Integrated and Coordinated Relief Logistics and Road Recovery Planning Problem

Vahid Akbari[a], Hamid R. Sayarshad[b,*]

[a]Nottingham University Business School, University of Nottingham, Jubilee Campus, Nottingham, NG8 1BB, United Kingdom
[b]School of Civil and Environmental Engineering, Cornell University, Ithaca, NY, 14853, USA

Abstract

Sudden onset disasters can block roads and hinder relief logistics. With the objective of facilitating access to critical locations in the disaster-stricken area, we propose a new mathematical model that determines the schedule and routes of a relief distribution team and a road restoration team. The road restoration team restores some of the blocked roads to provide faster access to critical nodes for the relief distribution team. We study the case in which the restoration times are stochastic, and our goal is to minimize the time by which the last demand node is met by the relief distribution team. We provide a detailed case study of our model with real data from Harris County in Texas, which was impacted by Hurricane Harvey during 2017. The results obtained from testing our model show that the objective function is decreased by up to 15% using the proposed non-myopic policy.

Keywords: Markov decision process (MDP), humanitarian logistics, road restoration, relief distribution, disaster response, restoration equipment positioning

1. Introduction

During the last two decades, the world has observed an ever increasing number of manmade and natural disasters (CRED & UNDRR 2020). The period 2000 to 2019 alone saw 7,348 disasters, which affected approximately 4.2 billion people and caused a global economic loss of nearly 2.97 trillion dollars. A commonly observed complication after a disaster is blockage of road segments by uprooted plantations, dislocated cars, twisted road signs and fallen lamp posts (Shiri & Salman 2020). After a disaster, regaining the accessibility of the road network is a crucial element in providing public and personal transport between home, school and work places which helps in keeping the economy safe Helderop & Grubesic (2019). Furthermore, such blockages can also hinder access to critical locations such as hospitals, medical centers, emergency assembly points, sources of relief aid, shelters and sites with casualties.

*Corresponding author
Email addresses: vahid.akbari@nottingham.ac.uk (Vahid Akbari), hs628@cornell.edu (Hamid R. Sayarshad)

One example of such a disaster was Hurricane Harvey, which hit Harris County, Texas, in August-September 2017 and massively disrupted the transportation network. Connections between vital elements of the infrastructure such as hospitals, power plants, water treatment plants, oil refineries and communication facilities were affected. Over 1 million cubic yards of debris and garbage had to be hauled by crews after the storm (approximately 26,000 truckloads). Texas ranked fourth in 2017 in America's Top States for Business; it provides nearly 8 percent of U.S. economic output, with a GDP of $1.5 trillion dollars, and much of this output came from oil refineries. Fifteen refineries were shut down due to major damage from Hurricane Harvey (Cohn 2017). These impacts of the storm on the energy infrastructure caused a reduction of economic growth, loss of jobs, and drove up gasoline prices. Likewise, power plants were largely disrupted by flooding or rain which affected generator fuel supplies and caused transmission outages leaving more than a quarter of a million consumers without power in Texas. As a result of Hurricane Harvey, two nuclear plants near Houston were entirely shut down, although 175 workers remained on-site during the storm (World-Nuclear-News 2017). Emergency crews were not able to reach to the generating and transmission facilities because of the lack of transport connectivity. Hence, the road clearance team has to act towards connectivity of the road network in providing access to some infrastructure facilities for people and emergency crews, given the limited-service time of clearance team and road clearance equipment. Figure 1 shows infrastructure facilities and the road network in Harris County.

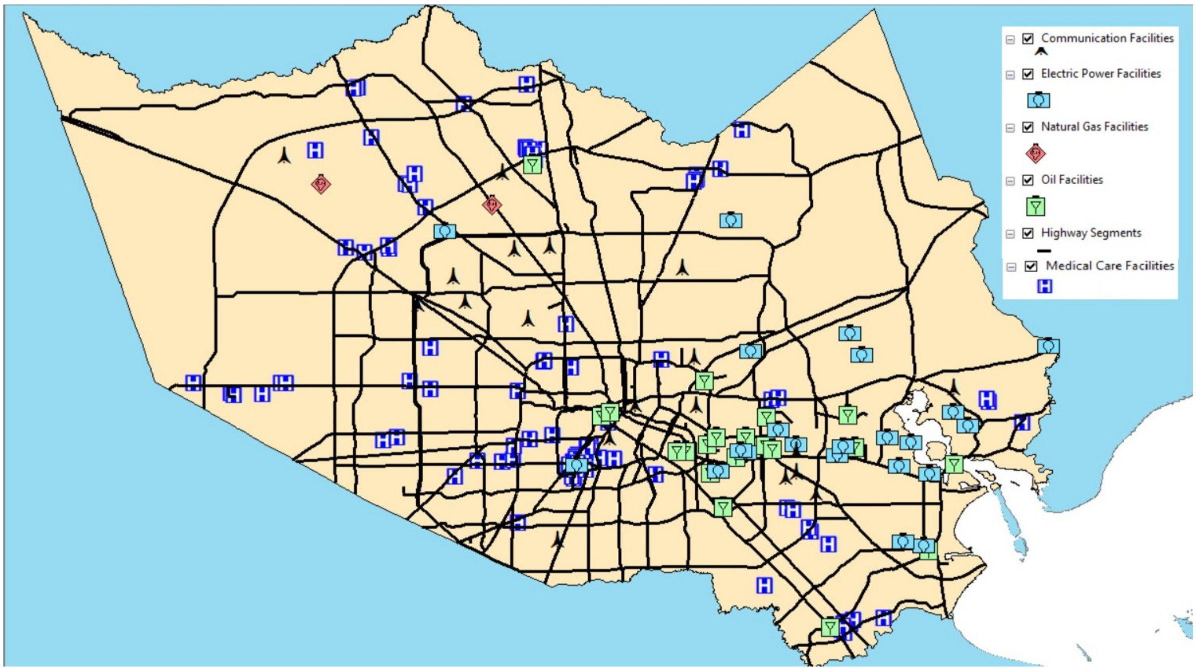

Figure 1: The transportation network and infrastructure facilities in Harris County (via ArcGIS)

Road network connectivity, accessibility and restoration in a post-disaster setting is one of the most prominent elements of disaster management and has been addressed and investigated in the literature extensively (Golla *et al.* 2020). Many of such studies had a particular focus on a case study and implemented their proposed models on real-life disaster scenarios. Tuzun Aksu & Ozdamar (2014) used real-life data sets from two districts of Istanbul, Turkey, to verify the performance of their model, in which, accessibility is maximized to restore survivor evacuation routes. Caunhye *et al.* (2020) used the real-life data sets from 2015 Gorkha earthquake that occurred in 76km northwest of the capital Kathmandu to test their robust route restoration model. In another study that used real-life data sets for implementation of their road restoration model, Coco *et al.* (2020) addressed the problem of restoring a set of disruptions in an urban road network while ensuring the connectivity of the network. They developed a multi-objective model and used the road network map of Troyes city in France to show the performance of their model. The data set of the 2010 earthquake in Port-au-Prince city in Haïti was used in Barbalho *et al.* (2021) to address a road restoration crew scheduling problem within multiple periods. Finally, Cartes *et al.* (2021) used the data set of a post-disaster road network from south of Chile to verify the performance of their approach for road network resilience recovery through restoration of blocked roads.

The main goal of the present study is to find the optimal routes for a relief distribution team and a road restoration team, and to schedule their operations such that the relief distribution team visits all the critical nodes and supplies them with relief items such as hygiene kits and water, blankets, while minimizing the time by which the last critical or demand node is supplied. The road restoration team carries the required tools and machinery to restore some of the blocked arcs with the aim of providing faster access to the critical nodes for the relief team. We use the terms unblocking, clearing, opening and restoring interchangeably to indicate the repairing of a blocked arc by the road restoration team. Restoration of a blocked arc requires the use of a certain amount of equipment and the road restoration team cannot use more equipment than is available. The road restoration equipment can include road repair machines, crawler excavators, bulldozers, road rollers, motor graders, drainage pump vehicles, lighting vehicles, wheel loader and satellite communication vehicles; these all require operators and other personnel, as well as their safety equipment such as hard hats, safety glasses/face shield, hearing protection, heavy work gloves and cut-resistant legwear (chain saw chaps). In our model and problem description, an equipment is considered to be the complete package of restoration items and their corresponding operators. We address these packages of restoration facilities and their operators as an equipment.

Simultaneous consideration of relief distribution and road restoration is crucial in the immediate post-disaster phase. In the sensitive time immediately after a disaster, victims seek for help in shelter locations and emergency assembly points. However, if these points are not equipped with necessary relief items, the stress level among the victims rises which in turn aggravates the situation. Moreover, some of the critical nodes might not be accessible from the rest of the road network and only the road restoration team can reconnect them to other nodes as the relief distribution team does not carry the machinery required to restore a blocked arc. To mitigate these issues and to trigger the relief logistic operations as soon as possible, distribution of relief items should start before time is wasted for restoration of the entire road network. As a result of this, since some of the road segments are blocked and hamper accessibility to critical locations, relief distribution and road restoration teams should start their operations simultaneously. While the relief distribution team delivers relief items to some of the critical locations, the road restoration team unblocks some of the road segments to provide access or faster access to rest of the critical nodes.

Another factor to consider in the formulation is that the blocked arcs are traversable by the relief distribution team only after they have been completely unblocked by the road restoration team. The calculation of this timing of restoration significantly complicates the problem. Since this coordination issue needs to be accounted for in planning the schedules of the relief distribution and road restoration teams, we refer to it as the *Coordinated Simultaneous Road Restoration and Relief Distribution Planning Problem with Stochastic Unblocking Times* (CSRRRDPP).

In this paper, a post-disaster problem in which the coordination of road restoration and relief distribution teams under stochastic blockage times is studied. We have developed a mathematical model that is capable of solving real-life instances. Our principal contributions are fourfold:

1. We propose a novel optimization formulation for the problem of identifying a coordinated simultaneous road restoration and relief distribution plan, with the goal of minimizing the time by when the last critical node is visited by the relief distribution team. We consider the simultaneous road restoration and relief distribution activities, and our model dynamically adds the newly unblocked arcs to the network. Only after a blocked arc is fully restored, it can be utilized by the relief distribution team. In our model, while the relief distribution team distributes relief items to the critical locations, the road restoration team recovers some of the blocked road segments to provide faster access to the critical nodes. The model is provided in such a way that a blocked road segment is not used by the relief distribution team unless it is fully recovered first. Without the coordination considerations, due to blockage at some of the roads, certain critical locations might not be accessible hindering delivery of relief items to them. In this case, if the coordination is not considered, and for example, first the road restoration and then the relief distribution plans are implemented, the delivery of relief items will be delayed significantly which can cause unrecoverable problems such as loss of life.

2. We investigate a dynamic assignment of restoration equipment problem with queuing which approxi-

mates delay from spatial coverage where future states need to be considered. We experimentally prove that the incorporation of dynamic assignment of restoration equipment using our non-myopic model can improve the objective function compared with myopic models. In addition, we develop a novel stochastic model that prioritizes blocked arcs. Our proposed approach can increase the social utility of restoration by connecting people to public facilities such as hospitals.

3. We introduce a reliability strategy for positioning of the restoration equipment items to support restoration team through roadway restoration that anticipates equipment requests in order to satisfy new requirements for each blocked arc. This suggests a more efficient use of the available resources. The strategy has significant practical importance due to the cost and complicated nature of road restoration operations.

4. We conduct our computational study on real data generated from Harris County after it was hit by Hurricane Harvey. We observe that simultaneous cooperation between the relief distribution and road restoration teams can decrease the objective function significantly. Furthermore, we also observe that if the road restoration team is not present, some of the nodes remain entirely inaccessible to the relief distribution team.

The rest of the paper is arranged as follows. In Section 2, we provide a detailed overview of the related literature. In Section 3, we provide the problem description together with an illustrative example. In Section 4, we give the mathematical model that we have developed to solve this problem. In Section 5, we report the information regarding the used data and the case study. We also provide the results of testing our model in this section. Finally, we present the concluding remarks in Section 6.

2. Literature review

This study focuses on the integration of relief distribution and road restoration. We consider inter-related and simultaneous routing problems in which the opening of blocked arcs by the road restoration team can affect the routes of the relief distribution team, and so the network needs to be dynamically updated. The objective of our problem is to find coordinated schedules for the relief distribution and road restoration teams such that a blocked arc is not traversed by the relief distribution team unless it has been opened by the road restoration team, while minimizing the overall tour length of the relief distribution team. We furthermore consider stochastic blockage times to model the time that is required for the road restoration team to open a blocked arc.

Several studies estimate the queue delay in the facility location problem for the allocation of resources between nodes using queuing systems. For instance, Marianov & Serra (2002) proposed a linear queuing delay constraint based on a multi-server queuing system to assign servers between nodes that minimizes that total cost. Sayarshad & Chow (2017) extended a p-median problem under look-ahead based on an multi-server queuing system ($M/M/s$) for the dynamic positioning of idle vehicles. They converted a nonlinear delay constraint into a linear queuing delay constraint. We similarly consider a linear queuing delay constraint to assign the restoration equipment to the blocked arcs. Berman & Drezner (2007) minimized the total travel cost and waiting cost based on a multi-server queuing system ($M/G/s$) for assigning the set of servers.

The remainder of this literature review is divided into three sections: in Section 2.1, we cover the literature on the distribution of relief after a disaster; in Section 2.2, we cover the literature on road restoration; and in Section 2.3, we address the studies that integrate road restoration and relief distribution.

2.1. Relief distribution

Ozdamar *et al.* (2004) presented a multi-commodity mathematical model for emergency disaster response that provides the routes for the relief distribution vehicles by considering the dynamic time-dependent transportation problem. Tzeng *et al.* (2007) developed a model with three objectives to design an optimal relief delivery system. The objectives are to maximize the minimum satisfaction rate while minimizing total cost and travel times within the planning horizon. Najafi *et al.* (2013) used a multi-objective stochastic model to provide robust decision planning in response to an earthquake. The first objective was to serve the survivors, the second was to ship the relief supplies, and the third was to minimize the number of vehicles used for relief distribution. They also considered multiple periods and multiple commodities, and the numbers of casualties in different categories are assumed to be uncertain.

Liu *et al.* (2019) also developed a multi-commodity model over a multiple period planning horizon which considers not only the relief logistics but also providing medical assistance for casualties while minimizing the weighted demand that has not been met throughout the planning horizon. Their model considered the required real-time adjustments to the existing distribution plans when deviations between the predicted and actual plans occur. They tested their models on data from the Great Wenchuan Earthquake that occurred in 2008 in China. More recently, Abazari *et al.* (2021) addressed the design of a relief distribution supply chain by considering pre-positioning of relief items as well as their redistribution. They developed a grasshopper algorithm to solve larger instances of the two-staged stochastic optimization model. They have also provided a case study from Tehran, Iran.

A number of studies address relief distribution while highlighting the importance of the damaged edges of a road network. In these studies, the blocked edges cannot be repaired have to be avoided in the process of relief distribution. Using a two-stage stochastic model, Rawls & Turnquist (2010) provided a placement strategy for the pre-positioning of relief items. They developed a Lagrangian L-shaped method that is able to tackle larger problems. They tested their models on a hurricane threat on the Gulf Coast area of the US. In order to address the distribution of relief items from warehouses to disaster-affected areas, Moreno *et al.* (2018) proposed a model to optimize location, transportation, and fleet sizing decisions. Their two-stage stochastic model incorporated uncertainties regarding the existence of routes, availability of supplies and the demand. They also developed matheuristic algorithms to solve their problem and they tested their model and algorithm on floods and landslides in the Serrana Region of Rio de Janeiro in 2011. In another study that used stochastic optimization, Hu *et al.* (2019) developed a multi-stage stochastic model of relief delivery by incorporating multiple types of vehicles while also considering the status of the road network. For larger problems, they developed a progressive hedging algorithm (PHA) and tested their model and algorithm on the Yaan earthquake in China. Under an online optimization framework, with a total latency minimization objective, Akbari & Shiri (2021) studied a relief distribution problems in which it is not known which roads are blocked. The blockage of the roads is revealed only when the relief distribution crew observe the blocked edges; once they are observed, the crew needs to find an alternative route to bypass them as they do not have the ability to restore them. Akbari & Shiri (2022) extended this problem and studied the case with multiple relief distribution crews and different levels of communication among them.

In another vein of studies, Wang *et al.* (2014) proposed a location-routing model for optimized relief distribution after a disaster. They studied a problem with three objectives of maximizing the reliability of relief distribution while minimizing total cost and travel time. They used both a non-dominating sorting genetic algorithm-II (NSGA-II) and a strength Pareto evolution algorithm (SPEA) to solve this multiple-objective problem. Pérez-Rodríguez & Holguín-Veras (2016) developed a heuristic inventory-allocation routing algorithm to maximize the benefits derived from the distribution of critical supplies to populations in need after a disaster. In that study, the optimal assignment of critical supplies that minimizes social costs was investigated and the authors used numerical experiments to verify the performance of their heuristic algorithm. Wei *et al.* (2020) incorporated time windows in a location-routing problem in emergency logistics. The objective in this study was to satisfy demand in affected areas in the shortest possible time while minimizing costs. A hybrid ant colony optimization (ACO) method was applied to solve this model. Our problem is different from all of the ones stated above, as none of them consider road restoration.

2.2. *Road restoration*

In the studies that examine road restoration operations, typically a main difference is whether they consider partial restoration or full restoration. Another important difference is whether they consider a single or multiple work crews for the restoration operations.

Some studies decompose damaged network into isolated components, and different goals are investigated, such as restoring the connectivity of the network is investigated. Among the studies that consider partial restoration, Kasaei & Salman (2016) studied two problems in which the authors addressed the optimization of a road clearance crew that reconnects elements of the road network. The objective function of the first problem is to schedule the route of the road restoration team to minimize the time it takes till all the formed disjoint components are reconnected again and accessibility among all the nodes within the network is guaranteed. The objective function of the second problem is to maximize the weighted prize of reconnecting disjoint components of the road network within a pre-specified time frame. In this variation, a prize is allocated to each of the disjoint components based on the population and importance of that component. In order to solve these problems, two mathematical models together with metaheuristic procedures was proposed in this study. Vodák *et al.* (2018) proposed an ACO algorithm to address the first problem introduced in Kasaei & Salman (2016) and explored a heuristic approach by considering nodes that are located in the boundaries of each disjoint component to reduce the size of the networks. The problems studied in Kasaei & Salman (2016) were generalized to the case with multiple work teams in two later studies. Akbari & Salman (2017b) studied the generalized version of the first problem introduced in Kasaei & Salman (2016) and investigated the case with multiple road restoration crews. The authors developed a mathematical model and proposed a matheuristic that is able to solve larger problems. This matheuristic is followed by a feasibility algorithm to ensure that the coordination between the road restoration teams is achieved. To address the multi-crew version of the second problem studied in Kasaei & Salman (2016), Akbari & Salman (2017a) proposed a mathematical model as well as a Lagrangian relaxation procedure as an efficient solution procedure. In another study that considered isolated components and multiple work teams, Morshedlou *et al.* (2018) developed two models that can consider the coordinated routing problem to schedule the routes of the road restoration teams. Moreover, to provide further flexibility, the number of road restoration teams designated for each disrupted component is set as a variable in their model. Morshedlou *et al.* (2021) proposed a heuristic method to solve this problem and the authors tested their models and algorithms on instances generated from the infrastructure network of the Shelby County in Tennessee, USA. More recently, Akbari *et al.* (2021a) studied the problem introduced in Akbari & Salman (2017b) and proposed a decomposition-based procedure that is able to solve problems with more edges and nodes. Souza Almeida *et al.* (2022) also studied the problem introduced in Akbari & Salman (2017a) and proposed a Greedy Randomized Adaptive Search Procedure (GRASP) metaheuristic that is more time-efficient over larger instances.

A number of the articles within this domain consider that exact clearance information is not obtained and only stochastic information of the restoration times of the damaged roads is available. Çelik *et al.* (2015) introduced a stochastic model to address a road clearance problem within multiple periods. Their model, dynamically captures the post-disaster status while considering incomplete information about the required time for road clearance operations. These information will be updated once more information is collected as the clearance operations proceeds. For each period, the proposed solution finds the blocked roads and the order in which they should be cleared. In this study, a Markov decision process (MDP) together with heuristic algorithms are developed and tested on both real-life and randomly generated data sets. Sayarshad *et al.* (2020) proposed a dynamic non-myopic debris clearance problem that incorporates re-positioning of equipment in a post-disaster stochastic environment to make connection between supply and demand nodes. Sanci & Daskin (2019) is another study that developed a two-stage stochastic model to integrate the pre-positioning of restoration equipment prior to a disaster and the network restoration operations after the disaster. To solve this model, the authors used a sample average approximation method. In a more recent study, Sanci & Daskin (2021) developed an integer L-shaped algorithm to solve the problem introduced in Sanci & Daskin (2019). This algorithm is an exact approach based on a branch-and-cut procedure. Different from these studies that used stochastic optimization to capture the uncertainties of road clearing times, Akbari *et al.* (2021b) used online optimization to solve the road network connectivity problem. In their study, the required time to clear a blocked road is not known a priori. Access to this information can only be granted once the blocked road segment is visited by the road restoration team and the amount of debris on it is assessed and measured by them. The authors developed a heuristic algorithm and a observe and re-optimize (OREO) procedure to tackle this problem. The heuristic algorithm was able to produce high quality solutions in a significantly shorter time compared to the OREO procedure.

2.3. Integrated relief distribution and road restoration

Some of the studies that simultaneously consider relief distribution and road restoration assume that a single work crew is responsible for both of these operations. For instance, Ajam *et al.* (2019) considered a single-crew problem in which the objective was to minimize the total time required to visit the relief nodes. In their problem, work crews were capable of both relief distribution and road restoration and the road unblocking times were deterministic. Ajam *et al.* (2022) extended this problem and studied the case with multiple teams in which each of the teams is responsible for both road restoration and relief distribution.

In some other studies, the road restoration and relief distribution are done by different teams. Yan & Shih (2009) separately considered two time–space networks for the relief distribution and the road restoration teams. Similar to our study, a blocked road could be traversed by the relief distribution team only if the road has been opened by the road restoration team. However, unlike in our problem, the clearance times were deterministic and equipment limitations in road restoration were neglected.

In another vein of studies, a node located in the middle of the corresponding edge represents damaged road links and therefore, in their models, repairing a node is equivalent to repairing an edge. In one of the first studies with this perspective, Duque *et al.* (2016) developed an exact dynamic programming (DP) algorithm, which is able to provide the schedule and route of a repair crew for small-scale instances. The authors also developed an iterated greedy randomized constructive procedure to solve large-scale instances. The objective was to minimize the total time for demand nodes to become accessible from the depot. In their problem, a demand node i is called accessible, if there exists a path, containing only intact and repaired nodes, that connects the depot to demand node i with a maximum length of D_i. Moreno *et al.* (2019) studied the same crew scheduling and routing problem (CSRP) that was introduced in Duque *et al.* (2016) and proposed a branch-and-benders-cut (BBC) algorithm to solve the CSRP. Later, Moreno *et al.* (2020a) extended their study on the CSRP and studied two new decomposition-based metaheuristics to solve this single-crew scheduling and routing problem. Using a new hybrid BBC algorithm, they were able to improve their solutions and find the optimal solutions for some of the benchmark cases. Moreno *et al.* (2020b) went on to address a heterogeneous multicrew scheduling and routing problem, with the objective of restoring damaged nodes that are located on the paths the connect a source node to the demand nodes. These paths were endogenous decisions of the problem and thus they were integrated into the restoration of the damaged nodes. The goal was to minimize the time for which the demand nodes remained disconnected from the source node. To address this problem, the authors developed three mathematical models and a number of valid inequalities incorporating the dominance of the paths between nodes in the damaged network.

Shin *et al.* (2019) considered simultaneous relief distribution and road recovery planning with two teams. They proposed a MILP model that finds the routes and schedules of these two teams to repair the damaged roads by the road restoration team and distribute the relief supplies to the demand nodes by the relief distribution team. They also proposed an ACO to provide solutions in shorter computational times. Different from our study, they proposed a static optimization model with no look-ahead and did not consider the availability of repair equipment. Their mathematical model was able to solve instances with up to 13 nodes. Briskorn *et al.* (2020) is another article that studied integration of relief distribution and road restoration under a multi-period setting in which there are strict deadlines for fulfilling the demands at each demand node. The goal of their problem is to minimize the time spent on road restoration while determining the blocked edges that need to be recovered and the amount of relief items that should to be delivered from each supply node to each demand node. Unlike Briskorn *et al.* (2020), we consider stochastic unblocking times and the objective function of our problem is minimization of the time by which the last demand node is met.

García-Alviz *et al.* (2021) addresses a post-disaster problem in which road restoration and relief distribution operations are considered simultaneously. Certain locations referred as Points of Interests (PIs) are pre-selected for relief distribution and the goal is to satisfy their demand. Furthermore, some blocked roads exist that are not traversable by relief delivery vehicles unless they are opened by road restoration teams. Different types of road blockage is considered and the fleet of road restoration vehicles are considered to be heterogeneous in the sense that they can only restore certain types of blockage. The authors provide a categorization of the literature, a MIP model to address this problem and an Ant Colony Optimization + Greedy Randomized Adaptive Search Procedure (ACO-GRASP) to solve this problem. Moreover, they present a case study of the problem. Different from our study in which the unblocking times are not known, they have a deterministic setting in which a non-linear mathematical model to address this myopic restoration and relief distribution is developed. The load in the points of interest is another different aspect of their problem. Given the defined demand values in their problem, each PI should be visited multiple times to satisfy its demand. In other words, each time a relief distribution vehicle, leaves the depot, it goes to one of the PIs and then comes back to the depot for loading and a new delivery. This will simplify the routing aspects of their problem which is another major difference of their study compared to ours.

In some of the studies that consider road recovery and relief distributions simultaneously, other operational challenges in form of their objective function have been considered. For instance, Li & Teo (2019) developed a bi-level mathematical model for post-earthquake network repair problem wherein the repair crew assignment and routing decisions are made in the upper level, while fairness of the relief allocation and finding shortest path to have quick response are the two other objectives for the decision makers of the lower level. Li *et al.* (2020) is another article that combines the Logistics Support Scheduling (LSS) and Repair Crew Scheduling and Routing Problem (RCSRP) and calls it LSS-RCSRP. In this study, a non-linear model and a heuristic algorithm is given to deal with this problem. The model is tested on VRP instances as well as a case study for an earthquake in Wenchuan. Different from our study in which the problem has a non-myopic setting, this article develops a multi-period bi-level programming model in under a myopic setting and with known unblocking times. Moreover, different from our study, in both Li & Teo (2019) and Li *et al.* (2020), the blockage is modeled on the nodes and the objective is to maximize the cumulative utility of repair.

There are other studies within the general domain of road restoration and relief distribution that have some major differences with our study. For example, Vahdani *et al.* (2018) developed an integer nonlinear multi-objective, multi-period, and multi-commodity model to locate the distribution centers for timely distribution of vital relief to the damaged areas, vehicles routing and emergency roadway repair operations. Different from our study in which the activities of the road restoration and relief distribution teams will impact on each other, in this study, they assume that the route for all transportation vehicles is already open. Moreover, their problem has a myopic nature which is another difference between this study and ours. There are some studies that address failure of road networks and recovery plannings to improve post-disaster relief distribution without considering the routing decisions for the road restoration and relief distribution teams. For example, Wisetjindawat *et al.* (2015) considers relocation of hubs that might reduce the total response time by incorporating the possibility that some links will be destroyed. They suggest strategies for preparation of resources and identify vulnerable destinations that are most likely to be cut off by the disaster. They provided their analysis base don the case study of Aichi Prefecture, Japan.

There are also a number of other studies that combine road restoration operations with activities other than relief distribution. For instance, Nabavi *et al.* (2021) studied the integrated victim evacuation and debris removal problem. A few studies in the existing literature integrate the road restoration problem and the traffic assignment problem to find the user equilibrium in the road network after a disaster. For instance, Gokalp *et al.* (2021) studied a dynamic programming based on Bellman equation that minimizes total travel time when the restoration team are repairing the roads. Li *et al.* (2019) applied the traffic assignment problem to find an optimal traffic evacuation strategy that provides a coordinated vehicle routing guidance for evacuees. Sohouenou *et al.* (2021) considered the correlation of link-failure in the road network after a disaster where the link combinations which have the highest impact on the total travel time is predicted. Zamanifar & Hartmann (2021) suggested six actions of decision makers after a disaster in the road network that improves the traffic evacuation strategy. These studies are clearly different from ours as we integrate the road restoration and relief logistics operations.

3. Problem description and illustrative example

In this paper, we consider the problem of planning simultaneous road restoration and relief distribution in the immediate response to a disaster. We render the road network of the impacted region by a directed and strongly connected graph denoted by $G = (V, A)$, where V gives the nodes set and A shows the set of all the arcs present before the incident. The strong connectivity of a connected graph means that there is a path in each direction between each pair of nodes. This assumption clearly holds for an intact road network. For each arc $(i, j) \in A$ there is a time allocated to travelling from node i to node j denoted by c_{ij}. Furthermore, a subset of the nodes denoted by $C \subset V$ gives the set of critical nodes. These critical nodes are often referred to as demand or relief nodes in other studies. These critical nodes are pre-identified; an example might be a school where casualties can receive aid. In our model, the relief distribution team's traversal time for the arcs ending at critical nodes is in fact the travel time plus the time taken to satisfy the demand at that node.

After the road network is damaged by a disaster, a subset of the arcs, $B \subset A$, will be blocked, which in turn impedes access to critical nodes. The undamaged arcs and the nodes form the graph $G_B = (V, A \setminus B)$. We can extract the blocked arcs perhaps from the use of helicopters, drones, open street maps, traffic or surveillance cameras and satellite images. As a result, we assume that the set B is given as an input of our problem. A road restoration team and a relief distribution team are initially placed in a depot node, denoted by $D \in V$; they are immediately dispatched once the information on the location of the blocked arcs is provided. While several works assume that the unblocking time for all the blocked links are known in advance, we assume that this information has a probabilistic nature.

The restoration time of a blocked arc depends on the amount of equipment assigned to it; it is expressed as a fraction, b_{ij}, of the traversal time. Thus, travelling and recovering a blocked arc $(i, j) \in B$ for a road restoration team takes $c_{ij} + b_{ij}c_{ij}$ units of time. While we refer to the damaged/impacted arcs as blocked arcs, they can also represent arcs with minor accumulation of debris. This could be represented by a smaller b_{ij} value compared with those blocked arcs for which the blockage is considerable and the b_{ij} values are hence much larger. We note that b_{ij} should be defined as a set of decision variables and its value decreases if more equipment is assigned for restoration of (i, j). However, a finite amount of equipment, Φ, is available for restoration. Moreover, the maximum allocation of equipment to arc $(i, j) \in B$ is given by S_{ij}. A blocked arc (i, j) is only traverasble for the relief distribution team after it is fully unblocked by the road restoration crew. For each blocked arc $(i, j) \in B$, the amount of restoration equipment requested is denoted by λ_{ij} and this is calculated using a Poisson process. The required service rate for each blocked arc, $(i, j) \in B$, is shown by μ_{ij} and is assumed to be independent and exponentially distributed.

In the following, we give an example of the CSRRRDPP to illustrate its properties and to give a visualization of inter-connectivity of the road restoration and relief distribution teams and how the road restoration team can facilitate access to critical nodes by the relief distribution team by unblocking some of the arcs.

Figure 2 illustrates an instance of the CSRRRDPP. The intact arcs are shown by solid grey lines and the blocked links by dotted black lines. Both the road restoration and the relief distribution teams are initially located in the depot node (1). The critical nodes nodes (2-6) are shown as pentagons. The rest of the nodes are the non-critical nodes (i.e. not depots but junctions for example). A very important observation in here is that we cannot reduce the problem to only critical nodes and form a complete graph. This is because the shortest paths length can change once some of the blocked arcs are restored. The problem is to extract the routes of the relief distribution and road restoration teams to minimize the time by which the last critical node is visited. The road restoration team needs to unblock the blocked arcs in the order that gives the relief distribution team the fastest access to the critical nodes.

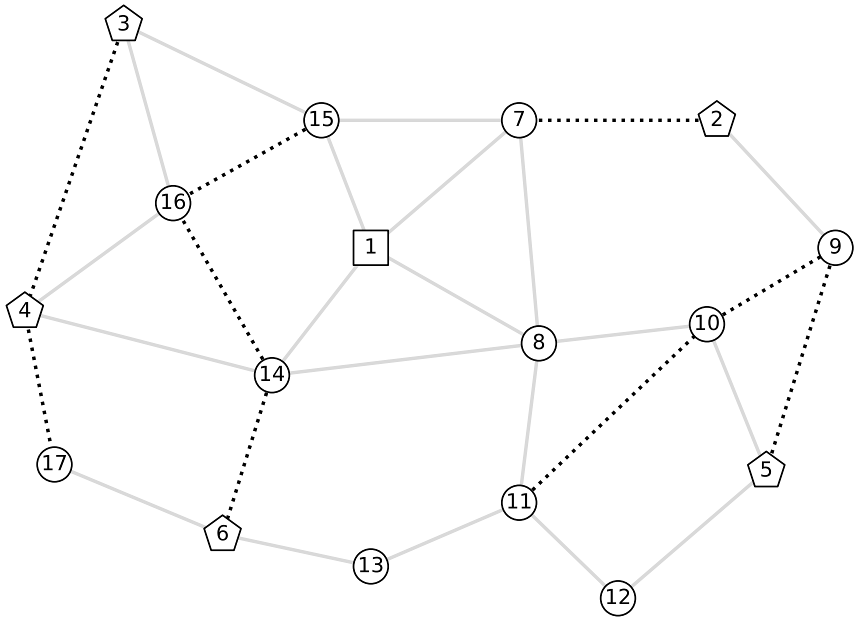

Figure 2: An instance of the CSRRRDPP

The traversal times for all the arcs in Figure 2 are given in Table 1. We assume that the directed graph we have defined has symmetric distances and for each blocked arc (i, j), arc (j, i) is also blocked, hence we give the blockage and traversal times in only one direction. For instance, the time required for the road restoration or the relief distribution team to traverse arc (1, 7) or (7, 1) is 25 units. The λ_{ij} and μ_{ij} values for the blocked arc $(i, j) \in B$ are also given in Table 1. These values are likewise assumed to be the same in either directions. The blocked arcs cannot be traversed by relief distribution teams until after they have been restored. For example, the relief distribution team cannot traverse arc (3, 4) until it is opened by the road restoration team. Once the road restoration team is on node 3, it takes $c_{34} + b_{34}c_{34}$ units of time to restore arc (3, 4) and then it will be possible for the relief distribution team to traverse it. Furthermore, b_{34} is dependent on the amount of unblocking equipment assigned to opening arc (3,4).

It can be observed that the critical node 2 does not have access to the depot node and if we did not have a road restoration team the relief distribution team could not access it. We have solved this instance once by setting the amount of available equipment equal to 1 ($\Phi = 1$) and once by setting it to 3 ($\Phi = 3$). The

Table 1: Information of the sample

Arc	c_{ij}	Arc	c_{ij}	Arc	c_{ij}	Blocked Arc	λ_{ij}	μ_{ij}
(1,7)	25	(4,16)	22.67	(8,10)	17.26	(2,7)	0.21	0.46
(1,8)	22.67	(4,17)	24.19	(8,11)	25.08	(3,4)	1.41	1.24
(1,14)	22.36	(5,9)	35.69	(8,14)	27.46	(4,17)	1.63	0.85
(1,15)	20.62	(5,10)	23.77	(9,10)	17.69	(5,9)	0.07	0.67
(2,7)	20	(5,12)	25	(10,11)	33.84	(6,14)	1.05	0.05
(2,9)	23.32	(6,13)	15.81	(11,12)	18.03	(9,10)	1.38	0.11
(3,4)	46.1	(6,14)	25.5	(11,13)	18.03	(10,11)	0.48	0.42
(3,15)	25	(6,17)	20.25	(14,16)	28.79	(14,16)	0.75	0.67
(3,16)	28.44	(7,8)	35.06	(15,16)	19.85	(15,16)	0.19	0.96
(4,14)	26.93	(7,15)	20					

optimal solution to the CSRRRDPP for this instance for $\Phi = 1$ is given in Figure 3. The route of the relief distribution team is given in red and the route of the road restoration team is given in blue. Both teams start at the depot at time 0. While the relief distribution team first goes to non-critical node 15 and then to critical nodes 3 and 4, (via non-critical node 16), the road restoration team goes first to node 5 (via non-critical nodes 8 and 10). When the road restoration team is at node 5, it opens the blocked arc (5,9). Meanwhile, the relief distribution team returns to node 1 after visiting critical nodes 3 and 4 and then goes to critical node 6 (via nodes 8, 11 and 13). It then goes to critical node 5 (via nodes 13, 11 and 12). At this point, the blocked arc (5,9) has already been opened by the road restoration team and the relief distribution team is able to traverse it to visit the last un-visited critical node, which is node 2. Node 2 is visited at time 363.49 and hence the objective function is 363.49 for this case with $\Phi = 1$.

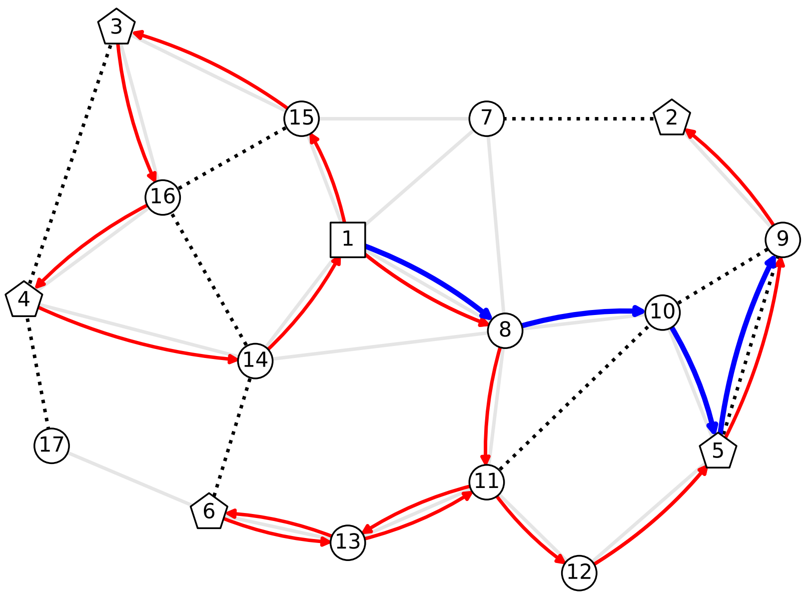

Figure 3: Solution of the given instance in Figure 2 and $\Phi = 1$

We have tested the same instance setting the amount of equipment available to 3 ($\Phi = 3$) (all other parameters are unchanged) and the optimal solution is given in Figure 4. It is expected that the optimal objective function value will decreases as Φ increases. In fact, for the case with $\Phi = 3$, the optimal value of the objective function decreases to 326.90 (more than 10% less than when $\Phi = 1$). As can be observed in Figure 4, the road restoration team opens blocked arcs (7,2) and (9,5). The relief distribution team first visits critical nodes 4 and 3, return to the depot and then visits critical nodes 2, 5 and 6. The relief distribution team opens two arcs, (7, 2) and (9, 5), rather than just one when $\Phi = 1$.

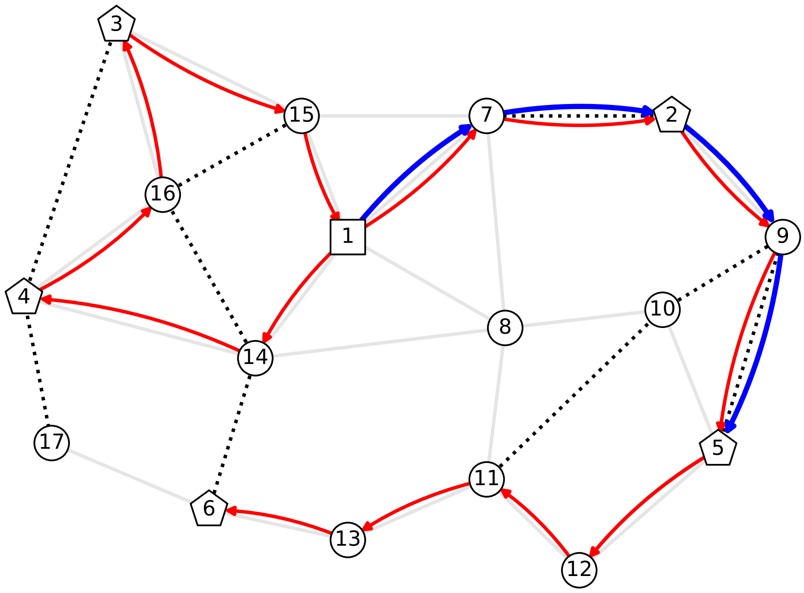

Figure 4: Solution of the given instance in Figure 2 and $\Phi = 3$

4. Mathematical model

Since in the CSRRRDPP the shortest path distances change, the problem cannot be reduced to only consider the demand nodes. Moreover, since a node can be traversed multiple times, we cannot define one index timing variables to denote the progression of time. Furthermore, in some extreme instances, the arcs can also be traversed by the relief distribution team more than once. As a result, we present a model under the assumption that arcs can be traversed only once by the relief distribution team. We refer to this model as Model I which is capable of solving all our intended instances within a reasonable time (1 hour). In Appendix A, we first illustrate an example for which the optimal route of the relief distribution team does not hold this property and an arc is traversed more than once and then give Model II that is able to incorporate this limitation of Model I. However, Model II is only able to solve smaller instances, such as the instance presented in Figure 2, and when the size of the problem increases, it is not able to find the optimal solutions within the intended one hour of CPU run time.

Model I

In this section, we present a mixed-integer mathematical model assuming that the relief distribution team can only traverse each arc once. We call this model as Model I. In Model I, we indicate time of arrival at each node considering the previous and the next nodes to be visited and define t^k_{ijl} as the time at which team k arrives at node j, coming from node i and heading to node l. This enable us to define a binary variable, x^k_{ijl}, to indicate whether team k goes from node i to j and then to l or not. Assuming that each arc can only be traversed once by each of the teams does not trigger any issues on the optimal route of the road restoration team as this is a property of the optimal solution (Proposition 1). However, given this assumption, the optimal route of the relief distribution team might be lost in some extreme examples. In both of the x^k_{ijl} and t^k_{ijl} variable sets, k is set to 1 and 2 for the relief distribution and the road restoration teams, respectively. The traversal time to reach a critical node is the sum of the travel time plus the service time at that critical node.

In the following, we show that, there exists an optimal solution in which arcs will not be traversed more than once by the road restoration team, and so we were able to define x^2_{ijl} as binary variables. We explain this feature in Proposition 1.

Proposition 1. *There exists an optimal solution to the CSRRRDPP in which none of the arcs is traversed more than once by the road restoration team.*

Proof. Christofides *et al.* (1986) proved that this dominance relationship holds for the directed rural postman problem (DRPP). The DRPP is an arc routing problem for which is sought the least-cost traversal of a set of specified arcs in a directed graph. For the road restoration team, once the set of arcs that need to be recovered is identified, the problem reduces to DRPP and hence the dominance relationship holds. □

In order to provide the mathematical formulation of this problem, we add a sink node, $n + 1$, where both the road restoration and the relief distribution teams finish their routes. Furthermore, we add an arc from every node in G to this sink node and set its traversal time equal to 0, i.e., $c_{in+1} = 0, \;\; i \in V$. We denote this set of dummy arcs as DA. We show the union of the arcs as $A' = A \cup DA$. We denote the nodes that have an incoming arc to any node $j \in V$ as δ_j throughout the article, i.e., $\delta_j = \{i : (i, j) \in A'\}$. For any node $j \in V$, we also define the set of nodes that are connected to j through an outgoing arc from it by δ'_j, i.e., $\delta'_j = \{i : (j, i) \in A'\}$. Furthermore, we incorporate the queuing delay constraint that maximizes the availability of restoration equipment for positioning items by anticipating of requests for new items requests in order to relocate items to blocked arcs. In what follows, we first present the table of notations including the sets, parameters and decision variables and then the mathematical model to solve the CSRRRDPP is provided.

Sets and other notations	
$G = (V, A)$	Graph representing the pre-disaster road network.
V	Set of nodes G.
A	Set of arcs in G.
$C \subset V$	Set of critical (demand) nodes.
$B \subset A$	Set of blocked arcs.
$G_B = (V, A \setminus B)$	Graph representing the immediate post-disaster network.
D	Index of the depot node.
$n + 1$	Index of the sink node.
DA	Set of dummy arcs from each node in V to the sink node.
$A' = A \cup DA$	Union of the arcs in G and the dummy arcs.
$\delta_{-}j$	Set of nodes with an incoming arc to $j \in V$.
$\delta^{'}_{j}$	Set of nodes with an outgoing arc from $j \in V$.
Parameters	
c_{ij}	Time to go traverse node arc $(i, j) \in A$.
Φ	Number of available road restoration equipment.
S_{ij}	Maximum number of restoration equipment that can be allocated to a blocked arc $(i, j) \in B$.
λ_{ij}	Amount of requested equipment for blocked arc $(i, j) \in B$.
μ_{ij}	Required service rate for blocked arc $(i, j) \in B$.
Decision variables	
$x^k_{ijl} \in \{0, 1\}$	Equals 1 if team $k \in \{1, 2\}$ visits nodes i, j and l consecutively and 0 otherwise.
$t^k_{ijl} \geq 0$	the time by which team $k \in \{1, 2\}$ is at node $j \in V$ coming from node $i \in \delta_j$ and going to node $l \in \delta'_j$. Nodes i, j and l are visited consecutively.
$y^m_{ij} \in \{0, 1\}$	equals 1 if the m^{th}, $(m \in \{1, ..., S_{ij}\})$ restoration item is assigned to blocked arc $(i, j) \in B$ and 0 otherwise.
$b_{ij} \geq 0$	Fraction of additional time that is required for unblocking blocked arc (i, j) given the equipment assigned to it, $(i, j) \in B$.

Table 2: Table of notations

$$\min \sum_{i \in \delta_j} \sum_{j \in V} t^1_{ijn+1} \tag{1}$$

$$x^k_{ijl} \leq \sum_{h \in \delta'_l} x^k_{jlh}, \quad k \in \{1, 2\}, j \in V, i \in \delta_j, l \in \delta'_j \setminus \{n + 1\} \tag{2}$$

$$x^k_{ijl} \leq \sum_{h \in \delta_i} x^k_{hij} \quad k \in \{1, 2\}, j \in V, i \in \delta_j \setminus \{D\}, l \in \delta'_j \tag{3}$$

$$\sum_{h\in\delta_i} x_{hij}^k \leq 1, \quad k \in \{1,2\}, (i,j) \in A' \tag{4}$$

$$\sum_{l\in\delta'_j} x_{ijl}^k \leq 1, \quad k \in \{1,2\}, (i,j) \in A \tag{5}$$

$$\sum_{(i,j)\in A} x_{ijn+1}^k = 1, \quad k \in \{1,2\} \tag{6}$$

$$\sum_{i\in\delta_j} \sum_{l\in\delta'_j} x_{ijl}^1 \geq 1, \quad j \in C \tag{7}$$

$$\sum_{l\in\delta'_j} x_{ijl}^1 \leq \sum_{l\in\delta'_j} x_{ijl}^2, \quad (i,j) \in B \tag{8}$$

$$t_{ijl}^k \leq M x_{ijl}^k, \quad k \in \{1,2\}, j \in V, i \in \delta_j, l \in \delta'_j \tag{9}$$

$$\sum_{l\in\delta'_j} t_{ijl}^k \geq \sum_{h\in\delta_i} t_{hij}^k + c_{ij} \sum_{l\in\delta'_j} x_{ijl}^k, \quad k \in \{1,2\}, (i,j) \in A \tag{10}$$

$$\sum_{l\in\delta'_j} t_{ijl}^2 \geq \sum_{h\in\delta_i} t_{hij}^2 + (c_{ij} + b_{ij}c_{ij}) - M(1 - \sum_{l\in\delta'_j} x_{ijl}^2), \quad (i,j) \in B \tag{11}$$

$$b_{ij} \geq \mu_{ij}[y_{ij}^1 \rho_{\alpha(i,j)1} + \sum_{m=2}^{S_{ij}} y_{ij}^m (\rho_{\alpha(i,j)m} - \rho_{\alpha(i,j)m-1})], \quad (i,j) \in B \tag{12}$$

$$\lambda_{ij} \sum_{l\in\delta'_j} x_{ijl}^2 \leq b_{ij} \quad (i,j) \in B \tag{13}$$

$$\sum_{(i,j)\in B} \sum_{m=1}^{S_{ij}} y_{ij}^m \leq \Phi \tag{14}$$

$$y_{ij}^m \leq y_{ij}^{m-1}, \quad (i,j) \in B \quad, m \in \{2, ..., S_{ij}\} \tag{15}$$

$$\sum_{l\in\delta'_j} t_{ijl}^1 \geq \sum_{l\in\delta'_j} t_{ijl}^2 + c_{ij} \sum_{l\in\delta'_j} x_{ijl}^1, \quad (i,j) \in B \tag{16}$$

$$x_{ijl}^k \in \{0,1\}, \quad k = \{1,2\}, j \in V, i \in \delta_j, l \in \delta'_j \tag{17}$$

$$t_{ijl}^k \geq 0, \quad k = \{1,2\}, j \in V, i \in \delta_j, l \in \delta'_j \tag{18}$$

$$y_{ij}^m \in \{0,1\}, \quad (i,j) \in B, m \in \{1, ..., S_{ij}\} \tag{19}$$

$$b_{ij} \geq 0, \quad (i,j) \in B \tag{20}$$

In objective function (1), the time by which the last critical node is visited by the relief distribution team is minimized. This also corresponds to the time in which the route of the relief distribution team is finished. Constraints (2) to (5) above ensure the continuity of the routes taken by the teams. By constraints (2), a team can traverse a node only if it leaves it in the next step. With constraints (3), a team can be at a node only if it came to that node from another location. With constraints (4) and (5), we ensure that an arc is traversed only once. We note that arcs might be traversed in different direction of travel, but a team can traverse an arc in a particular direction at most one time. Constraints (6) ensures that both teams finish their routes in the sink node. Constraints (7) requires all the demand nodes to be served by the relief distribution team. With constraints (8), a blocked arc is traversable only after the road restoration team opens it. With constraints (9), only nodes that have been visited will have a positive visiting time. In this constraints, we can set M to a significantly large value or the planning horizon. Constraints (10) calculates the progression of time on all arcs for both the relief distribution and the road restoration teams. Constraints (11) calculates the progression of time for the road restoration team while traversing a blocked arc is calculated. By these constraints, the time at which the unblocking of arc $(i, j) \in B$ is finished is set to the time that the road restoration team arrived at node i, plus the travel and restoration times of (i, j).

The time taken to restore a blocked arc is dependent on the amount of equipment assigned to it. In this paper, we propose a dynamic road restoration and relief distribution model under a non-myopic policy. Decisions that investigate a look-ahead policy under uncertainty are called Markov decision process (MDP). Our proposed model is formulated as a MDP with discrete time intervals based on Bellman equation (Powell 2007) which is presented in equation (21), where the first term of value function V_t is the immediate payoff C_t to make decision x_t where decisions are related to state variable R_t. The second term of the value function is computed using the expected value of the delay. This conditional term depends on the current state R_t and the future state R_{t+1} where γ is a discount factor and E is an expectation. In this paper, the conditional function of delay is approximated using a multi-server queuing system ($M/M/s$).

$$V_t(R_t) = min_{x_t}(C_t(R_t, x_t) + \gamma E[V_{t+1}(R_{t+1})|(R_t, x_t)]) \tag{21}$$

Due to the complexity of non-myopic models in the network-based studies, exact computation of equation (21) using standard approaches is extremely difficult (Oyola *et al.* 2018, Munari *et al.* 2019). Therefore, an approximation method is needed to estimate the conditional expectation $E[V_{t+1}(R_{t+1})|(R_t, x_t)]$ in equation (21) (Sayarshad 2015, Nadimi-Shahraki *et al.* 2021).

According to the infinite horizon policy of dynamic models, our approach is based on using an infinite horizon performance measure as an approximation of short-term future conditions where the value function is approximated as a fixed point that is time-invariant. The queuing delay has been used in several studies to approximate of the fixed point (Daganzo 1978, Waserhole & Jost 2016, Sayarshad & Chow 2017). A dynamic policy based on equation (21) is translated for this problem setting as $C_t(R_t, x_t)$ being the relief time associated with allocation of equipment items to new blocked edges, while the conditionally expected cost in equation (21) is approximated with a queuing delay function. An approximation delay constraint based on a multi-server queuing system (M/M/s) is considered that anticipates the new request for equipment to restore each arc and assigns the minimum amount required similar to how the study by (Marianov & Serra 2002) incorporated a facility location problem to have queuing. Therefore, the $E[V_{t+1}(R_{t+1})|(R_t, x_t)]$ can be derived as an average queuing delay using an $M/M/s$ with an exogenously constructed utilization rate, which is indicated in constraints (12) and (13). The model is used in a dynamic setting, using steady state parameters to approximate future conditional expected costs/time. So for each case, a certain number of equipment will be recommended to allocate to the nodes in order to increase expected coverage and reduced future costs/time (based on the reduction in queue delay as an approximation). Thus, our model is able to allocate an equipment item by a queuing delay function at future state in order to calculate opportunity costs.

The conditionally expected cost in equation (21) is approximated with queuing delay constraints based on a multi-server queuing system ($M/M/s$), which is expressed in constraints (12) and (13). We incorporate the queue delay constraints into a non-myopic dynamic policy, where the policy is to optimize the allocation of the available resources to blocked arcs. Upon unblocking an arc, when equipment requirement for an arc occurs, these constraints incorporate the necessary queuing delays for the available resources. For each blocked arc $(i, j) \in B$, the requests for equipment, with a rate of λ_{ij} arrives according to a Poisson process and the service time μ_{ij} is assumed to be independent and exponentially distributed. Specifically, a reliability constraint is proposed that assigns the minimum amount of restoration equipment required at each arc in order to satisfy the equipment utilization rate, as shown in constraints (12) and (13).

We use a linear constraint that accounts the queuing delay for an available item of equipment. That is, when a new arc is unblocked which have the probability larger than the service reliability level α, there would be no more than r other arcs waiting for an item. The coefficient ρ for any service reliability α, as illustrated in constraints (12) for a given number, m, of items, can be determined exogenously by finding the root of (22). Prior to running the model, the values of ρ are calculated for any reliability level α. For instance, when $\alpha = 0.95$ and $r = 0$, then calculating for $\rho_{\alpha(i,j)m}$ for $m = 1, 2$, we determine $\rho_{0.95(i,j)1} = 0.2236$ and $\rho_{0.95(i,j)2} = 0.6417$. The reader is referred to Marianov & Serra (2002) for more details.

$$\frac{1}{1-\alpha} \leq \sum_{k=0}^{m-1} \frac{(m-k)m!m^r}{k!}\left(\frac{1}{\rho^{m+r+1-k}}\right) \tag{22}$$

Constraint (14) ensures that the total amount of utilized restoration equipment does not exceed the amount available. Constraints (15) guarantees the $(m-1)^{th}$ equipment item is assigned before allocating the m^{th} equipment item. Constraints (16) ensures that the time at which the road restoration team starts to traverse a blocked arc is after that blocked arc is recovered by the road restoration team. Note that this constraints is important to ensure the coordination of the routes for relief distribution and the road restoration teams. For a blocked arc $(i, j) \in B$, $\sum_{l\in\delta_j} t^2_{ijl}$ gives the time at which the blocked arc (i, j) is opened. Since traversal of this arc takes c_{ij} units of time, the relief distribution team cannot finish traversing arc (i, j) earlier than $\sum_{l\in\delta_j} t^2_{ijl} + c_{ij} \sum_{l\in\delta_j} x^1_{ijl}$. The rest of the constraints (17 - 20) are to set the variables.

The route extraction sub-routine

Since the objective function of Model I does not incorporate the route of the road restoration team, it is possible that the road restoration team takes unnecessary additional steps or takes longer routes while going from a blocked arc to another. One way to remedy this issue is to add a second-degree objective function to the presented model and in the second objective, minimize the route of the road restoration team. This would change the objective function of Model I to following:

$$\min \sum_{i\in\delta_j} \sum_{j\in V} t^1_{ijn+1}$$

$$\min \sum_{i\in\delta_j} \sum_{j\in V} t^2_{ijn+1}$$

However, this can increase the run time of the mathematical model which is undesirable. In order to solve this issue, we present the route-extraction subroutine which enable us to extract the optimized route of the road restoration team without adding a second-degree objective function to our mathematical model.

The optimal solution from the Model I identifies the blocked arcs that are recovered by the road restoration team. For example, if we denote the value of the optimal x variables obtained from the mathematical model by ${x^k_{ijl}}^*$, for any blocked arc $(i, j) \in B$, if $\sum_{l\in\delta'_j} {x^2_{ijl}}^* = 1$, then blocked arc $(i, j) \in B$ is opened by the road restoration team. In this case, using the optimal timing variables, we can also identify which blocked arc is opened earlier. For example, when comparing two opened blocked arcs, (i, j) and (u, v), if $\sum_{l\in\delta'_j} {t^2_{ijl}}^* < \sum_{l\in\delta'_v} {t^2_{uvl}}^*$, then blocked arc (i, j) is opened before blocked arc (u, v). Given this description, from the solution of the mathematical model, we can find the set $\mathcal{B}$, which includes all the blocked arcs that are opened by the road restoration team. Moreover, for the the arcs in $\mathcal{B}$, we can also sort them in the order that they are opened. For that, if we show $\mathcal{B} = \{\mathcal{B}_1, \mathcal{B}_2, ..., B_{|\mathcal{B}|}\}$, then in the solution of the mathematical model, $\mathcal{B}_i$ is opened before $\mathcal{B}_{i+1}$. With the set $\mathcal{B}$ at hand, we can apply the following sub-routine to extract the route of the road restoration team.

In this sub-routine, since the order in which the blocked arcs are opened is known, the road restoration team takes the shortest path distance between these arcs and opens them. The graph is dynamically updated, as the shortest path distances might change once some of the blocked arcs are opened.

Route extraction sub-routine

Input:

a: $G_B = (V, A \setminus B)$ ▹ initial graph excluding the blocked arcs
b: $\mathcal{B}$ ▹ set of blocked arcs in the order they are opened
c: D ▹ the depot of the road restoration team

Initiate:

a: $\mathcal{R} = \emptyset$ ▹ the route of the road restoration team
b: $\bar{l} = D$ ▹ the location of the road restoration team
c: flag = True ▹ sub-tour termination criteria

While flag **do:**
    $(i, j) \leftarrow \mathcal{B}_1$ ▹ (i, j) : the first opened arc in set $\mathcal{B}$.
    $\mathcal{R} = \mathcal{R} \cup SP(G_B, \bar{l}, i)$ ▹ find the route from $\bar{l}$ to node i
    ▹ $SP(G_B, \bar{l}, i)$: the shortest path route from node $\bar{l}$ to node i on graph G_B.
    $\mathcal{R} = \mathcal{R} \cup \{(i, j)\}$ ▹ open arc (i, j)
    $\mathcal{B} = \mathcal{B} \setminus \{(i, j)\}$ ▹ remove (i, j) from $\mathcal{B}$
    $\bar{l} = j$ ▹ update the location of the team
    $G_B = (V, A \setminus B)$ ▹ update the graph from which the shortest path routes are extracted.
    if $\mathcal{B} = \emptyset$ **then:** ▹ if all the blocked arcs are opened.
        flag = 0 ▹ termination Point.
end while
Output: $\mathcal{R}$

In all our presented results, we first solved the problem using Model I and then applied the route extraction sub-routine to obtain the final routes of the relief distribution and road restoration teams.

5. Data generation and results

In this section, we first present the generated data sets from Hurricane Harvey in Harris County and then present the results of our computational experiments. All maps are created using ArcGIS Version 10.8.1. We used a computer with 8 GB of RAM, a 2.50 GHz processor, Intel Core i5-2450 and a 64-bit Windows 10 to conduct our experiments. The model was coded in Julia and we solved the mathematical models using CPLEX 12.10.

5.1. Data from Hurricane Harvey

Our model and numerical experiments are run on Harris County, which has a total of 351 nodes (9 emergency response nodes, 68 critical (demand) nodes, 274 trans-shipment nodes), as depicted in Figures 5 and 6. In Figure 5, emergency operation nodes are shown as black triangles and the rest of the nodes as blue circles. In Figure 6, the critical nodes (those requiring relief) are given as black circles. Figure 6 also gives the index used for all of these nodes.

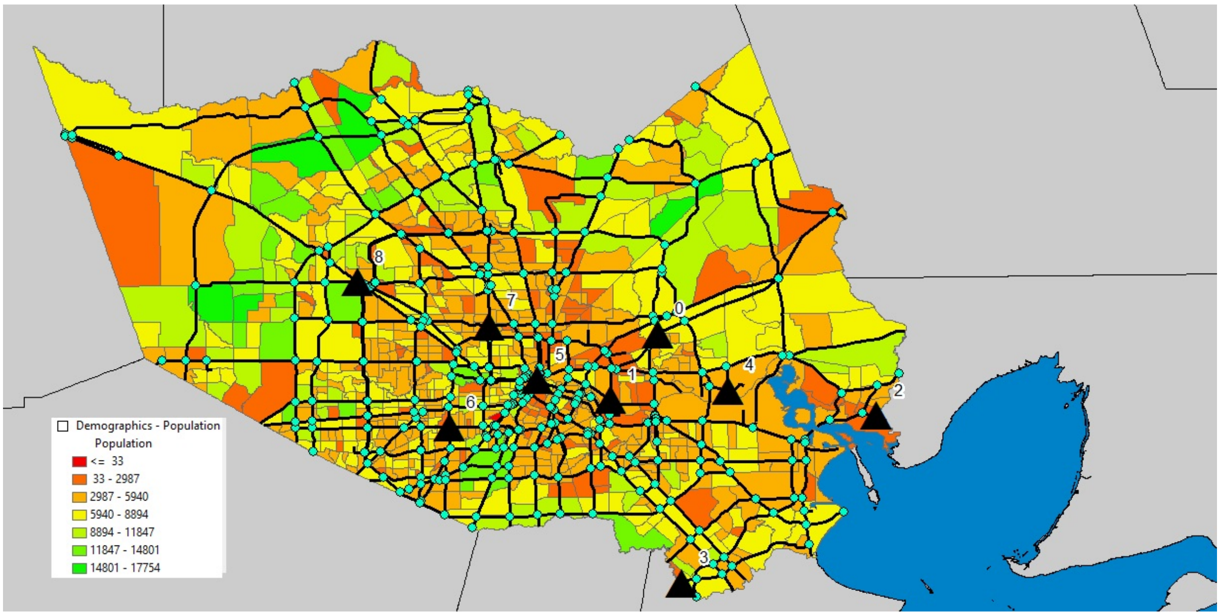

Figure 5: The road network in Harris County with emergency centers (black triangles)(via ArcGIS).

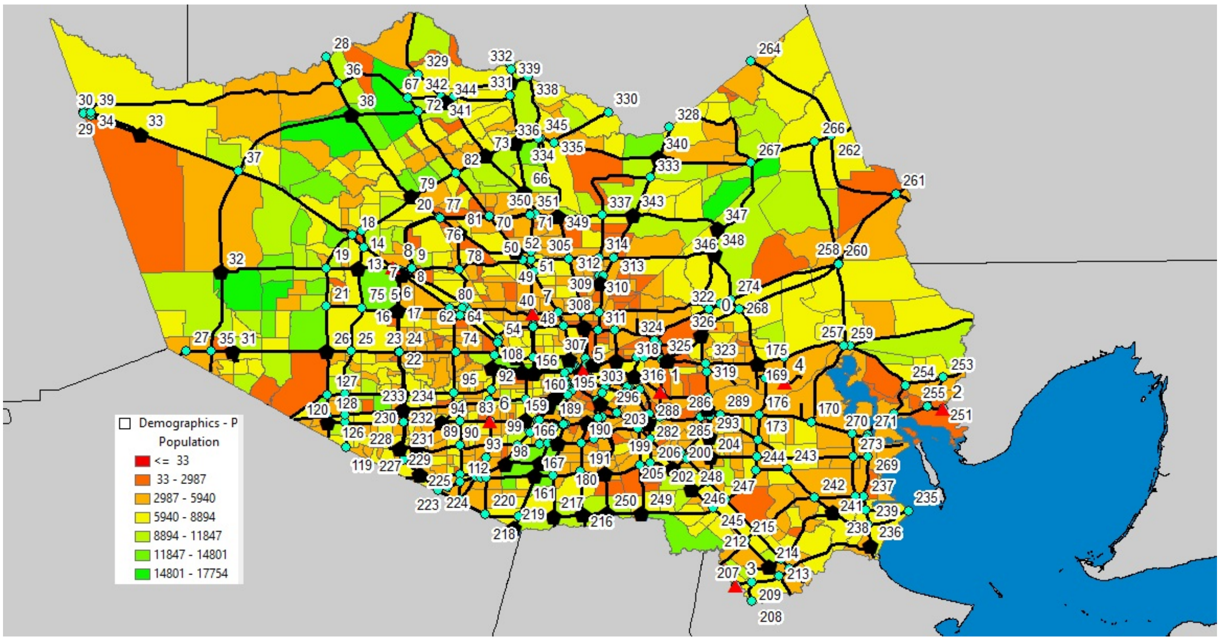

Figure 6: The road network in Harris County with critical nodes (black circles) and their index(via ArcGIS)

As stated above, Harris County has 9 emergency response nodes. Each has its own identified geographical regions of authority and responsibility, ans so we have clustered the nodes of this county accordingly (See Table 3). In Table 3, columns $|V|$ and $|A|$ give the number of nodes and the number of arcs, respectively. $|C|$ gives the number of critical or relief nodes in the specified region. Φ gives the amount of equipment available for road restoration in that region and $|B|$ is the number of blocked arcs. The last row in Table 3 gives the cumulative data for the nine regions. These 9 regions have 351 nodes in total. The cumulative number of arcs for these regions is 966, and a total of 76 nodes are identified as critical or relief nodes; the total amount of equipment is 128 and in total 112 blocked arcs are considered.

Region	Center Name	$\|V\|$	$\|A\|$	$\|C\|$	Φ	$\|B\|$
0	Jacino City Emergency Operation Center	37	96	10	10	18
1	Galena Park Emergency Operation Center	40	114	8	6	12
2	Baytown Emergency Operation Center	24	56	8	20	12
3	Nassau Bay Emergency Operation Center	44	114	12	20	14
4	City of Houston Emergency Operation Center	38	90	7	25	10
5	La Porte Emergency Operation Center	39	108	6	25	10
6	Bellaire CITY Emergency Operation Center	47	146	10	10	10
7	City of Houston Emergency Operation Center	43	122	7	6	14
8	Jersey Village Emergency Operation Center	39	120	8	6	12
	Total	351	966	76	128	112

Table 3: The nine regions in the case study

In each of the nine regions, both relief and restoration teams start from the emergency center. In reality, each emergency center has authority and responsibilities for their own region. Therefore, Model I is efficient to solve the real-case study. However, an efficient heuristic algorithm for commercial purposes will be studied in future research. The critical nodes are allocated based on demographic data such as population and the number of households. We estimate a set of blocked arcs based on the amount of damage and debris on the arcs. We have generated the request rate λ_{ij} for restoration equipment at each arc in a way that it is directly proportional to the amount of debris. To determine the service rate μ_{ij}, we use a guideline which is provided by FEMA (2010) that estimates debris removal after the disaster. The reliability level is assumed to be α=0.95, where $r = 0$. The value, ρ, is calculated exogenously by finding the root of (22). The travel time between road intersections is determined using Euclidean distances.

5.2. Results

In this section, we first give the results of testing Model I on the Harris County case study in subsection 5.2.1. In subsection 5.2.2, we provide two different types of analysis with our proposed model and its characteristics. We first discuss the case in which the routing time of the road restoration team is incorporated in the objective function and then highlight how considering a stochastic unblocking time and assignment of equipment to blocked arcs can improve the results. In subsection 5.2.3, we investigate incorporation of providing access to infrastructure facilities and finally, in subsection 5.2.4, we address the importance of considering how road restoration teams can provide access to some of the critical facilities.

5.2.1. *Results summary for Harris County*

We have implemented Model I together with the route extraction sub-routine procedure on each of the 9 clusters of the Harris County data and present a summary of the results in Table 4. The detailed results and the routes for each of the regions are provided in Appendix B. The OFV column gives the value of the objective function, which is the finishing time of the route of the relief distribution team or the time at which the last critical node in that region is visited (in hours). We have given the route time for the road restoration team in the third column. The CPU run-time in seconds is provided in the fourth column. As can be observed in Table 4, the longest relief time is for region 2 at 139.16. In all nine regions, the road restoration team finishes before the relief distribution team. This is because the objective is to minimize the time at which the last critical node is visited by the relief distribution team. In the last two columns, we can see that only in two regions was all the equipment entirely used; in the other seven regions, increasing the amount of equipment would not improve the obtained solutions.

Region	OFV (time of relief) (hours)	Time of road restoration (hours)	CPU Time (seconds)	# of opened blocked arcs	# of utilized equipment	% of used equipment
0	91.70	33.85	459.07	2	9	90%
1	48.28	8.53	537.96	1	2	33%
2	139.16	131.51	10.97	4	19	95%
3	100.31	84.96	601.86	2	16	80%
4	38.47	25.90	143.79	3	25	100%
5	68.06	23.00	31345.62	1	9	36%
6	75.66	18.18	8873.61	1	8	80%
7	78.38	20.70	2489.20	2	4	67%
8	135.96	27.55	91.86	1	6	100%

Table 4: Summary of the results for the 9 regions

In order to provide a visualization of the obtained routes for one of the regions, we present the results for region 3 in Figure 7. We have selected this region because the density of the nodes is lower and so the diagram is clearer. The route of the relief distribution team is shown in blue and that of the road restoration team in red. The brown spots show the location of debris and it can clearly be seen that blocked arcs for this region include (208, 209), (210, 236), (245, 215), (245, 249), (224, 225), (225, 226), (229, 232), (209, 208), (236, 210), (215, 245), (249, 245), (225, 224), (226, 225), and (232, 229). Blocked arcs $(224, 225)$ and $(225, 226)$ were opened by the road restoration team to enable access to critical nodes by the relief distribution team. Arc (224, 225) has been unblocked by time 81.78 and arc (225, 226) by 84.96. The relief distribution team used both of these arcs. This team entered arcs (224, 225) and (225, 226) at times 88.14 and 90.97, respectively. The route of the relief distribution team ended at time 100.31 and the route of the road restoration team was finished at time 84.96. From the route of the road restoration team, it can be observed that blocked arc (215, 245) was not restored, as priority was given to the blocked arcs on the optimal route for the relief distribution team.

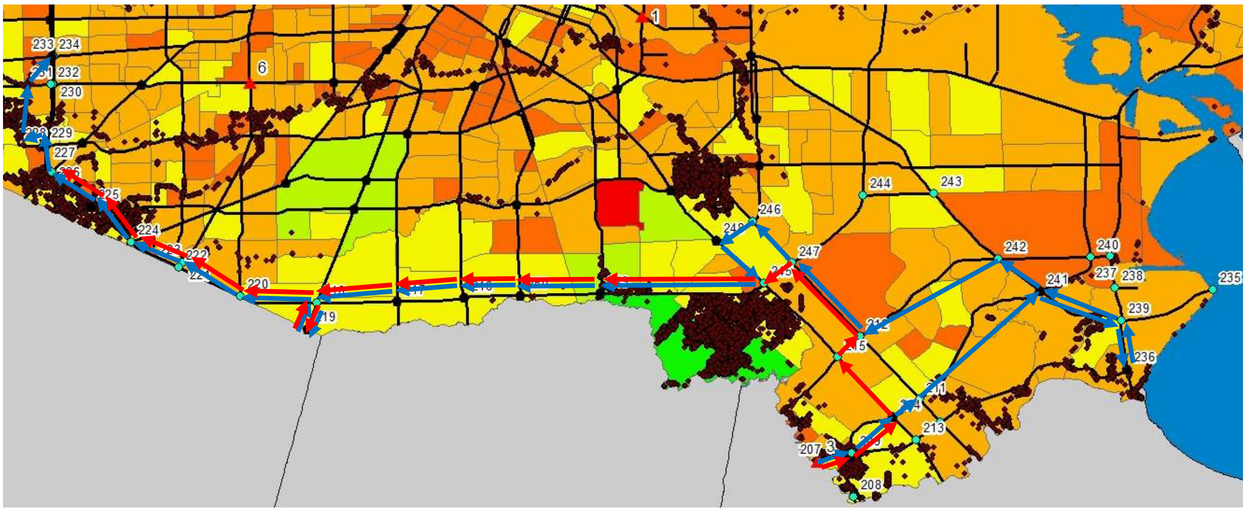

Figure 7: Results for region 3 (via ArcGIS)

5.2.2. Analysis of the non-myopic policy of the CSRRRDPP

In this section, two policies are compared to evaluate the proposed model. In the non-myopic policy, (called policy A), we use the strategy that optimally allocates the equipment available. In the myopic policy (called policy B), we use a strategy in which the queuing approximation for equipment allocation is ignored i.e., constraints (12) and (13). Other constraints and parameters are kept the same. In order to provide this analysis, we set the objective function by incorporating the route of both of the teams. For that, we change the objective function as follows:

$$\min \sum_{i \in \delta_j} \sum_{j \in V} (t^1_{ijn+1} + t^2_{ijn+1}) \tag{23}$$

For this comparison, we have selected region 8 and tested the myopic and non-myopic models using the modified objective function. For the non-myopic model, the modified objective function gives similar results to the objective function where only the route of the relief distribution team is considered in the objective function (1). For this case, the route of the relief distribution team ended at time 135.96 and the route of the relief distribution team was finished at time 27.55. The road restoration team facilitated access to relief nodes by opening one blocked arc using all the assigned equipment.

The non-myopic results for routes in region 8 are depicted in Figure 8. As in Figure 7 the route of the road restoration team is shown in red and the route of the relief distribution in blue. As can be observed, blocked arc (20, 38) is the only one opened arc by the road restoration team. This was finished at time 27.55 and the arc was used by the relief distribution team at time 47.02. All the available equipment was assigned to arc (20, 38) for its recovery.

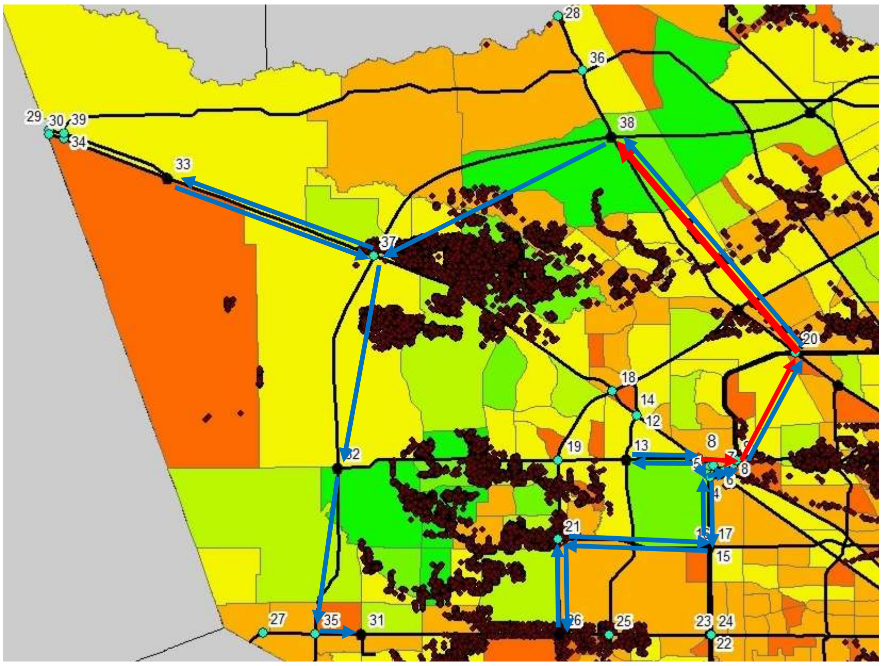

Figure 8: Results for region 8 (via ArcGIS)

For the myopic solution, we eliminate constraints (12) and (13) and solve the problem for region 8 again. In this case, the problem does not incorporate appropriate assignment of the equipment to the blocked arcs based on the queuing delays and since two constraint sets are eliminated, the obtained solutions are initially better than in the non-myopic case when queuing is ignored. For the relief distribution team, the finishing time is now 103.30, and the road restoration team now finishes at time 27.98. The blocked arc (26, 31) was opened by the road restoration team at time 27.98 and was immediately used by the relief distribution team. However, in order to provide a comparison between the obtained results, the routes extracted from the myopic problem need to be converted into a solution for the non-myopic problem where the appropriate queuing delays are also considered. In order to calculate the additional term that should be added to the route of the road restoration team to incorporate the queuing delays, we use the following formula extracted from Sayarshad & Chow (2017).

$$\sum_{(i,j)\in B} \frac{c_{ij}\lambda_{ij}\sum_{l\in\delta'_j} X_{ijl}^2}{\lambda_{ij}\sum_{l\in\delta'_j} X_{ijl}^2 - \mu_{ij}\sum_m y_{ij}^m} \tag{24}$$

In this case, the only unblocked arc is (26, 31) for which the λ and μ parameters are 2.3275 and 0.211, respectively. Also, there are 6 equipment that are allocated to this region and since this arc is the only unblocked arc in this solution, all of these equipment will be allocated to it. Finally, given the value of $c_{26,31}$ which is equal to 10.6068, we can calculate this the ignored queuing delay time as $\frac{10.6068 \times 2.3275}{2.3275 - 0.211 \times 6} =$ 23.26. This means that the road restoration team is able to unblock arc (26, 31) only at time 51.24, after which the arc is available for the relief distribution team. This means that the route of the relief distribution team will be shifted by 23.26 units of time and it will be finished at time 137.16. As it can be observed, the adjusted routes of both the relief distribution and road restoration teams in the myopic case are longer than those of in non-myopic version, because the non-myopic case accounts the expected future cost using a queuing delay. That is, under the non-myopic policy, the total cost decreases by 15% compared with the myopic case for this region. This highlights the importance of non-myopic modelling and consideration of stochastic unblocking times. We note that by using objective function (1), once the blocked arcs and the order in which they should be recovered is known for the road restoration team, then it is straightforward to extract its minimized route to reach the blocked arcs in the desired order.

5.2.3. The connectivity of infrastructure facilities

The road restoration team helps the relief distribution team only by enabling access to critical nodes. In this section, we analyze the case where the road restoration team has to connect infrastructure facilities while helping the relief distribution team to gain faster access to critical nodes. We are particularly interested in providing access to facilities such as hospitals, but still with limited amount of road restoration equipment. The objective function remains the same (it minimizes the time at which the last critical node is served by the relief distribution team). The connection of facilities is ensured by unblocking arcs that end or start at a facility. In order to incorporate this into our model, we define I as the set of facilities such as hospitals and BI as the set of blocked arcs that end or start from them, i.e., $BI = \{(i, j) \in B : i \text{ or } j \in I\}$. Furthermore, we define Ψ as the minimum number of unblocked arcs from the set BI. We then add the following constraint to the model:

$$\sum_{(i,j)\in BI} \sum_{l\in\delta(j)} x^2_{ijl} \geq \Psi \tag{25}$$

As the value of Ψ increases, the level of required connectivity increases. Hence, the road restoration team will require more equipment. In order to test this modified version of the problem, we first have to identify the location of the facilities (in particular hospitals) and assign them to the closest nodes in the road networks. We then extract the blocked arcs that start or end at the facilities, to form the set BI. We have tested this variation on region 6 and the output routes are given in Figure 9. In this variation, the input data remain as given in Table 3. We have set the value of Ψ at 2, which means that at least two blocked arcs with one end at a hospital need to be recovered. With this additional constraint, the value of the objective function increases to 80.49 from 75.66 given in Table 4. The road restoration team opens blocked arcs (85, 83) and (109, 110) to ensure access to hospitals located at nodes 83, 109 and 110. The relief distribution team uses both of these unblocked arcs to gain faster access to critical nodes and finishes its route at node 120, at time 80.49. We have also tested the same problem with the equipment value set at 8, and, as expected, the value of the objective function increases to 84.78.

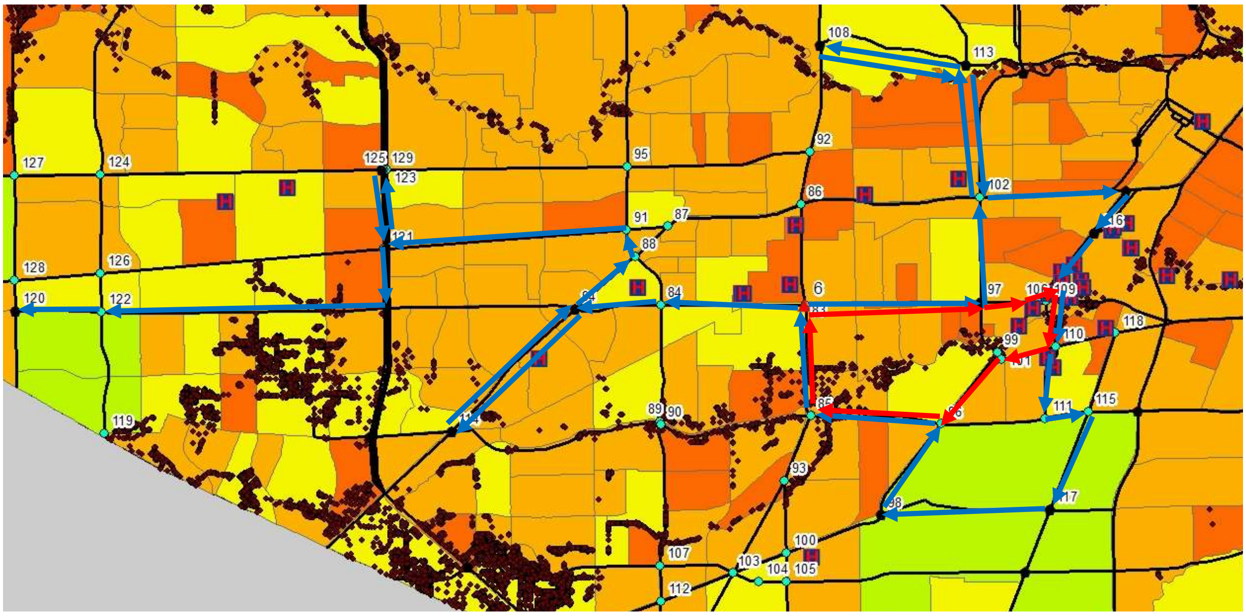

Figure 9: Results for region 6 considering the connection of infrastructure facilities (via ArcGIS)

5.2.4. *Impact of road restoration operations*

In this subsection, we investigate the importance of the road restoration team and how it contributes in improving the obtained objective function value. To do this, we eliminate the road restoration team and proceed the operations only using the relief distribution team. In order to do this, we have changed constraints (8) to the following:

$$\sum_{l \in \delta_j} x^1_{ijl} = 0, \quad (i, j) \in B \tag{26}$$

In 7 regions out of 9 (that is, with the exception of regions 1 and 6), without a road restoration team the relief distribution team cannot access and serve all the critical locations. As a result of this, the problem was infeasible in these cases, which highlights the importance of considering the road restoration teams in providing accessibility to all of the critical nodes. For regions 1 and 6, the relief distribution team is able to serve all the critical nodes. As expected, the value of the objective function in these modified versions is increased. In region 2, this increase is not significant. The relief distribution team is able to serve all the critical nodes within 48.32 units of time which is slightly more than what is achieved when the road restoration team opens arc (282, 287). For region 6 however, the value of the objective function when the road restoration team is not present is 84.29, which is a 11.40% increase compared with to the case where the road restoration team facilitates accessing the critical nodes by recovering blocked arc (108, 92).

6. Conclusion

We propose a novel dynamic simultaneous relief distribution and road restoration problem with stochastic unblocking times where the main decisions consist of: 1) selecting the road segments that need to be restored by the road restoration team so that connection between supply and critical nodes for the relief team can be established as efficiently as possible, 2) routing of the relief distribution and road restoration teams such that the road restoration team unblocks selected roads and the relief distribution team does not traverse a blocked arc unless it is fully recovered by the relief distribution team while serving all the critical nodes, and 3) minimizing the time by which the last critical node is served by the relief distribution team.

The problem has important implications in the area of stochastic network design, as well as significant practical importance due to the size, cost, and complicated nature of post-disaster management operations. We incorporate the movement of (possibly multiple items of) restoration equipment into the modeling approach. We apply a queuing delay to approximate the look-ahead cost of restoration equipment that considers a balance between the rate of restoration items and the service capacity of the restoration team at each blocked arc. We provide an experimental study that uses a non-myopic approach on real-world data taken from Hurricane Harvey in Harris County. We cluster the road network of this county into 9 regions and test our model on each of them. Using the Hurricane Harvey dataset, the proposed non-myopic policy reduces total cost by 15% compared with the myopic policy.

We consider the priority of blocked arcs for the restoration team in the post-disaster stage in order to facilitate access to public facilities such as hospitals. The results show that in 7 regions out of 9, full coverage of the critical nodes is impossible without the work of of the road restoration team, and in the remaining two regions the relief time decreases by 12% compared with the case where a road restoration team is not present. Extensive computational experiments are implemented to highlight the benefits of using our proposed model in response to disaster.

In future research, the proposed model can be used to solve large-scale problems, and effective metaheuristics can be adapted to achieve shorter computational time. Nevertheless, an exact solution is produced for a medium number of nodes. Furthermore, an inventory and delivery problem with a look-ahead policy to allocate relief items to the critical nodes could be also considered in future research (Sayarshad & Mahmoodian 2021). Another important generalization that can be studied is when multiple relief distribution and road restoration teams are considered. In this case, coordination between all the teams regarding the usage of blocked edges should be considered. For instance, when a blocked arc is recovered by one of the road restoration teams, all the relief distribution and other road restoration teams can use that recovered arc. When these complications are resolved, the case in which, teams from different regions can assist each other after they have finished relief operations of their own region can be studied. Considering concurrent restoration teams would also significantly improve the objective function. Therefore, job-shop scheduling or other areas could be considered in future research. Lastly, a dynamic post-disaster debris collection and recycling problem would be an interesting extension for future studies (Mirdar Harijani *et al.* 2017).

Acknowledgments

This research did not receive any grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Model II

As mentioned in Section 4, in Model I, we assume that each arc can be traversed by the relief distribution team only once. However, this assumption can eliminate the optimal solution in some extreme examples. For instance, consider the myopic example illustrated in Figure A.10. In this example, given that it represents a myopic problem, the exact values of b_{ij} are known. Moreover, similar to Figure 2, node 1 is the depot, the pentagons represent the critical nodes and the rest of the nodes are the non-critical nodes. The c_{ij} and b_{ij} values for this example are also presented in Table A.5. In this example, we assume that the traversal and unblocking times in either directions of an edge are similar to each other and hence only gave them in once direction.

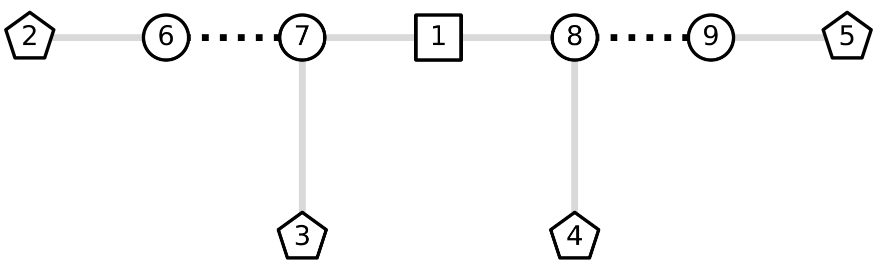

Figure A.10: An extreme example of the CSRRRDPP

In this example, the optimal route of the relief distribution team is $1 \rightarrow 8 \rightarrow 4 \rightarrow 8 \rightarrow 1 \rightarrow 7 \rightarrow 3 \rightarrow 7 \rightarrow 6 \rightarrow 2 \rightarrow 6 \rightarrow 7 \rightarrow 1 \rightarrow 8 \rightarrow 9 \rightarrow 5$ and the optimal route of the road restoration team is

Table A.5: Information of the sample

Arc	c_{ij}	Arc	c_{ij}	Arc	c_{ij}	Blocked Arc	b_{ij}
(1, 7)	1	(3, 7)	100	(6, 7)	200	(6, 7)	100
(1, 8)	1	(4, 8)	100	(8, 9)	200	(8, 9)	100
(2, 6)	100	(5, 9)	100				

$1 \rightarrow 7 \rightarrow 6 \rightarrow 7 \rightarrow 1 \rightarrow 8 \rightarrow 9$. The restoration team first goes to node 7 and then unblocks arc $(6, 7)$. The restoration of this arc finishes at time 301. After this, the restoration team opens arc (6, 7) and goes to node 8 to open arc (8, 9). The restoration team arrives to node 8 at time 603 and finishes opening arc (8, 9) at time 903. The relief team, first goes to relief node 4 through node 8 and then goes to relief node 3 through arcs (4, 8), (8, 1), (1, 7) and (7, 3). The relief team then goes back to node 7 and arrives to this node at time 403. Given that arc (7, 6) was opened at time 301, the relief team can traverse arc (7, 6) to reach node 2 at time 703. It then goes back to node 6 and arrives to this node at time 803. Given that arc (6, 7) was opened at time 601, the relief team can traverse this arc and go to node 8 through nodes 6, 7, 1 and 8. Since unblocking of arc (8, 9) was finished at time 903 and the relief team arrives to node 8 at time 1105, it can traverse arc (8, 9) and reach node 5 at time 1305 which is the optimal objective function value. As can be observed from the optimal route of the relief distribution team, in this optimal solution, arc (1, 8) is traversed more than once. Using Model I, if we force the relief distribution team to traverse each arc at most once, the obtained solution for the relief team will be $1 \rightarrow 7 \rightarrow 3 \rightarrow 7 \rightarrow 6 \rightarrow 2 \rightarrow 6 \rightarrow 7 \rightarrow 1 \rightarrow 8 \rightarrow 4 \rightarrow 8 \rightarrow 9 \rightarrow 5$. In this solution however, the corresponding objective function value is 1503, which is clearly larger than the optimal objective function value of 1305 which was obtained above.

In this section, we present a model that incorporates this feature and allows the relief distribution team to traverse arcs more than once. We refer to this model as Model II. Model II can be used to solve extreme examples such as the one given above. Nevertheless, Model I is capable of solving any instance, however, it might give sub-optimal solutions to some extreme examples. In order to show Model II, we have added a number of notations. We show the union of the critical nodes and the depot by $C_D = C \cup \{D\}$ and the union of the critical nodes and the sink node by $C_{n+1} = C \cup \{D\}$. We also define a set Q that gives all the subsets of $C \cup \{D, n+1\}$ with a size of at least 2. In the following, we first give the decision variables and then the proposed model.

- $x_{ijl} \in \{0, 1\}$: equals 1 if the road restoration team visits nodes i, j and l consecutively and 0 otherwise.
- $X_{uv}^{ij} \in \{0, 1\}$: equals 1 if the relief distribution team traverses arc $(i, j) \in A'$ on the route from node $u \in C_D$ to node $v \in C_{n+1}$.

- $t_{ijl} \geq 0$: the time by which the road restoration team is at node $j \in V$ coming from node $i \in \delta_j$ and going to node $l \in \delta'_j$. Nodes i, j and l are visited consecutively.
- $T^{ij}_{uv} \geq 0$: the time by which the relief distribution team finishes traversing arc $(i, j) \in A'$ on the route from node $u \in C_D$ to node $v \in C_{n+1}$.
- $z_{uv} \in \{0, 1\}$: equals 1 if critical node $u \in C_D$ and $v \in C_{n+1}$ are visited in this order and 0 otherwise.
- $y^m_{ij} \in \{0, 1\}$: equals 1 if the m^{th}, $(m \in \{1, ..., S_{ij}\})$ restoration item is assigned to blocked arc $(i, j) \in B$ and 0 otherwise.
- $b_{ij} \geq 0$: fraction of additional time that is required for unblocking blocked arc (i, j) given the equipment assigned to it, $(i, j) \in B$.

$$\min \sum_{u \in C_D} \sum_{i \in \delta_{n+1}} T^{i(n+1)}_{u(n+1)} \tag{A.1}$$

$$x_{ijl} \leq \sum_{h \in \delta'_l} x_{jlh}, \quad j \in V, i \in \delta_j, l \in \delta'_j \setminus \{n+1\} \tag{A.2}$$

$$x_{ijl} \leq \sum_{h \in \delta_i} x_{hij} \quad j \in V, i \in \delta_j \setminus \{D\}, l \in \delta'_j \tag{A.3}$$

$$\sum_{h \in \delta_i} x_{hij} \leq 1, \quad (i, j) \in A' \tag{A.4}$$

$$\sum_{l \in \delta'_j} x_{ijl} \leq 1, \quad (i, j) \in A \tag{A.5}$$

$$\sum_{(i,j) \in A} x_{ijn+1} = 1 \tag{A.6}$$

$$t_{ijl} \leq M x_{ijl}, \quad j \in V, i \in \delta_j, l \in \delta'_j \tag{A.7}$$

$$\sum_{l \in \delta'_j} t_{ijl} \geq \sum_{h \in \delta_i} t_{hij} + c_{ij} \sum_{l \in \delta'_j} x_{ijl}, \quad (i, j) \in A \tag{A.8}$$

$$\sum_{l \in \delta'_j} t_{ijl} \geq \sum_{h \in \delta_i} t_{hij} + (c_{ij} + b_{ij} c_{ij}) - M(1 - \sum_{l \in \delta'_j} x_{ijl}), \quad (i, j) \in B \tag{A.9}$$

$$\sum_{v \in C_D \setminus \{v\}} z_{uv} = 1, \quad v \in C_{n+1} \tag{A.10}$$

$$\sum_{v \in C_{n+1} \setminus \{u\}} z_{uv} = 1, \quad u \in C_0 \tag{A.11}$$

$$\sum_{u \in C_D \setminus \{v\}} z_{uv} - \sum_{w \in C_{n+1} \setminus v} z_{vw} = 0, \quad v \in C \tag{A.12}$$

$$\sum_{(u,v) \in q} z_{uv} \leq |q| - 1, \quad q \in Q \tag{A.13}$$

$$\sum_{(i,j)\in A'} X_{uv}^{ij} \leq |C| z_{uv}, \quad u \in C_D, v \in C_{n+1}, u \neq v \tag{A.14}$$

$$\sum_{j\in\delta'_u} X_{uv}^{uj} = z_{uv}, \quad u \in C_D, v \in C_{n+1}, u \neq v \tag{A.15}$$

$$\sum_{i\in\delta_v} X_{uv}^{iv} = z_{uv}, \quad u \in C_D, v \in C_{n+1}, u \neq v \tag{A.16}$$

$$\sum_{i\in\delta_j} X_{uv}^{ij} - \sum_{l\in\delta'_j} X_{uv}^{jl} = 0, \quad u \in C_D, v \in C_{n+1}, u \neq v, j \in V \setminus \{u, v\} \tag{A.17}$$

$$T_{uv}^{ij} \leq M X_{uv}^{ij}, \quad u \in C_D, v \in C_{n+1}, u \neq v, (i, j) \in A' \tag{A.18}$$

$$T_{uv}^{ij} \geq \sum_{l\in\delta_i} T_{uv}^{li} + c_{ij} X_{uv}^{ij} - M\left(1 - x_{uv}^{ij}\right), \quad u \in C_D, v \in C_{n+1}, u \neq v, (i, j) \in A' \tag{A.19}$$

$$\sum_{i\in\delta'_u} T_{uv}^{ui} \geq \sum_{j\in\delta_u} T_{wu}^{ju} + \sum_{i\in\delta'_u} c_{ui} X_{uv}^{ui} - M\left(1 - z_{wu} z_{uv}\right), \quad w \in C_D, u \in C, v \in C_{n+1}, w \neq u \neq v \tag{A.20}$$

$$X_{uv}^{ij} \leq \sum_{l\in\delta'_j} x_{ijl}, \quad (i, j) \in B, u \in C_D, v \in C_{n+1}, u \neq v \tag{A.21}$$

$$T_{uv}^{ij} \geq \sum_{l\in\delta'_j} t_{ijl} + c_{ij} X_{uv}^{ij} - M\left(1 - X_{uv}^{ij}\right), \quad (i, j) \in B, u \in C_D, v \in C_{n+1}, u \neq v \tag{A.22}$$

$$b_{ij} \geq \mu_{ij}[y_{ij}^1 \rho_{\alpha(i,j)1} + \sum_{m=2}^{S_{ij}} y_{ij}^m (\rho_{\alpha(i,j)m} - \rho_{\alpha(i,j)m-1})], \quad (i, j) \in B \tag{A.23}$$

$$\lambda_{ij} \sum_{l\in\delta'_j} x_{ijl} \leq b_{ij} \quad (i, j) \in B \tag{A.24}$$

$$\sum_{(i,j)\in B} \sum_{m=1}^{S_{ij}} y_{ij}^m \leq \Phi \tag{A.25}$$

$$y_{ij}^m \leq y_{ij}^{m-1}, \quad (i, j) \in B \ \ , m \in \{2, ..., S_{ij}\} \tag{A.26}$$

$$x_{ijl} \in \{0, 1\}, \quad j \in V, i \in \delta_j, l \in \delta'_j \tag{A.27}$$

$$t_{ijl} \geq 0, \quad j \in V, i \in \delta_j, l \in \delta'_j \tag{A.28}$$

$$X_{uv}^{ij} \in \{0, 1\}, \quad (i, j) \in A', u \in C_D, v \in C_{n+1}, u \neq v. \tag{A.29}$$

$$T_{uv}^{ij} \geq 0, \quad (i, j) \in A', u \in C_D, v \in C_{n+1}, u \neq v. \tag{A.30}$$

$$z_{uv} \in \{0, 1\}, \quad u \in C_D, v \in C_{n+1}, u \neq v \tag{A.31}$$

$$y_{ij}^m \in \{0, 1\}, \quad (i, j) \in B, m \in \{1, ..., S_{ij}\} \tag{A.32}$$

$$b_{ij} \geq 0, \quad (i, j) \in B \tag{A.33}$$

(A.1) sets the objective function that minimizes the time at which the route of the relief distribution team ends. Constraints (A.2) to (A.9) are to set the route and timing of the road restoration team. These constraints are similar to the ones of Model I except that in Model II, the team index is removed and these constraints only hold for the road restoration team. Constraint sets (A.10) to (A.13) are to ensure that all the critical nodes are visited and there are no sub-tours in visiting them. Constraint sets (A.14) to (A.17) are to ensure the continuity of the route of the relief distribution team. Constraint sets from (A.18) to (A.20) are to propagate time of the route of the relief distribution team. Constraints (A.21) are to ensure that blocked arcs are not traversed by the relief team unless they are opened by the restoration team. Constraints (A.22) are to guarantee that the relief team traverse blocked arcs after they are opened. Constraints (A.23) to (A.26) are similar to the ones from Model I and the rest of the constraints are to set the variables.

Appendix B. Detailed results of the case study regions

Appendix B.1. Results for Region 0

The results of region 0 with Jacino City Emergency Operation Center as its depot are presented in Table B.6. All the information regarding the blocked arcs, critical nodes and number of available equipmentis given in the upper section of this table. The results of the optimization model, including the optimal value of the objective function, the optimal routes for the relief distribution and road restoration teams and the opened blocked arcs are given in the lower section. For all the remaining regions, we use the same table structure to present the results.

The optimal value of the objective function is the time at which the last critical node (which is here node 344) is visited by the relief distribution team (here at time 91.70). As can be observed, all the critical nodes were visited by the relief distribution team as they all are included on its route. Although the amount of available equipment was set to 10, only 9 items were used. The road restoration team unblocked arcs (347, 343) and (337, 349) and assigned 7 items of equipment to (347, 343) and 2 items to (337, 349). The reason why one of the items was not used is that using it could not decrease the value of the objective function. The unblocking of arc (347, 343) was finished at time 24.79 and the relief distribution team started using this arc at time 26.22. The unblocking of arc (337, 349) was finished at time 33.85, when the route of the road restoration team terminated, and the relief distribution team entered this arc at time 53.77.

Problem setup for region 0	
Number of available equipment (Φ)	10
Critical nodes (C)	[318, 326, 348, 347, 343, 340, 349, 336, 339, 344]
Blocked arcs (B)	(338, 332), (335, 330), (337, 349), (349, 350), (317, 324), (318, 323), (324, 316), (347, 343), (331, 336), (332, 338), (330, 335), (349, 337), (350, 349), (324, 317), (323, 318), (316, 324), (343, 347), (336, 331)

Obtained solution for region 0	
Optimal objective function value (hours)	91.70
Relief distribution route	315 → 326 → 318 → 326 → 315 → 322 → 321 → 346 → 348 → 347 → 343 → 333 → 340 → 333 → 337 → 349 → 345 → 336 → 345 → 338 → 339 → 342 → 344
Road restoration route	315 → 322 → 321 → 346 → 348 → 347 → 343 → 337 → 349
Time progression for relief distribution (hours)	0 → 1.95 → 6.94 → 11.93 → 13.88 → 15.59 → 16.41 → 22.45 → 23.00 → 26.22 → 35.87 → 41.03 → 43.76 → 46.48 → 53.77 → 58.68 → 68.91 → 71.40 → 73.89 → 81.89 → 83.91 → 90.61 → 91.70
Time progression for road restoration (hours)	0 → 1.72 → 2.53 → 8.58 → 9.12 → 12.34 → 24.79 → 28.33 → 33.85
Opened blocked arcs	(347, 343), (337, 349)
Number of equipment assigned for unblocking	(347, 343):7, (337, 349):2

Table B.6: Results of region 0

Appendix B.2. Results for Region 1

The results of region 1, with Galena Park Emergency Operation Center as its depot, is given in Table B.7. In this region, of the 6 items of equipment available, only 2 were used, to open blocked arc (282, 287). The unblocking of this arc was finished at time 8.53. The relief distribution team entered this arc at time 22.51 and finished traversing it at time 25.76. We can see that the correct timing of the availability of the blocked arcs again applies in this instance. All the critical nodes were visited by the relief distribution team. Critical node 309 was the last critical node visited by the relief distribution team, at time 48.28, which corresponds to the optimal value of the objective function.

Problem setup for region 1	
Number of available equipment (Φ)	6
Critical nodes (C)	288, 293, 280, 301, 302, 307, 309, 303
Blocked arcs (B)	(300, 311), (309, 312), (309, 310), (310, 312), (282, 287), (284, 279), (311, 300), (312, 309), (310, 309), (312, 310), (287, 282), (279, 284)
Obtained solution for region 1	
Optimal objective function value (hours)	48.28
Relief distribution route	275 → 278 → 280 → 281 → 285 → 286 → 293 → 286 → 285 → 281 → 280 → 279 → 277 → 288 → 282 → 287 → 290 → 298 → 301 → 297 → 302 → 303 → 311 → 307 → 304 → 308 → 309
Road restoration route	275 → 276 → 277 → 282 → 287
Time progression for relief distribution (hours)	0 → 5.30 → 6.85 → 6.96 → 7.44 → 7.79 → 10.44 → 13.09 → 13.45 → 13.92 → 14.03 → 15.32 → 19.93 → 21.29 → 22.51 → 25.76 → 27.05 → 28.53 → 28.59 → 30.77 → 31.97 → 34.60 → 39.03 → 40.66 → 42.49 → 44.51 → 48.28
Time progression for road restoration (hours)	0 → 2.16 → 3.26 → 4.48 → 8.53
Opened blocked arcs	(282, 287)
Number of equipment assigned for unblocking	(282, 287):2

Table B.7: Results of region 1

Appendix B.3. Results for Region 2

The results of region 2 are given in Table B.8. The depot in this region is Baytown Emergency Operation Center. As can be observed, although 20 items of equipment were available, only 19 items were utilized: 2 items for blocked arc (253, 252), 2 for (252, 253), 8 for (259, 260) and 7 equipment for (266, 267).

The first blocked arc opened was (253, 252). The unblocking of this arc was finished at time 9.70. The road restoration team then returned to node 253 and finished recovering blocked arc (252, 253) at time 13.55. The traversal of these blocked arcs was started by the relief distribution team (after they had been unblocked) at times 26.75 and 29.90 for arcs (253, 252) and (252, 253), respectively. The next arc to be unblocked was (259, 260), at time 46.23. This is exactly when the relief distribution team entered this arc. The last blocked arc to be recovered was arc (266, 267), at time 131.51. This arc is the last arc traversed by the relief distribution team and its traversal starts exactly when the unblocking ends, at time 131.51 and finishes at time 139.16 which corresponds to the optimal objective function i.e., the time at which the last critical node was visited by the relief distribution team.

Problem setup for region 2	
Number of available equipment (Φ)	20
Critical nodes (C)	264, 267, 274, 257, 260, 271, 252, 265
Blocked arcs (B)	(263, 267), (260, 261), (252, 253), (266, 267), (259, 260), (256, 254), (267, 263), (261, 260), (253, 252), (267, 266), (260, 259), (254, 256)
Obtained solution for region 2	
Optimal objective function value (hours)	139.16
Relief distribution route	251 → 255 → 256 → 271 → 256 → 255 → 253 → 252 → 253 → 254 → 257 → 259 → 260 → 258 → 274 → 265 → 274 → 258 → 266 → 262 → 264 → 262 → 266 → 267
Road restoration route	251 → 255 → 253 → 252 → 253 → 254 → 257 → 259 → 260 → 258 → 266 → 267
Time progression for relief distribution (hours)	0 → 1.71 → 5.68 → 9.62 → 18.66 → 22.62 → 26.75 → 29.90 → 33.05 → 37.42 → 45.45 → 46.23 → 56.84 → 56.92 → 69.92 → 71.23 → 72.55 → 85.55 → 101.40 → 103.38 → 116.46 → 129.53 → 131.51 → 139.16
Time progression for road restoration (hours)	0 → 1.71 → 5.85 → 9.70 → 13.55 → 17.92 → 25.94 → 26.72 → 46.23 → 46.31 → 62.17 → 131.51
opened blocked arcs	(253, 252), (252, 253), (259, 260), (266,267)
Number of equipment assigned for unblocking	(253, 252):2, (252, 253):2, (259, 260):8, (266,267):7

Table B.8: Results of region 2

Appendix B.4. Results for Region 3

The results of region 3, where Nassau Bay Emergency Operation Center is the depot, is given in Table B.9. We have provided the visual representation of the routes in Figure 7. While 20 items of equipment were allocated to this region, only 16 were used: 14 for arc (224, 225) and 2 for arc (225, 226). The last critical node to be visited is node 334, which was visited at time 100.31.

Problem setup for region 3	
Number of available equipment (Φ)	20
Critical nodes (C)	219, 217, 250, 216, 249, 248, 214, 241, 236, 225, 229, 234
Blocked arcs (B)	(208, 209), (210, 236), (245, 215), (245, 249), (224, 225), (225, 226), (229, 232), (209, 208), (236, 210), (215, 245), (249, 245), (225, 224), (226, 225), (232, 229)
Obtained solution for region 3	
Optimal objective function value (hours)	100.31
Relief distribution route	207 → 209 → 214 → 211 → 241 → 239 → 236 → 239 → 241 → 242 → 212 → 247 → 246 → 248 → 245 → 249 → 250 → 216 → 217 → 218 → 219 → 218 → 220 → 222 → 224 → 225 → 226 → 229 → 228 → 231 → 234
Road restoration route	207 → 209 → 214 → 215 → 212 → 247 → 245 → 249 → 250 → 216 → 217 → 218 → 219 → 218 → 220 → 222 → 224 → 225 → 226
Time progression for relief distribution (hours)	0 → 1.75 → 4.61 → 6.24 → 14.70 → 19.00 → 21.73 → 24.45 → 28.75 → 31.48 → 39.49 → 44.78 → 47.82 → 49.87 → 53.21 → 61.25 → 65.18 → 67.91 → 71.21 → 75.15 → 76.69 → 78.22 → 82.01 → 85.42 → 88.14 → 90.97 → 93.70 → 95.25 → 95.32 → 98.73 → 100.31
Time progression for road restoration (hours)	0 → 1.75 → 4.61 → 8.89 → 10.52 → 18.54 → 23.37 → 26.86 → 32.01 → 33.76 → 46.61 → 50.54 → 53.27 → 56.57 → 60.51 → 62.05 → 63.58 → 67.37 → 70.77 → 73.50 → 81.78 → 84.96
Opened blocked arcs	(224, 225) , (225, 226)
Number of equipment assigned for unblocking	(224, 225):14, (225, 226):2

Table B.9: Results of region 3

Appendix B.5. Results for Region 4

The results for region 4 are given in Table B.10. In this region, 25 equipment items were allocated for road restoration and all of them were utilized: 11 for arc (154, 156) and 11 for this arc in the opposite direction (156, 154). The unblocking of arcs (154, 156) and (156, 154) was finished at times 10.27 and 15.96, respectively. The relief distribution team arrived at arc (154, 156) at time 6.95, when this arc had not yet been restored and so could not be traversed. But when the arc had been fully restored at time 10.27, the relief distribution team started traversing it, which took 3.4 units of time, and so it finished its traversal at time 13.67. By that time, the relief distribution team was at node 156, and the unblocking of arc (156, 154) had not yet been finished. But when that arc was unblocked, at time 15.96, the relief distribution team started traversing from node 156 towards node 154, which it reached at 19.36 (15.96 + 3.40). The last blocked arc to be was (137, 166), at time 25.90. The relief distribution team arrived at node 137 at time 24.69 and waited until this unblocking procedure was finished, at 25.90, to start traversing this arc. The last critical node to be visited was node 167, at time 38.47.

Problem setup for region 4	
Number of available equipment (Φ)	25
Critical nodes (C)	166, 137, 167, 142, 151, 145, 156
Blocked arcs (B)	(130, 131), (131, 138), (138, 146), (150, 154), (154, 156), (137, 166), (131, 130), (138, 131), (146, 138), (154, 150), (156, 154), (166, 137)
Obtained solution for region 4	
Optimal objective function value (hours)	38.47
Relief distribution route	130 → 132 → 135 → 136 → 147 → 141 → 140 → 139 → 153 → 152 → 148 → 151 → 148 → 152 → 153 → 154 → 156 → 154 → 153 → 155 → 160 → 159 → 158 → 157 → 137 → 166 → 165 → 163 → 162 → 161 → 167
Road restoration route	130 → 132 → 135 → 139 → 153 → 154 → 156 → 154 → 153 → 152 → 148 → 151 → 145 → 141 → 147 → 136 → 137 → 166
Time progression for relief distribution (hours)	0 → 0.33 → 2.24 → 2.78 → 3.65 → 4.02 → 4.11 → 4.25 → 5.08 → 5.23 → 5.54 → 5.67 → 5.80 → 6.10 → 6.25 → 6.95 → 13.67 → 19.36 → 20.06 → 21.41 → 22.87 → 23.27 → 23.39 → 23.52 → 24.69 → 29.64 → 29.75 → 32.13 → 34.80 → 36.42 → 38.47
Time progression for road restoration (hours)	0 → 0.33 → 2.24 → 3.05 → 3.88 → 4.58 → 10.27 → 15.96 → 16.66 → 16.81 → 17.11 → 17.24 → 17.46 → 17.58 → 17.95 → 18.81 → 19.62 → 25.90
Opened blocked arcs	(154, 156), (156, 154), (137, 166)
Number of equipment assigned for unblocking	(154, 156):11, (156, 154):11, (137, 166):3

Table B.10: Results for region 4

Appendix B.6. Results for Region 5

The results of region 5 are presented in Table B.11. The depot for this region is La Porte Emergency Operation Center and there are six critical nodes. Out of 25 available items of equipment, 9 were used, to recover arc (204, 202), which was achieved at time 23.00; the relief distribution team arrived at this node exactly at time 23.00 and used this arc to visit all the critical nodes. The last critical node to be visited is 194, at time 68.06. We note that assigning the remaining recovery equipment to blocked arc (204, 202) does not improve the objective function since the arrival of the relief distribution team at this arc is the time when that arc is opened using only 9 items of equipment.

Problem setup for region 5	
Number of available equipment (Φ)	25
Critical nodes (C)	201, 205, 197, 194, 193, 170
Blocked arcs (B)	(169, 175), (181, 203), (200, 202), (202, 204), (202, 205), (175, 169), (203, 181), (202, 200), (204, 202), (205, 202)

Obtained solution for region 5	
Optimal objective function value (hours)	68.06
Relief distribution route	168 → 171 → 175 → 171 → 176 → 173 → 174 → 204 → 202 → 177 → 206 → 205 → 199 → 178 → 180 → 178 → 181 → 184 → 189 → 184 → 181 → 183 → 186 → 185 → 182 → 194
Road restoration route	168 → 171 → 176 → 173 → 174 → 204 → 202
Time progression for relief distribution (hours)	0 → 3.57 → 5.62 → 7.66 → 12.55 → 15.74 → 17.87 → 23.00 → 25.75 → 31.09 → 32.31 → 34.90 → 41.30 → 44.62 → 49.95 → 55.28 → 57.41 → 57.87 → 59.20 → 60.53 → 60.98 → 62.74 → 63.18 → 64.33 → 65.26 → 68.06
Time progression for road restoration (hours)	0 → 2.26 → 7.15 → 10.34 → 12.47 → 17.60 → 23.00
opened blocked arcs	(204, 202)
Number of equipment assigned for unblocking	(204, 202):9

Table B.11: Results for region 5

Appendix B.7. Results for Region 6

In Figure B.11, the routes of the relief distribution and road restoration teams are depicted in blue and red, respectively. The only blocked arc to be restored is (108, 92) and its unblocking procedure ends at 18.18 (Table B.12). While 10 items of equipment are allocated to this region, only 8 are used. The relief distribution team arrives at node 108 at time 35.27, by when arc (108, 92) has already been recovered and ready to be utilized. Node 120 is the last critical node to be visited by the relief distribution team at time 75.66.

Problem setup for region 6	
Number of available equipment (Φ)	10
Critical nodes (C)	98, 117, 94, 114, 125, 113, 108, 116, 97, 120
Blocked arcs (B)	(85, 83), (109, 110), (85, 90), (90, 107), (108, 92), (83, 85), (110, 109), (90, 85), (107, 90), (92, 108)

Obtained solution for region 6	
Optimal objective function value (hours)	75.66
Relief distribution route	83 → 97 → 99 → 96 → 98 → 117 → 115 → 111 → 110 → 101 → 99 → 106 → 116 → 102 → 113 → 108 → 92 → 86 → 87 → 88 → 94 → 114 → 94 → 88 → 91 → 121 → 125 → 121 → 122 → 120
Road restoration route	83 → 86 → 102 → 113 → 108 → 92
Time progression for relief distribution (hours)	0 → 4.07 → 5.47 → 7.77 → 10.54 → 14.45 → 17.18 → 18.19 → 20.11 → 21.41 → 21.61 → 23.26 → 25.51 → 28.33 → 31.84 → 35.27 → 38.10 → 39.51 → 42.64 → 43.75 → 45.72 → 50.04 → 54.37 → 56.33 → 57.07 → 62.74 → 64.83 → 66.93 → 73.67 → 75.66
Time progression for road restoration (hours)	0 → 2.66 → 6.80 → 10.31 → 13.74 → 18.18
Opened blocked arcs	(108, 92)
Number of equipment assigned for unblocking	(108, 92):8

Table B.12: Results for region 6

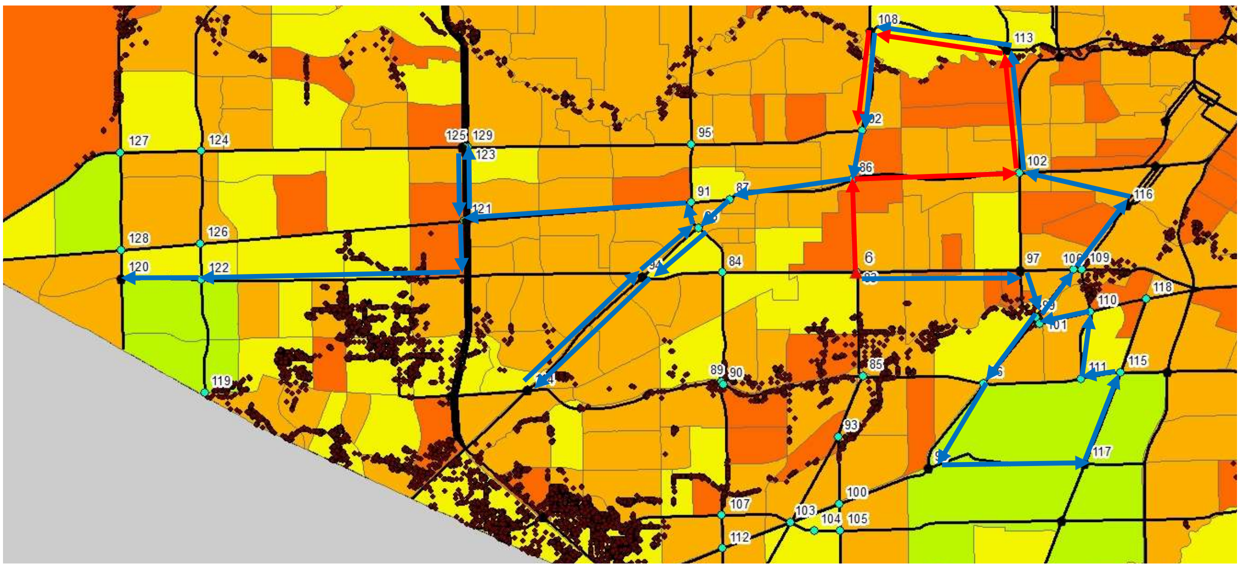

Figure B.11: Results for region 6 (via ArcGIS)

Appendix B.8. Results for Region 7

The results for region 7 are given in Table B.13. In this region, out of the 6 available items of equipment, 4 were used all for recovery of arcs (55, 60) and (60, 55) (2 items for each direction). The unblocking of arc (55, 60) was finished at time 13.18 and, in the opposite direction (60, 55), it was finished at time 20.70. The relief distribution team arrived at node 55 at time 16.66. In the opposite direction, the traversal of arc (60, 55) was started by the relief distribution team at time 20.70, exactly at the time in which its recovery was finished. The last critical node to be visited was 79, at time 78.38.

Problem setup for region 7	
Number of available equipment (Φ)	6
Critical nodes (C)	79, 73, 57, 66, 52, 81, 60
Blocked arcs (B)	(72, 82), (76, 79), (70, 82), (78, 50), (48, 60), (48, 47), (55, 60), (82, 72), (79, 76), (82, 70), (50, 78), (60, 48), (47, 48), (60, 55)
Obtained solution for region 7	
Optimal objective function value (hours)	78.38
Relief distribution route	40 → 42 → 44 → 43 → 42 → 43 → 56 → 57 → 56 → 63 → 55 → 60 → 55 → 44 → 42 → 40 → 41 → 45 → 50 → 52 → 81 → 52 → 51 → 71 → 65 → 66 → 73 → 82 → 79
Road restoration route	40 → 42 → 44 → 55 → 60 → 55
Time progression for relief distribution (hours)	0 → 1.38 → 1.67 → 1.80 → 2.09 → 2.39 → 6.41 → 8.23 → 13.07 → 14.87 → 16.66 → 20.70 → 24.73 → 28.73 → 29.01 → 30.39 → 35.14 → 35.84 → 37.67 → 38.99 → 45.86 → 52.73 → 54.41 → 59.24 → 59.30 → 62.13 → 68.55 → 72.60 → 78.38
Time progression for road restoration (hours)	0 → 1.38 → 1.66 → 5.66 → 13.18 → 20.70
Opened blocked arcs	(55, 60), (60, 55)
Number of equipment assigned for unblocking	(55, 60):2, (60, 55):2

Table B.13: Results of region 7

Appendix B.9. Results for Region 8

Table B.14 gives the details regarding region 8, which has Jersey Village Emergency Operation Center as its depot. As can be observed, the optimal objective function corresponds to the time at which node 31 the last critical node), was is visited by the relief distribution team, at time 135.96.

Problem setup for region 8	
Number of available equipment (Φ)	6
Critical nodes (C)	$6, 13, 26, 31, 32, 33, 38, 16$
Blocked arcs (B)	(38, 20), (18, 37), (32, 19), (19, 21), (31, 26), (25, 26), (20, 38), (37, 18), (19, 32), (21, 19), (26, 31), (26, 25)

Obtained solution for region 8	
Optimal objective function value (hours)	135.96
Relief distribution route	$1 \rightarrow 13 \rightarrow 1 \rightarrow 2 \rightarrow 4 \rightarrow 15 \rightarrow 21 \rightarrow 26 \rightarrow 21 \rightarrow 15 \rightarrow 16 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 8 \rightarrow 10 \rightarrow 20 \rightarrow 38 \rightarrow 37 \rightarrow 33 \rightarrow 37 \rightarrow 32 \rightarrow 35 \rightarrow 31$
Road restoration route	$1 \rightarrow 9 \rightarrow 20 \rightarrow 38$
Time progression for relief distribution (hours)	$0 \rightarrow 3.85 \rightarrow 7.70 \rightarrow 8.50 \rightarrow 8.96 \rightarrow 13.44 \rightarrow 21.50 \rightarrow 27.31 \rightarrow 33.13 \rightarrow 41.19 \rightarrow 41.25 \rightarrow 45.53 \rightarrow 46.07 \rightarrow 46.41 \rightarrow 47.02 \rightarrow 47.35 \rightarrow 54.67 \rightarrow 71.24 \rightarrow 85.94 \rightarrow 97.98 \rightarrow 110.01 \rightarrow 123.18 \rightarrow 133.49 \rightarrow 135.96$
Time progression for road restoration (hours)	$0 \rightarrow 1.99 \rightarrow 9.32 \rightarrow 27.55$
Opened blocked arcs	(20, 38)
Number of equipment assigned for unblocking	(20, 38): 6

Table B.14: Results of region 8

References

Abazari, S. R., Jolali, F., & Aghsami, A. 2021. Designing a humanitarian relief network considering governmental and non-governmental operations under uncertainty. *International Journal of System Assurance Engineering and Management*.

Ajam, Meraj, Akbari, Vahid, & Salman, F. Sibel. 2019. Minimizing latency in post-disaster road clearance operations. *European Journal of Operational Research*, **277**(3), 1098 – 1112.

Ajam, Meraj, Akbari, Vahid, & Salman, F. Sibel. 2022. Routing multiple work teams to minimize latency in post-disaster road network restoration. *European Journal of Operational Research*, **300**(1), 237–254.

Akbari, Vahid, & Salman, F. Sibel. 2017a. Multi-vehicle prize collecting arc routing for connectivity problem. *Computers and Operations Research*, **82**, 52–68.

Akbari, Vahid, & Salman, F. Sibel. 2017b. Multi-vehicle synchronized arc routing problem to restore post-disaster network connectivity. *European Journal of Operational Research*, **257**(2), 625–640.

Akbari, Vahid, & Shiri, Davood. 2021. Weighted online minimum latency problem with edge uncertainty. *European Journal of Operational Research*, **295**(1), 51–65.

Akbari, Vahid, & Shiri, Davood. 2022. An online optimization approach for post-disaster relief distribution with online blocked edges. *Computers & Operations Research*, **137**, 105533.

Akbari, Vahid, Sadati, Mir Ehsan Hesam, & Kian, Ramez. 2021a. A decomposition-based heuristic for a multicrew coordinated road restoration problem. *Transportation Research Part D: Transport and Environment*, **95**, 102854.

Akbari, Vahid, Shiri, Davood, & Sibel Salman, F. 2021b. An online optimization approach to post-disaster road restoration. *Transportation Research Part B: Methodological*, **150**, 1–25.

Barbalho, Thiago Jobson, Santos, Andréa Cynthia, & Aloise, Dario José. 2021. Metaheuristics for the work-troops scheduling problem. *International Transactions in Operational Research*, **n/a**(n/a).

Berman, O, & Drezner, Z. 2007. The multiple server location problem. *Journal of the Operational Research Society*, **58**(1), 91–99.

Briskorn, Dirk, Kimms, Alf, & Olschok, Denis. 2020. Simultaneous planning for disaster road clearance and distribution of relief goods: a basic model and an exact solution method. *OR Spectrum*, **42**(3), 591 – 619.

Cartes, Pablo, Echaveguren Navarro, Tomás, Giné, Alondra Chamorro, & Binet, Eduardo Allen. 2021. A cost-benefit approach to recover the performance of roads affected by natural disasters. *International Journal of Disaster Risk Reduction*, **53**, 102014.

Caunhye, Aakil M., Aydin, Nazli Yonca, & Duzgun, H. Sebnem. 2020. Robust post-disaster route restoration. *OR Spectrum*, **42**(4), 1055–1087.

Çelik, Melih, Ergun, Özlem, & Keskinocak, Pınar. 2015. The Post-Disaster Debris Clearance Problem Under Incomplete Information. *Operations Research*, **63**(1), 65–85.

Christofides, Nicos, Campos, V., Corberán, A., & Mota, E. 1986. *An algorithm for the Rural Postman problem on a directed graph*. Berlin, Heidelberg: Springer Berlin Heidelberg. Pages 155–166.

Coco, Amadeu A., Duhamel, Christophe, & Santos, Andréa Cynthia. 2020. Modeling and solving the multi-period disruptions scheduling problem on urban networks. *Annals of Operations Research*, **285**(1), 427–443.

Cohn, Scott. 2017. *CNBC.COM Texas and Florida hurt by the economic body blow from hurricanes Harvey and Irma*. https://www.cnbc.com/2017/09/15/texas-and-florida-face-economic-blow-from-hurricanes-harvey-and-irma.html. Accessed: 2020-12-17.

CRED, & UNDRR. 2020. *Human cost of disasters: An overview of the last twenty years 2000-2019*. Tech. rept. Centre for Research on the Epidemiology of Disasters and UN Office for Disaster Risk Reduction.

Daganzo, Carlos F. 1978. An approximate analytic model of many-to-many demand responsive transportation systems. *Transportation Research*, **12**(5), 325–333.

Duque, Pablo Maya, Dolinskaya, Irina S., & Sörensen, Kenneth. 2016. Network repair crew scheduling and routing for emergency relief distribution problem. *European Journal of Operational Research*, **248**(1), 272–285.

FEMA. 2010. *The Federal Emergency Management Agency Publication 1*. Tech. rept. The Federal Emergency Management Agency.

García-Alviz, Juliette, Galindo, Gina, Arellana, Julián, & Yie-Pinedo, Ruben. 2021. Planning road network restoration and relief distribution under heterogeneous road disruptions. *OR Spectrum*, **43**(4), 941 – 981.

Gokalp, Can, Patil, Priyadarshan N., & Boyles, Stephen D. 2021. Post-disaster recovery sequencing strategy for road networks. *Transportation Research Part B: Methodological*, **153**, 228–245.

Golla, Arpan Paul Singh, Bhattacharya, Shankha Pratim, & Gupta, Sumana. 2020. The accessibility of urban neighborhoods when buildings collapse due to an earthquake. *Transportation Research Part D: Transport and Environment*, **86**, 102439.

Helderop, Edward, & Grubesic, Tony H. 2019. Streets, storm surge, and the frailty of urban transport systems: A grid-based approach for identifying informal street network connections to facilitate mobility. *Transportation Research Part D: Transport and Environment*, **77**, 337–351.

Hu, Shaolong, Han, Chuanfeng, Dong, Zhijie Sasha, & Meng, Lingpeng. 2019. A multi-stage stochastic programming model for relief distribution considering the state of road network. *Transportation Research Part B: Methodological*, **123**, 64–87.

Kasaei, Maziar, & Salman, F. Sibel. 2016. Arc routing problems to restore connectivity of a road network. *Transportation Research Part E: Logistics and Transportation Review*, **95**, 177–206.

Li, Shuanglin, & Teo, Kok Lay. 2019. Post-disaster multi-period road network repair: work scheduling and relief logistics optimization. *Annals of Operations Research*, **283**(1), 1345–1385.

Li, Shuanglin, Ma, Zujun, & Teo, Kok Lay. 2020. A new model for road network repair after natural disasters: Integrating logistics support scheduling with repair crew scheduling and routing activities. *Computers and Industrial Engineering*, **145**, 106506.

Li, Zhenning, Yu, Hao, Chen, Xiaofeng, Zhang, Guohui, & Ma, David. 2019. Tsunami-induced traffic evacuation strategy optimization. *Transportation Research Part D: Transport and Environment*, **77**, 535–559.

Liu, Yajie, Lei, Hongtao, Wu, Zhiyong, & Zhang, Dezhi. 2019. A robust model predictive control approach for post-disaster relief distribution. *Computers & Industrial Engineering*, **135**, 1253 – 1270.

Marianov, Vladimir, & Serra, Daniel. 2002. Location–Allocation of Multiple-Server Service Centers with Constrained Queues or Waiting Times. *Annals of Operations Research*, **111**(1), 35 – 50.

Mirdar Harijani, Ali, Mansour, Saeed, Karimi, Behrooz, & Lee, Chi-Guhn. 2017. Multi-period sustainable and integrated recycling network for municipal solid waste – A case study in Tehran. *Journal of Cleaner Production*, **151**, 96 – 108.

Moreno, Alfredo, Alem, Douglas, Ferreira, Deisemara, & Clark, Alistair. 2018. An effective two-stage stochastic multi-trip location-transportation model with social concerns in relief supply chains. *European Journal of Operational Research*, **269**(3), 1050–1071.

Moreno, Alfredo, Munari, Pedro, & Alem, Douglas. 2019. A branch-and-Benders-cut algorithm for the Crew Scheduling and Routing Problem in road restoration. *European Journal of Operational Research*, **275**(1), 16–34.

Moreno, Alfredo, Munari, Pedro, & Alem, Douglas. 2020a. Decomposition-based algorithms for the crew scheduling and routing problem in road restoration. *Computers & Operations Research*, **119**, 104935.

Moreno, Alfredo, Alem, Douglas, Gendreau, Michel, & Munari, Pedro. 2020b. The heterogeneous multicrew scheduling and routing problem in road restoration. *Transportation Research Part B: Methodological*, **141**, 24–58.

Morshedlou, Nazanin, González, Andrés D., & Barker, Kash. 2018. Work crew routing problem for infrastructure network restoration. *Transportation Research Part B: Methodological*, **118**(dec), 66–89.

Morshedlou, Nazanin, Barker, Kash, González, Andrés D., & Ermagun, Alireza. 2021. A heuristic approach to an interdependent restoration planning and crew routing problem. *Computers & Industrial Engineering*, **161**, 107626.

Munari, Pedro, Moreno, Alfredo, De La Vega, Jonathan, Alem, Douglas, Gondzio, Jacek, & Morabito, Reinaldo. 2019. The Robust Vehicle Routing Problem with Time Windows: Compact Formulation and Branch-Price-and-Cut Method. *Transportation Science*, **53**(4), 1043–1066.

Nabavi, S.M., Vahdani, Behnam, Nadjafi, B. Afshar, & Adibi, M.A. 2021. Synchronizing victim evacuation and debris removal: A data-driven robust prediction approach. *European Journal of Operational Research*.

Nadimi-Shahraki, Mohammad H., Taghian, Shokooh, & Mirjalili, Seyedali. 2021. An improved grey wolf optimizer for solving engineering problems. *Expert Systems with Applications*, **166**, 113917.

Najafi, Mehdi, Eshghi, Kourosh, & Dullaert, Wout. 2013. A multi-objective robust optimization model for logistics planning in the earthquake response phase. *Transportation Research Part E: Logistics and Transportation Review*, **49**(1), 217 – 249.

Oyola, Jorge, Arntzen, Halvard, & Woodruff, David L. 2018. The stochastic vehicle routing problem, a literature review, part I: models. *EURO Journal on Transportation and Logistics*, **7**(3), 193–221.

Ozdamar, Linet, Ekinci, Ediz, & Küçükyazici, Beste. 2004. Emergency Logistics Planning in Natural Disasters. *Annals of Operations Research*, **129**(1), 217 – 245.

Powell, Warren B. 2007. *Approximate Dynamic Programming: Solving the curses of dimensionality*. Vol. 703. John Wiley & Sons.

Pérez-Rodríguez, Noel, & Holguín-Veras, José. 2016. Inventory-Allocation Distribution Models for Postdisaster Humanitarian Logistics with Explicit Consideration of Deprivation Costs. *Transportation Science*, **50**(4), 1261–1285.

Rawls, Carmen G., & Turnquist, Mark A. 2010. Pre-positioning of emergency supplies for disaster response. *Transportation Research Part B: Methodological*, **44**(4), 521–534.

Sanci, Ece, & Daskin, Mark S. 2019. Integrating location and network restoration decisions in relief networks under uncertainty. *European Journal of Operational Research*.

Sanci, Ece, & Daskin, Mark S. 2021. An integer L-shaped algorithm for the integrated location and network restoration problem in disaster relief. *Transportation Research Part B: Methodological*, **145**, 152–184.

Sayarshad, H. 2015. *Smart Transit Dynamic Optimization and Informatics*. Ph.D. thesis, Ryerson University, Toronto.

Sayarshad, Hamid R., & Chow, Joseph Y.J. 2017. Non-myopic relocation of idle mobility-on-demand vehicles as a dynamic location-allocation-queueing problem. *Transportation Research Part E: Logistics and Transportation Review*, **106**, 60–77.

Sayarshad, Hamid R., & Mahmoodian, Vahid. 2021. An intelligent method for dynamic distribution of electric taxi batteries between charging and swapping stations. *Sustainable Cities and Society*, 102605.

Sayarshad, Hamid R., Du, Xinpi, & Gao, H. Oliver. 2020. Dynamic post-disaster debris clearance problem with re-positioning of clearance equipment items under partially observable information. *Transportation Research Part B: Methodological*, **138**, 352 – 372.

Shin, Youngchul, Kim, Sungwoo, & Moon, Ilkyeong. 2019. Integrated optimal scheduling of repair crew and relief vehicle after disaster. *Computers & Operations Research*, **105**, 237 – 247.

Shiri, Davood, & Salman, F. Sibel. 2020. Online Optimization of First-responder Routes in Disaster Response Logistics. *IBM Journal of Research and Development*, **64**, 13:1–13:9.

Sohouenou, Philippe Y.R., Neves, Luis A.C., Christodoulou, Aris, Christidis, Panayotis, & Lo Presti, Davide. 2021. Using a hazard-independent approach to understand road-network robustness to multiple disruption scenarios. *Transportation Research Part D: Transport and Environment*, **93**, 102672.

Souza Almeida, Luana, Goerlandt, Floris, Pelot, Ronald, & Sörensen, Kenneth. 2022. A Greedy Randomized Adaptive Search Procedure (GRASP) for the multi-vehicle prize collecting arc routing for connectivity problem. *Computers & Operations Research*, **143**, 105804.

Tuzun Aksu, Dilek, & Ozdamar, Linet. 2014. A mathematical model for post-disaster road restoration: Enabling accessibility and evacuation. *Transportation Research Part E: Logistics and Transportation Review*, **61**, 56–67.

Tzeng, Gwo-Hshiung, Cheng, Hsin-Jung, & Huang, Tsung Dow. 2007. Multi-objective optimal planning for designing relief delivery systems. *Transportation Research Part E: Logistics and Transportation Review*, **43**(6), 673 – 686. Challenges of Emergency Logistics Management.

Vahdani, Behnam, Veysmoradi, D., Shekari, N., & Mousavi, S. Meysam. 2018. Multi-objective, multi-period location-routing model to distribute relief after earthquake by considering emergency roadway repair. *Neural Computing and Applications*, **30**, 835 – 854.

Vodák, Rostislav, Bíl, Michal, & Křivánková, Zuzana. 2018. A modified ant colony optimization algorithm to increase the speed of the road network recovery process after disasters. *International Journal of Disaster Risk Reduction*, **31**, 1092–1106.

Wang, Haijun, Du, Lijing, & Ma, Shihua. 2014. Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake. *Transportation Research Part E: Logistics and Transportation Review*, **69**, 160 – 179.

Waserhole, Ariel, & Jost, Vincent. 2016. Pricing in vehicle sharing systems: Optimization in queuing networks with product forms. *EURO Journal on Transportation and Logistics*, **5**(3), 293–320.

Wei, Xiaowen, Qiu, Huaxin, Wang, Dujuan, Duan, Jiahui, Wang, Yanzhang, & Cheng, T.C.E. 2020. An integrated location-routing problem with post-disaster relief distribution. *Computers & Industrial Engineering*, **147**, 106632.

Wisetjindawat, Wisinee, Ito, Hideyuki, & Fujita, Motohiro. 2015. Integrating Stochastic Failure of Road Network and Road Recovery Strategy into Planning of Goods Distribution after a Large-Scale Earthquake. *Transportation Research Record*, **2532**(1), 56–63.

World-Nuclear-News. 2017. *Texan nuclear plant runs through Hurricane Harvey*. https://www.world-nuclear-news.org/RS-Texan-nuclear-plants-run-through-Hurricane-Harvey-2908174.html. Accessed: 2020-12-20.

Yan, Shangyao, & Shih, Yu-Lin. 2009. Optimal scheduling of emergency roadway repair and subsequent relief distribution. *Computers & Operations Research*, **36**(6), 2049 – 2065.

Zamanifar, Milad, & Hartmann, Timo. 2021. Decision attributes for disaster recovery planning of transportation networks; A case study. *Transportation Research Part D: Transport and Environment*, **93**, 102771.