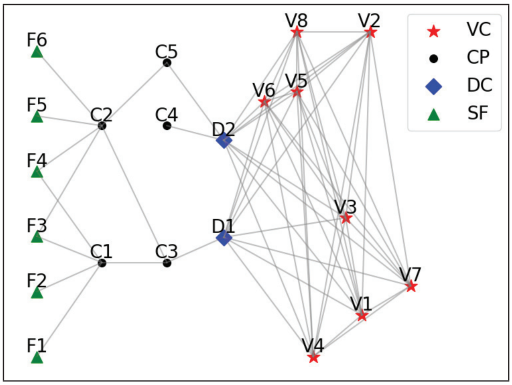

Fig. 2. Example of the problem in a graph form for the first case.

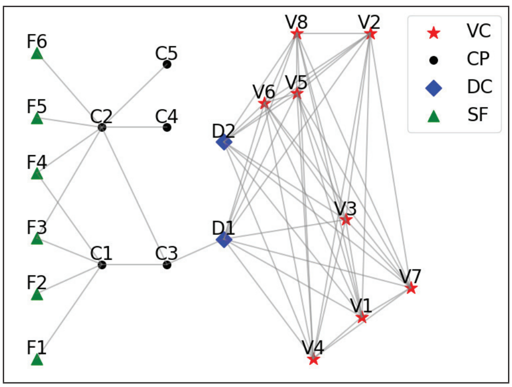

Fig. 3. Example of the problem in a graph form for the second case.

connecting F1 to D2 in Figure 2, the index of this pair will not be included in the model. This is very useful for reducing the solver's computation time.

We used Gurobi Optimizer version 11.0.3, running on an Intel® Core™ i5 CPU @ 1.80GHz, with Python as the programming language. The data is represented in two different cases. In the first case, as seen in Fig. 2, and the other in Fig. 3. The purpose of these two cases is to observe the behavior of the model. The intended behavior is that the model does not generate solutions with non-existent paths.

The solutions for both cases are shown in Figs. 4 and 5. Based on the objective function, the first case outperforms the second due to the presence

Algorithm 1 Feasible path generation

```
Extract all 𝓕 and 𝓓 pairs.
procedure FINDPATHS(data, origin, destination, path)
    Initialize path to empty if not provided.
    if origin == destination then
        return [path + [origin]]
    end if
    if origin is not in data then
        return empty list.
    end if
    for all neighbor in data[origin] do
        if neighbor ∉ path then
            Recursively call FINDPATHS and collect new paths.
        end if
    end for
end procedure
Output: Set of paths
```

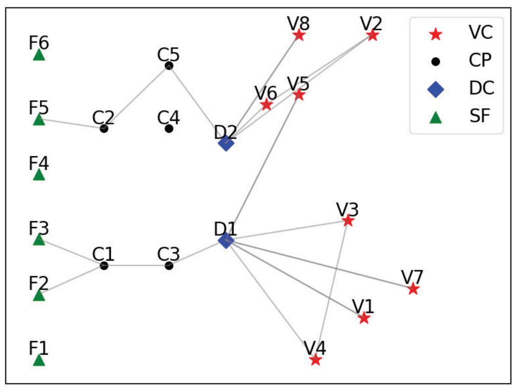

Fig. 4. Solution of the first case.

of two DCs serving all VCs. However, the effectiveness of the restoration in stage I significantly influences the performance of the system under study, i.e., the transportation problem and the location routing problem.

We also conducted an analysis of the performance changes with respect to the increase in restoration time in a single period. We carried out this analysis to streamline decision-making regarding the timing of planning, taking into account the restoration time for each period. This performance indicates the resilience level of the system under study against changes in restoration time for each period. In this example, given the $z^{(\tau)} \in \mathcal{Z}$ where $\tau \in \mathcal{T}$ and $j \in \{15, 30, 45\}$ as scenarios of restoration time. The objective function at each scenario is maximizing the performance ($\mathcal{R}$) defined in Eq. 27.

The results can be seen in Fig. 6 and Fig. 7. Fig. 6 shows the resilience level against changes in restoration time (each tick of the axis represents 22.5 mins). Each period indicates improvements on the damaged road sections. The faster the restoration, the better, but it will require sufficient resources, such as a larger number of crews for faster restoration. This resilience level allows for accurate decision-making based on the available resources. In addition, we can see Fig. 7 to evaluate the results. Both figures point to $\tau = 6$ for being the best period to distribute the relief goods. However, the decision-maker should consider the effect of the period chosen based on these two indicators.

$$\mathcal{R} = \frac{\text{Max}(\mathcal{Z}) - z^{(\tau)}}{\text{Max}(\mathcal{Z}) - \text{Min}(\mathcal{Z})} \tag{27}$$

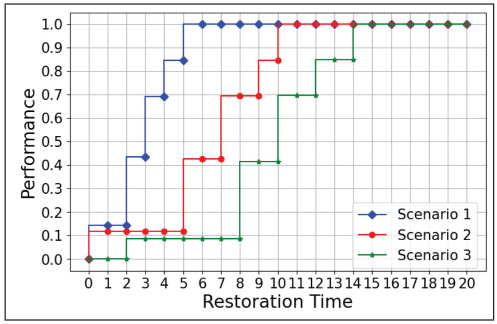

Fig. 6. Performance curve towards restoration time in period τ.

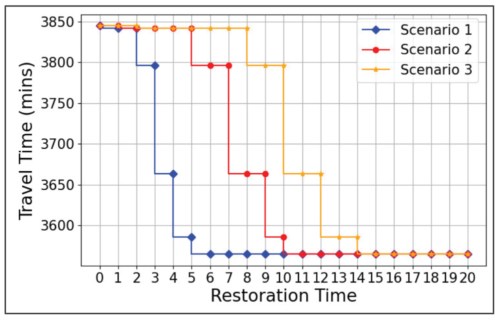

Fig. 7. Travel time changed based on the chosen restoration time in period τ.

5. Conclusion and Future Works

This study examines a combination of shortest path, transportation, and UAV routing problems. Typically, the delivery costs from warehouses to distribution centers are predetermined. This paper, however, considers the impact of infrastructure damage, specifically the condition of roads used by trucks traveling from warehouses to distribution centers. Due to the impracticality of ground routes for land fleets, delivery to affected communities is conducted using multiple UAVs. The condition of infrastructure necessitates policies that limit road capacity during specific periods. Throughout the restoration phase, the restricted capacity will incrementally increase until the restoration process is complete and the performance of the system reaches 100%.

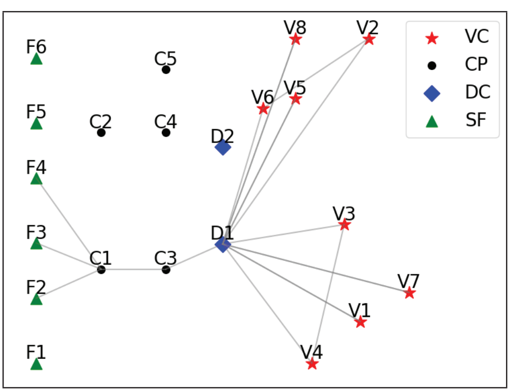

Fig. 5. Solution of the second case.

Future work presents an intriguing area of exploration. In this model, we decompose the problem into two sub-models. However, calculating the optimal s_h^* first can potentially result in an overall near-optimal solution to the larger scale problem. Hence, the challenge lies in integrating these sub-models into a single model. This integration also enhances the flexibility for incorporating additional parameters, such as the use of vehicles in finding the shortest path, avoiding the damaged road while delivering relief goods, and simultaneous problem solving with stage II. Additionally, this problem is NP-hard, particularly in stage II, necessitating the development of algorithms capable of solving the problem within a reasonable computation time.

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