



**Restoration and Humanitarian Aid Delivery
on Interdependent Transportation and
Communication
Networks After an Extreme Event**

THESIS

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AFIT-ENS-MS-15-M-142

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RESTORATION AND HUMANITARIAN AID DELIVERY
ON INTERDEPENDENT TRANSPORTATION AND COMMUNICATION
NETWORKS AFTER AN EXTREME EVENT

THESIS

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Abstract

Among the devastating consequences of extreme events, whether natural or man-made, is the disruption of transportation, communication, and other critical infrastructure systems. The restoration of these systems can be especially challenging due to the fact that damaged infrastructures are often characterized by complex interdependencies. Given a region with interdependent transportation and communication networks, both of which have sustained some damage due to an extreme event, we seek to maximize the satisfaction of geographically distributed demands for relief items over time by scheduling work crews to selected restoration tasks and routing the delivery of resources. We develop a mixed-integer linear programming formulation that captures the interdependencies exhibited by the transportation and communication networks, accounts for policy constraints that limit the delivery of resources into the affected region, and ensures that machine movement is feasible given the transportation network status when scheduling machines to tasks. After conducting tests on a variety of model instances, we establish the importance of relief operations during the initial phase of the scheduling horizon, demonstrate how changes in selected network parameters affect optimal scheduling decisions, and identify several key facilities whose construction is vital to the fulfillment of demand for relief items.

To my beautiful wife. Thank you for your constant love, support, and encouragement. I am privileged to have you as a teammate and friend.

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RESTORATION AND HUMANITARIAN AID DELIVERY ON INTERDEPENDENT TRANSPORTATION AND COMMUNICATION NETWORKS AFTER AN EXTREME EVENT

I. Introduction

Among the devastating consequences of extreme events, whether natural or man-made, is the disruption of transportation, communication and other critical infrastructure systems. Relief efforts to aid victims within regions affected by an extreme event are limited in their effectiveness by the operability of these key infrastructure systems. For example, a functional transportation network is important for successfully delivering humanitarian aid. A month after Typhoon Haiyan made landfall in the Philippines in 2013, many rural communities remained isolated from relief efforts due to uncleared debris on roads (see Chughtai [9]). An operable communication network is key to relief efforts as well. Chiu *et al.* [8] observed that reliable lines of communication between the U.S. military forces and non-government organizations participating in the Typhoon Haiyan relief effort were critical to the relief effort's success. Likewise, Moroney *et al.* [25] note the serious impact of either having or not having an effective communication network on each of four United States humanitarian missions in Burma (2008), Indonesia (2009), Pakistan (2010) and Japan (2011).

Certainly, the restoration of these infrastructure systems constitutes an integral part of relief efforts in regions affected by extreme events. However, infrastructure restoration decisions can be especially challenging due to the fact that damaged infrastructures are often characterized by complex interdependencies. That is, the

performance of one or more components of an infrastructure system may depend on the performance of another infrastructure system (see Rinaldi *et al.* [30]). For example, by repairing or building cellular towers or other communication entities, relief organizations gain a means by which they can communicate to the public the locations of distribution centers where relief items can be acquired. As noted by Abramson and Redlener [1] in their review of post Hurricane Sandy response, efforts to direct and aid the public are useless without the ability to communicate. This relationship links the communication and transportation networks in a way that makes restoration decisions interdependent. More specifically, repairing roads is only beneficial in-so-far as those in need of aid know which roads to take in order to get to the location where relief items are distributed. Furthermore, the ability to establish an effective communication network may require a certain level of operability in the transportation infrastructure. Work crews may not be able to restore communication entities to improve the state of the communication network until certain roads have been repaired. These interdependencies must be considered in order to fully capture the impact of complex decisions that managers make after extreme events.

Problem Statement. Given a region with interdependent transportation and communication infrastructure networks, both of which have sustained some damage due to an extreme event, we seek to maximize the satisfaction of geographically distributed demands for relief items over time by scheduling work crews to selected network-specific restoration tasks and routing the delivery of resources (i.e., work crews and relief items).

The effectiveness of relief efforts may be measured by the amount of relief items (e.g., mosquito nets, food, water, medicine) disseminated to affected areas (see Moroney *et al.* [25]). In the aftermath of an extreme event, affected villages, neighbor-

hoods, cities, or other locations may require a certain amount of material aid. These locations can be classified as demand points, each with a particular demand for relief items. However, it is often the case that humanitarian efforts are limited by resource constraints. Flooding an affected region with too many resources may overwhelm infrastructure systems within the region and overwhelm their ability to handle and transport relief items. To prevent this issue, the impacted region may implement policy that limits air traffic in and out of the country, wherein delivery of resources such as restoration work crews and relief items is restricted (see Moroney *et al.* [25]). These policy constraints represent a limiting factor in the amount of demand that can be met at each demand point.

Relief items may be brought into the affected area at airports, loading docks, or some other kind of warehouse. We classify these locations as supply depots. Typically, relief items are not transferred directly from supply depots to demand points. More often, they are transported to a distribution center at which they can be collected, repackaged, and processed. From a distribution center, the relief items can either be delivered to or collected by individuals from a nearby demand point [8]. Ideally, one would want to transfer enough relief items through supply depots to distribution centers in order to meet the demand at all of the demand points. However, damage sustained by the transportation, communication, and other infrastructure systems due to an extreme event may limit the amount of demand that can be met at each demand point. First, if road damage is substantial, it may not be possible to deliver any relief items from a distribution center to a demand node until a certain amount of road repairs are made. Furthermore, the supply depots and distribution centers may themselves require a certain level of repair before they can be utilized as part of the relief effort. Even after repairs are made, decision makers must consider the limitations of each road, supply depot, and distribution center before including them

as part of the relief plan. That is, each of these entities is likely characterized by some maximum capacity for relief items.

In addition to policy constraints, infrastructure damage, and infrastructure capacities, another factor that limits the amount of demand that can be met at each demand point is the inability to communicate after an extreme event. Namely, individuals at a demand point need some way of learning where to go to collect relief items. We model the satisfaction of this requirement in two ways. The location of a distribution center is made known to a demand point by virtue of its physical proximity to the distribution center. Alternatively, the location of a distribution center is made known to a demand point by transmitting the information through a nearby cellular tower, loud speaker or some other communication entity. For demand points that do not have a distribution center within close physical proximity, communication must come from a repaired or newly constructed communication entity. Furthermore, it is assumed that each distribution center is aware of the locations of all of the other distribution centers within the affected area. Therefore, once a demand point begins collecting relief items from one distribution center, it learns the location of all distribution centers.

In order to use a math program to decide the optimal restoration and routing decisions, the relevant infrastructures and their interdependencies must be accurately represented. This is achieved by representing each infrastructure system as a network consisting of nodes and arcs. Supply depots, distribution centers, communication entities, and demand points are represented by nodes within a network. Likewise, roads are represented by directed arcs. We attribute repair times, supply and demand values, capacities for relief items, and other relevant parameters to each of the nodes and arcs within the network in order to properly model the affected area. Using our network representation, demand for relief items is satisfied by flowing relief items

from supply nodes, through distribution center nodes, to demand nodes over a set of directed arcs. We model a demand point’s knowledge of the location of distribution centers as the flow of communication between distribution center nodes, communication entity nodes, and the corresponding demand node. The repair or construction of roads, supply depots, distribution centers, and communication entities corresponds to the restoration of directed arcs or nodes in the representative network. Our model ensures that this can only be achieved if work crews are able to traverse a set of directed arcs from a supply node to the node or the directed arc in need of repair. The goal of this thesis is to equip a centralized decision maker of restoration activities, such as an emergency manager, with a method for optimally selecting and scheduling the repair of damaged transportation and communication network components in order to maximize the satisfaction of demand of relief items within the scheduling horizon. We test representative data sets using commercial software to validate the proposed model and solution as a viable decision making tool for real time restoration activities.

Main Contributions. The results of our research include the following. (i) Capturing the interdependencies between the transportation and communication networks. (ii) Modeling of policy resource constraints on the delivery of relief items and machines¹ into the impacted area. (iii) Detailed modeling of scheduling machines, ensuring their movement between tasks is feasible given the transportation network status. (iv) Determining how to set up distribution points, communication capabilities, and flow of relief items into an area after an extreme event. (v) Sensitivity analysis on how adjustments to selected network and model parameters affect optimal network restoration and scheduling decisions.

¹In an effort to be consistent with the notation traditionally ascribed to scheduling problems, restoration work crews are referred to as “machines” for the remainder of this thesis.

The remainder of this thesis is organized as follows. In Chapter 2, we review network flow models and interdependent network concepts, and we highlight related temporal and static approaches to humanitarian logistics and interdependent network restoration. In Chapter 3, we set forth a mixed-integer linear programming (MILP) formulation to solve the interdependent Transportation and Communication network Restoration and Distribution (TCRD) problem. In Chapter 4, we conduct computational tests on realistic networks using a commercial solver and analyze the results. We conclude the thesis in Chapter 5 wherein we highlight key results from this research and suggest future research possibilities.

II. Literature Review

Heightened awareness of the devastation wrought by events such as the September 11 attacks on the United States and the 2004 Indian Ocean Tsunami has resulted in an increased volume of operations research literature devoted to disaster relief and management (see Altay & Green III [3] and Wright *et al.* [35]). This chapter reviews literature relevant to the modeling and application of disaster relief. First, we discuss the maximum flow problem, network restoration, interdependent network modeling, and other selected network flow models. Second, we highlight a variety of contributions made toward disaster relief planning and humanitarian logistics by those in the operations research community. Finally, we summarize our findings and share conclusions drawn from the literature review.

2.1 Network Flows

Fundamental to our model is the flow of supplies from one location to another using a combined physical-and-virtual infrastructure. This coincides with traditional network flow models. In this section we review the maximum flow problem, followed by a discussion of applications to network flow models with a focus on network restoration. We survey both static and temporal approaches to network restoration problems. Furthermore, we discuss the concept of network interdependencies, and we survey models developed for solving interdependent network restoration problems. Finally, we briefly introduce network design and network interdiction, and we address their relationship to the problem at hand.

2.1.1 Maximum Flow.

Ahuja *et al.* [2] introduce four foundational network flow problems: the minimum cost flow problem, the shortest path problem, minimum spanning trees, and the maximum flow problem. Most relevant to our model is the maximum flow problem. The maximum flow problem seeks to determine the maximum amount of flow across a network originating at a source node and ending at a sink node while adhering to arc capacities. The maximum flow problem may be formulated as a linear program in which the objective is to maximize the sum of all continuous flow variables into the sink node. Linear constraints ensure flow balance and adherence to flow bounds.

2.1.2 Network Restoration.

While there is no standard network restoration problem, a common application of the problem concerns situations in which a decision maker must determine which nodes and/or arcs to repair within a damaged network in order to optimize a given objective function. The mixed-integer linear programming formulation presented by Magnanti & Wong [24] for the transportation network design problem establishes a foundation for network restoration modeling. The authors seek to minimize the combined construction and routing costs by determining which transportation arcs to construct and by specifying the routing of commodities through the network such that customer demands for each commodity are met. We note that the considerations associated with network design are also important for network restoration. Namely, a network design problem can be utilized to solve the restoration of a network for which a decision maker must decide which arcs to build or repair in order to meet customer demand while considering construction and transportation costs.

Magnanti & Wong [24] present a static approach to network design, whereas Guha *et al.* [15] demonstrate that network design and restoration problems may be either

static or temporal. Guha *et al.* [15] consider problems associated with restoring a dysfunctional electrical network after a wide scale electrical power outage. The electrical network consists of customer, generator, and relay nodes joined by a set of edges such that the network is connected. After a power outage, a subset of relay vertices are removed from the network, resulting in some of the customer nodes being disconnected from the generator node. A static approach to this problem is to decide, given limited resources, which relay nodes to restore in order to maximize the weighted number of customer nodes reconnected to the generator node. The authors also consider a temporal approach that requires the recovery of all the generator nodes over multiple time periods. Repairs are scheduled in order to minimize the total weighted latency incurred by each customer node, subject to budget constraints.

As noted by Nurre *et al.* [26], budget constraints and minimum cost objectives are not always appropriate for network restoration problems. The authors develop an integrated network design and scheduling model in which restoration decisions focus on maximizing weighted demand met over all periods in the scheduling horizon. Solution methods proposed for the integrated network design and scheduling problem include an integer programming formulation that links the network design and scheduling decisions, and a heuristic dispatching rule based on residual network optimality conditions and a weighted shortest processing time dispatching rule.

Certain situations require that precedence relationships be observed when scheduling network repairs. Ang [4] provides a recovery optimization (RECOP) model for optimizing the scheduled recovery of a damaged electrical power grid subject to precedence constraints. The formulation seeks to minimize power shed over the scheduling horizon. A scenario-based approach was used to demonstrate the effectiveness of the RECOP model. In a terrorist attack scenario wherein a small percentage of the network is damaged, the RECOP model was solved to optimality within twenty minutes.

The author provides a two-phase solution method to identify near optimal solutions for instances having a relatively high percentage of the electrical network damaged, such as after a hurricane or other natural disaster.

Repairing arcs within a damaged network may reduce network flows during the time period in which the arc is being repaired. Boland *et al.* [5] consider how to schedule arc maintenance for networks that require an arc to be non-operational while it is being maintained. The authors develop a MILP formulation for the maximum total flow with flexible arc outages, and they test four local search heuristics to solve the problem for instances using both randomly generated and real-world data. They found that some of the local search heuristics outperform traditional solvers on larger instances.

Some scenarios impose deadlines regarding when network repairs must be made. For example, Feng & Wang [13] develop a transportation network restoration model for post-earthquake scenarios in which effective emergency response requires highway repairs to be scheduled within 72 hours after the earthquake. The authors consider three unique objective functions for respectively (1) maximizing the total length of repaired roads, (2) maximizing the number of lives saved (where each potential node repair has an associated value of people effected), and/or (3) minimizing the total risk of the repairs (where each potential node repair has an associated risk value). Under their MILP formulation, the authors observed a trade-off relationship between total length of repaired roads and the maximum number of lives saved. Rather than impose deadlines, other scenarios stipulate the rate at which network repairs can be made. For example, Kalinowski *et al.* [19] develop a network design and restoration model that seeks to maximize the cumulative flow over a specified scheduling horizon, given that only one arc can be added to the network in each time period.

Parameters associated with network restoration problems are not always determin-

istic. For example, processing times associated with restoration scheduling decisions may be uncertain. Xu *et al.* [36] present a stochastic scheduling approach for optimizing restoration of an electric power network after an earthquake when processing times are non-deterministic. They apply a genetic algorithm to solve a stochastic integer program that seeks to minimize the average time each customer is without power. Like processing times, demand in transportation networks may be stochastic. Ukkusuri & Patil [33] employ stochastic math programming to solve a flexible transportation network design formulation for situations such as these. Finally, the disruption of a network may itself be characterized as a stochastic event. Shen [31] formulates a MILP for designing and restoring a network when the disruption of each arc in the network is a stochastic event.

2.1.3 Interdependent Networks.

Rinaldi *et al.* [30] describe how human infrastructures are often characterized by physical, cyber, logical, or geographic interdependencies. Due to these interdependencies, damage to a component of one infrastructure can cause damage to components of other infrastructures (see O’Rourke [27]). In the context of network restoration, this implies that restoration of a single network is often only a part of the larger effort to restore multiple interdependent networks.

Lee *et al.* [20] develop an interdependent layered network (ILN) model to account for network interdependencies. The ILN model does not assume a particular configuration of infrastructures nor a certain type of extreme event. It only requires that some unpredictable extreme event damages a subset of physical components within a general infrastructure system (Lee *et al.* [21]). They seek to decide which network arcs to restore within a set of damaged interdependent networks to optimize a minimum cost flow objective function. Restoration decisions are subject to flow balance,

demand, and resource constraints, and commodity flows are contingent upon network interdependencies. However, the ILN model only informs the decision maker which network arcs must be repaired in order to restore the services provided by each of the infrastructures; it does not indicate how or when each arc should be repaired. Gong *et al.* [14] build upon the ILN model by formulating a methodology for answering these questions. Given a scheduling horizon, a set of machines, and the set of network arcs that have been selected to be repaired, they seek to optimally schedule the repair of these arcs by selecting the time periods to assign each machine to repair damaged network arcs. Examined as a whole, these authors provide a method for sequentially selecting the arcs of the interdependent network to repair (Lee *et al.* [20]) and then deciding how and when they should be repaired (Gong *et al.* [14]).

Cavdaroglu *et al.* [7] note that making these decisions sequentially may be impractical, given that restoration and scheduling decisions often conflict. They provide an integrated restoration and scheduling model for making the restoration and scheduling decisions simultaneously. That is, the model seeks to decide which network arcs to restore, at what time period, and by which machine. By synthesizing the ILN and scheduling models provided by Lee *et al.* [20] and Gong *et al.* [14], they are able to minimize total cost, where the total cost is based upon flow, unmet demand, and installation costs. We note, however, that the integrated restoration and scheduling model does not consider the movement of machines through the network at each time period.

2.1.4 Additional Network Flow Applications.

The previous section highlights how network design techniques can be used to solve network restoration problems. However, network design is applied to a variety of other types of problems. For example, Daskin [10] develops a facility location model

that seeks to maximize the expected coverage of demand within an existing network by selecting locations within the network at which to construct supply facilities. For additional applications of network design, see Owen & Daskin [28].

Related to network design and network restoration is the network interdiction problem. In a network interdiction problem, an interdictor seeks to alter upper bounds on arc flow in an enemy network so as to hinder the enemy’s ability to achieve an objective. Example applications of this problem include Wood [34] who provides a deterministic approach to minimizing the enemy’s maximum flow through a capacitated network using limited resources, and Israeli & Wood [18] who demonstrate how to deterministically maximize the enemy’s shortest path through the network using limited resources. For a review of interdiction models, see Smith [32].

2.2 Operations Research in Humanitarian Logistics

Altay & Green III [3] show that applications of operations research to disaster relief are not limited to the post-disaster planning phase. A variety of operations research methodologies have been employed to solve problems associated with natural and man-made disasters at different stages of disaster relief planning.

While our model is designed to aid a central decision maker immediately following an extreme event, work has been done to aid emergency managers at different stages of the disaster relief cycle. In discussing the role of operations research in disaster recovery planning, Bryson *et al.* [6] note, “There are opportunities for applying [operations research] at all levels of [disaster recovery] planning, development, implementation and operation.” They develop a mixed-integer model for solving the subplan selection problem, which aims to maximize the expected value of an organization’s ability to recover after an extreme event by determining which subplans should be adopted for each possible disaster effect.

Rawls & Turnquist [29] consider how to improve preparedness for an extreme event by deciding the locations and quantities for prepositioning emergency supplies. The authors develop a two-stage stochastic mixed-integer program that accounts for variability in network reliability and forecasted demand of emergency supplies. They apply a heuristic solution method that capitalizes on the inherent network structure of the stochastic mixed-integer program model. Duran *et al.* [11] also study the effect of emergency supply pre-positioning in the pre-disaster phase. They develop a mixed integer programming formulation that seeks to determine where regional warehouses should be opened to prepare for a variety of disaster types. Their study indicates that strategically selecting warehouse locations can improve response times and reduce freight costs associated with supply distribution.

Ergun *et al.* [12] discuss the unique challenges confronted by supply chain managers in humanitarian response situations. Disaster relief supply networks can be very large, being composed of a variety of players and multiple stakeholders. It can be difficult to coordinate donors, non-government organizations, military members, and other actors in the delivery of large volumes of relief items. The authors explain how analytical tools can be utilized at each stage of disaster relief planning to improve disaster relief supply chain management. They encourage future researchers to develop models that account for each stage of disaster relief planning, since decisions in one stage will likely affect or depend upon decisions in another stage.

When preparing for humanitarian emergencies at a national level, policy makers must decide how to allocate resource investments between natural disaster preparedness and defense capabilities. Zhuang & Bier [37] develop a game theoretic approach to this problem. Their formulation seeks to determine the optimal investment a decision maker should make in protecting a predefined set of targets from incurring natural or man-made damage. Their study offers qualitative insights into the effects

of overinvesting or underinvesting in national defense.

Operations research can improve humanitarian logistics in non-emergency situations. For example, work has been done to optimize the distribution of goods to homeless shelters and food banks. Lien *et al.* [22] develop a sequential resource allocation model developed specifically for non-profit organizations. In consideration of the unique goals and limitations of food distribution organizations, they present a dynamic program with an objective function that seeks to ensure equity and reduce waste rather than maximize profit or reduce cost.

The utilization of an equity-based objective function by Lien *et al.* [22] highlights the importance of considering social costs in humanitarian relief applications of operations research. Holguín-Veras *et al.* [17] develop the case that objective functions that minimize financial costs may not be appropriate for disaster relief planning models. The authors discuss to what extent economic costs should be incorporated in disaster relief planning models, and they provide example formulations that account for human suffering in their respective objective functions. Holguín-Veras *et al.* [16] provide further discussion as to which features, in addition to the inclusion of social costs, make disaster relief problems unique.

2.3 Summary

From this literature review, we conclude that disaster relief planning and, in particular, network restoration problems can be modeled and solved in a variety of ways. We introduced the maximum flow problem and surveyed formulations and solution techniques to both static and temporal approaches of single and interdependent network restoration problems. We briefly discussed network design and interdiction problems, and we highlighted other applications of operations research in emergency planning and humanitarian logistics.

III. Model and Formulation

In this chapter we set forth the notation necessary to mathematically describe the TCRD problem. Herein, we describe the network utilized with associated components representing the transportation, communication, and distribution center systems. These interdependent networks are then modeled using a mixed-integer programming formulation where it is decided (i) how much of each resource (machines and relief items) is brought into the impacted area at each time, (ii) the movement of machines for the restoration of the transportation network, (iii) the movement of the machines for establishment of the communication network, (iv) the movement of machines for the establishment of the distribution centers, and (v) the amount of relief demand that is met in each time period.

3.1 Model Notation

In this section we list the notation selected to represent the sets, parameters, and decision variables used in the mixed-integer linear programming formulation.

Sets:

- $i \in N$: set of nodes in the network, with a designated super source node, s , and super sink node, τ .
 - $i \in N_S$: the set of supply nodes which are connected to the super source node s .
 - $i \in N_D$: the set of demand nodes which are connected to the super sink node τ .
 - $i \in N_P$: the set of nodes in the network at which a distribution center arc leads into.

- $i \in N_C$: the set of nodes in the network at which a communication entity arc leads into.
- $(i, j) \in A$: the set of directed arcs in the network.
 - $(i, j) \in A_t$: the set of operational arcs at time t
 - $(i, j) \in A'_t$: the set of non-operational arcs at time t
 - We note that the starting set of operational and non-operational arcs is denoted by A_0 and A'_0 , respectively.
- $G = (N, A)$: the underlying network.
- $\mu \in M$: the set of machines.
 - $\mu \in M_{ij}$: the set of machines which are able to restore arc $(i, j) \in A'_0$.
- $t \in T$: the set of discrete time periods that cover the scheduling horizon.

Parameters:

- u_{ij}^r : the capacity for relief items on arc (i, j) .
- u_{ij}^c : the capacity for communication flow on arc (i, j) .
- u_{ij}^μ : the capacity for machine flow on arc (i, j) .
- u_t : the space allotted to allow entry of machines and relief items into the network at each $t \in T$.
- p_{ij} : the time necessary to transition non-operational arc (i, j) to operational.
- a_μ : the necessary space to allow entry of machine μ into the network.
- w_t : the weight associated with v_t at each $t \in T$.

Decision Variables:

- x_{ijt}^r : the continuous flow of relief items on arc (i, j) at time t .
- x_{ijt}^c : the continuous flow of communication on arc (i, j) at time t .
- x_{ijt}^μ : the continuous flow of machine μ on arc (i, j) at time t .
- β_{ijt} : equals 1 if arc (i, j) is operational at time t , 0 otherwise.
- λ_{it}^μ : equals 1 if machine μ is idle at node i at time t , 0 otherwise.
- $\alpha_{\muijt}$: equals 1 if machine μ completes (i, j) at time t , 0 otherwise.
- v_t : the maximum flow of relief items in the network at time t .

3.2 Mixed-Integer Linear Programming Formulation

$$\max \sum_{t \in T} w_t v_t \quad (1)$$

subject to:

$$\sum_{j:(i,j) \in \{A_0 \cup A'_0\}} x_{ijt}^r - \sum_{j:(j,i) \in \{A_0 \cup A'_0\}} x_{jit}^r = \begin{cases} v_t, & \text{if } i = s \\ 0, & \text{if } i \in N \setminus \{s, \tau\} \\ -v_t, & \text{if } i = \tau \end{cases}, \quad \forall t \in T, \quad (2)$$

$$\sum_{j:(i,j) \in \{A_0 \cup A'_0\}} x_{ijt}^c - \sum_{j:(j,i) \in \{A_0 \cup A'_0\}} x_{jit}^c = 0, \quad \forall t \in T, i \in \{N_C \cup N_D \cup N_P\}, \quad (3)$$

$$\sum_{(i,j) \in \{A_0 \cup A'_0\}: j \in N_p} x_{ijt}^r \geq v_t, \quad \forall t \in T, \quad (4)$$

$$0 \leq x_{ijt}^k \leq u_{ij}^k, \quad \forall (i, j) \in A_0, k \in \{c, r, \mu\}, t \in T, \quad (5)$$

$$0 \leq x_{ijt}^k \leq \beta_{ijt} u_{ij}^k, \quad \forall (i, j) \in A'_0, k \in \{c, r, \mu\}, t \in T, \quad (6)$$

$$x_{i\tau t}^r \leq u_{i\tau} x_{i\tau t}^c, \quad \forall i \in N_D, t \in T, \quad (7)$$

$$\sum_{\mu \in M} a_\mu (\lambda_{s,t-1}^\mu - \lambda_{st}^\mu) + \sum_{j:(s,j) \in \{A_0 \cup A'_0\}} x_{sjt}^r \leq u_t, \quad \forall t \in T, \quad (8)$$

$$\beta_{ijt} - \beta_{ij,t-1} = \sum_{\mu \in M_{ij}} \alpha_{\mu ijt}, \quad \forall (i, j) \in A'_0, t \in T, \quad (9)$$

$$\sum_{(i,j) \in A'_0; \mu \in M_{ij}} \sum_{s=t}^{\min\{T, t+p_{ij}-1\}} \alpha_{\mu ijs} \leq 1, \quad \forall t \in T, \mu \in M \quad (10)$$

$$\sum_{t=1}^{p_{ij}-1} \beta_{ijt} = 0, \quad \forall (i, j) \in A'_0, \quad (11)$$

$$\sum_{\mu \in M_{ij}} \sum_{t=1}^{p_{ij}-1} \alpha_{\mu ijt} = 0, \quad \forall (i, j) \in A'_0, \quad (12)$$

$$\sum_{j:(s,j) \in \{A_0 \cup A'_0\}} x_{sjt}^\mu = \lambda_{s,t-1}^\mu - \lambda_{st}^\mu, \quad \forall t \in T, \mu \in M, \quad (13)$$

$$\begin{aligned} & \sum_{j:(j,i) \in \{A_0 \cup A'_0\}} x_{jit}^\mu + \sum_{j:(j,i) \in A'_0, \mu \in M_{ji}} \alpha_{\mu jit} \\ & - \sum_{j:(i,j) \in \{A_0 \cup A'_0\}} x_{ijt}^\mu - \sum_{j:(i,j) \in A'_0, \mu \in M_{ij}} \alpha_{\mu ijt+p_{ij}-1} \\ & = \lambda_{it}^\mu - \lambda_{i,t-1}^\mu, \quad \forall i \in N \setminus \{s, \tau\}, \mu \in M, t \in T, \end{aligned} \quad (14)$$

$$\lambda_{i0}^\mu = \begin{cases} 1, & \text{if } i = s \\ 0, & \text{if } i \in N \setminus \{s\} \end{cases}, \quad \forall \mu \in M. \quad (15)$$

$$\alpha_{\mu ijt} \in \{0, 1\}, \quad \forall t \in T, (i, j) \in A'_0, \mu \in M_{ij}, \quad (16)$$

$$\beta_{ijt} \in \{0, 1\}, \quad \forall t \in T, (i, j) \in A'_0, \quad (17)$$

$$\lambda_{it}^\mu \in \{0, 1\}, \quad \forall i \in N, \mu \in M, t \in T \setminus \{0\}, \quad (18)$$

The objective function (1) calculates the sum of the weighted maximum flow of

relief items through the network over all time periods, where each maximum flow is bounded by the total demand and time-weighted. With regard to flow balance, Constraint (2) ensures that the flow of relief items emanates from s and terminates at τ , respectively, and maintains the conservation of flow of relief items through all intermediary nodes. Flow balance for communication is maintained by Constraint (3).

Constraint (4) bounds the flow of v_t by the summation of the flow of relief items through all distribution center nodes at time t . Constraints (5) and (6) require the flows of communication, relief items, and machines to be non-negative and bounded by arc capacities. Note also that Constraint (6) does not permit flow on non-operational arcs. Constraint (7) ensures that a demand node cannot receive relief items until it can receive communication flow from at least one distribution center or communication entity. Constraint (8) requires that the combined flow of relief items and machines into the network does not exceed the total capacity associated with each time period. With respect to these constraints, it should be noted that this formulation assumes that capacities are set appropriately. Specifically, Constraint (3) assumes that the capacity of communication flow on arcs terminating at some node $j \in \{N_P \cup N_C\}$ is infinite. Arcs intended to carry communication flow from either a distribution center node or communication entity node to a demand node should have communication flow capacitated by a value of 1, and their corresponding relief flow and machine flow capacities should be set at 0. Arcs emanating from demand nodes and terminating at the super sink, τ , should have communication flow capacities equal to 1. All other arcs should have communication flow capacities equal to 0. If a demand node $i \in N_D$ is characterized by a particular demand level, d_i , this should be modeled by setting $u_{i\tau}^r = d_i$.

Scheduling requirements are maintained by Constraints (9)–(12). Constraint (9)

guarantees that, at each time period, an arc transitions status, specifically from non-operational to operational, directly following the completion of its processing. In addition to requiring machines to work on non-operational arcs for their respective processing times before the arcs become operational, Constraint (10) ensures that machines do not work on more than one task at a time. Constraints (11) and (12) jointly prohibit non-operational arcs from becoming operational until the total time that has passed with repair assets allocated to it is at least as long as the processing time associated with the arc.

With respect to the flow of machines, Constraint (13) requires that machines enter the network at exactly one supply depot before they can begin repairing damaged arcs. Constraint (14) enforces machine flow balance by requiring that, for each node i , if a machine (i) flows into i , (ii) completes work on an arc that leads into i , or (iii) was idle at i one time period prior, then the machine must (i) immediately flow out of i , (ii) immediately begin working on an arc that begins at i , or (iii) be idle at i for the current time period.

Constraint (15) requires all machines to be idle at the super source node at the beginning of the scheduling horizon, and Constraints (16)–(18) enforce selected binary variable restrictions.

IV. Experimental Results

Herein, we provide the results of experiments conducted with realistic network data on the TCRD problem. We begin with a description of the the original network data set and the preprocessing required for the experiments conducted in this thesis. We then discuss how changes in certain parameters of interest affect solution values, and interpretations of these results are offered. The chapter concludes with a summary of the experimental test results.

4.1 Test Network Data

The network data used to test the mathematical formulation of the TCRD problem originates from a data set developed by Loggins *et al.* [23] that represents the transportation, telecommunications, power and other interdependent infrastructure systems covering an artificial county. Experimentation conducted for this thesis utilized a modified transportation and communication network based upon the data set developed by Loggins *et al.* [23].

The arcs and nodes belonging to the transportation system in the original data set are extracted to form the modified network. For each node, i , we either classify the node as a transshipment node or we assign the node to the set of communication nodes N_C , the set of demand nodes N_D , the set of distribution center nodes N_P , or the set of supply nodes N_S based on the node infrastructure type. Table 1 depicts the classification rule applied to the original network in order to classify nodes in the modified network. Census points and emergency communication centers represent intuitive options for classifying demand and communication nodes, respectively. Classifying distribution center and supply nodes requires special consideration. In an undamaged network, relief items should be able to flow from supply points through

distribution centers and meet the total demand at each demand node. Our classification rule ensures this requirement is met, whereas more intuitive options for supply and distribution center nodes, such as airports and shelters, prohibit this capability.

Table 1. Node Classification

Node i infrastructure type	Node i classification	Number of nodes
Census Point	Demand Point	77
Emergency Communication Center	Communication Entity	6
Gas Station	Distribution Center	26
Hospital	Supply Point	6
<i>All others</i>	<i>Transshipment node</i>	688

After classifying the nodes, we generate communication entity and distribution center arcs. This is accomplished by applying the following changes to the network. First, a new transshipment node, i' , is created for each node $i \in N_C \cup N_P$. For any arc (j, i) that originates at some node j and terminates at communication entity or distribution center node i , the arc is relabeled (j, i') so that the arc terminates at i' instead. Finally, a single directed arc, (i', i) is added. By adding these arcs, all network restoration decisions are associated with arcs; nodes are not removed from the network for experimental testing.

As the satisfaction of demand is enabled only with both flow of goods and communication, the new network requires the addition of arcs that allow for the flow of communication from distribution center or communication entity nodes to selected demand nodes. The original data set includes GIS coordinates for each node. We use these coordinates to calculate the Euclidean distance¹ between a distribution center or communication entity and a selected demand node. If the distance to the selected demand node falls within a specified radius, then an arc is generated that allows

¹Given the relatively small geographic area covered by the data set, it is assumed that the Euclidean distance between two points accurately approximates their actual distance. For larger regions, Euclidean distances may not account for curvature of the Earth enough to be accurate distance measurements.

communication to flow from the distribution center or communication entity to the demand node. For base case testing, the communication radius for communication entity nodes is set to 500,000 GIS coordinate units. This radius allows for total communication coverage with limited redundancy. We conduct additional test instances with the communication radius for communication entity nodes increased by 50% to 750,000 units in order to observe the effect of having redundant communication coverage. For all test instances, the communication radius for distribution center nodes is set to 50,000 units. This allows communication to flow from distribution centers to demand nodes only when demand nodes are in the immediate vicinity of the distribution center.

Finally, a super source, s , and a super sink, τ , are added to the network. Directed arcs are added to connect s to each supply point $i \in N_S$ and to connect each demand point $i \in N_D$ to τ . When communication radii for distribution center and communication entity nodes are set at their base levels (50,000 units and 500,000 units, respectively), the resulting network, $G = (N, A)$, is composed of $|N| = 805$ nodes and $|A| = 2,191$ arcs. The total demand over all demand nodes for one time period is 4,334. This value represents the maximum flow of relief items over the undamaged network.

4.2 Experimental Tests

We test multiple instances based on adjustments to selected network and model parameters. In Appendix A are listed the network and model parameter values for each network configuration. All communication entity and distribution center arcs are assigned to A'_0 for each test instance. The percentage of damaged arcs indicates the percentage of arcs removed from the remaining transportation network. The arcs to be removed are selected at random based on one of five integer seeds. For

instances with machine configuration set to ‘General’, machines can work on all arcs. Under this configuration, $a_\mu = 2,000$ for each machine, $\forall \mu \in M$. For instances with machine configuration set to ‘Specialized’, each machine can only work on a specific subset of damaged arcs. Namely, half of the machines are restricted to working on transportation network arcs, and the other half of the machines are restricted to working on communication entity arcs. Under this configuration, $a_\mu = 1,250$ for each machine, $\forall \mu \in M$. By changing a_μ for each machine configuration, we can compare the effectiveness of having access to fewer machines which are generalized in their ability to complete tasks as opposed to having access to a greater number of machines which are restricted in the types of jobs they can complete. The final two columns of Table 3 in Appendix A indicate the type of policy constraint implemented for each half of the scheduling horizon.

All test instances of the TCRD problem were solved by invoking IBM ILOG CPLEX Optimization Studio (version 12.6) with Visual Studio 2008 on an Intel(R) Xeon E5-1620 3.6 Ghz processor having 32 GB memory. Solution times were limited to 2,700 seconds. Results of the experimental tests are summarized in Table 4.

4.2.1 Initial Results.

Figure 1 depicts the percentage of demand met at each scheduling period at base case settings for each of the five random integer seeds, where percentage of demand met is calculated by dividing the maximum flow in the network at time t , v_t , by the total demand summed over all of the demand nodes. We note that using different random integer seeds to select the set of transportation arcs that belong to A'_0 does not significantly affect solution values. In general, most repairs are made during an initial subset of scheduling periods, resulting in increased flow values. For the remainder of the scheduling horizon, the ability to meet demand for relief items does

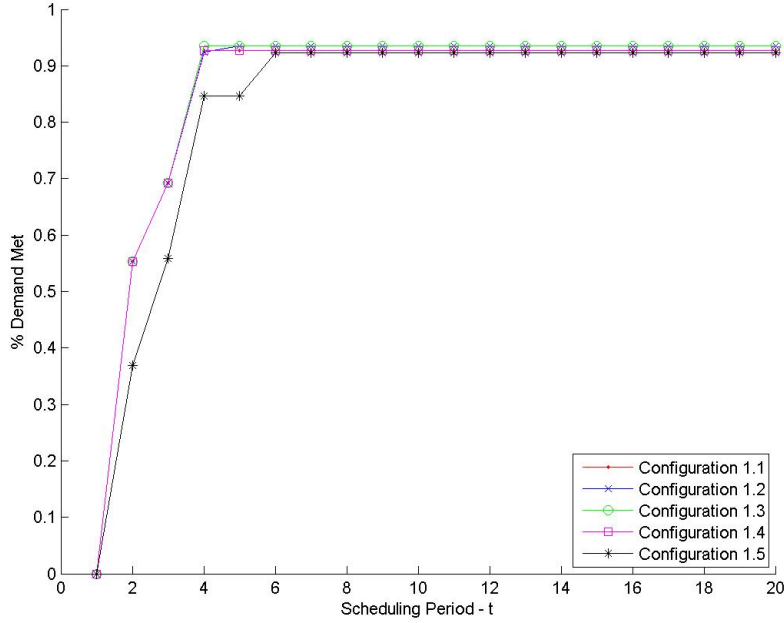


Figure 1. Percentage of demand met by scheduling period for base case network configurations.

not improve. This pattern can be attributed to the following network characteristic. In the undamaged network, there exists at least one directed path from the super source, s , to every other node in the network. However, this is not necessarily true of other nodes. Namely, machines are able to reach any node in the network when they begin at the super source, but once a machine leaves the super source in a damaged network and completes a certain number of repairs, there may not be any directed paths from its current node that lead to another damaged arc on which it can begin repairs. Given a finite number of machines, it is not guaranteed that every arc in A'_0 will be repaired, even if the scheduling horizon were extended. We leave exploration of this observation for future work and propose specific ways to address it in Section 5.2.

4.2.2 Increased Communication Capabilities.

We wish to test whether or not increased communication capabilities result in the ability to meet a higher percentage of demand for relief items. This is accomplished by solving test instances in which the communication radius is increased by 50%. When the communication radii of communication entity nodes are set to their base case value of 500,000 GIS coordinate units, all six communication entity nodes must be repaired in order to obtain communication coverage for all of the demand nodes. With increased communication radii, it is not necessary to repair all six communication entities in order to provide communication coverage to all of the demand nodes. Table 2 highlights the difference in the number of demand nodes that can receive communication flow from each of the communication entity nodes for the different communication radius values.

Table 2. Number of demand nodes within the communication radius (R) of each communication entity node.

Communication Entity Node ID	<i># Demand Nodes</i>	
	$R = 500000$	$R = 750000$
5753	10	29
5754	11	51
5755	8	15
5756	15	51
5757	35	49
5758	12	15

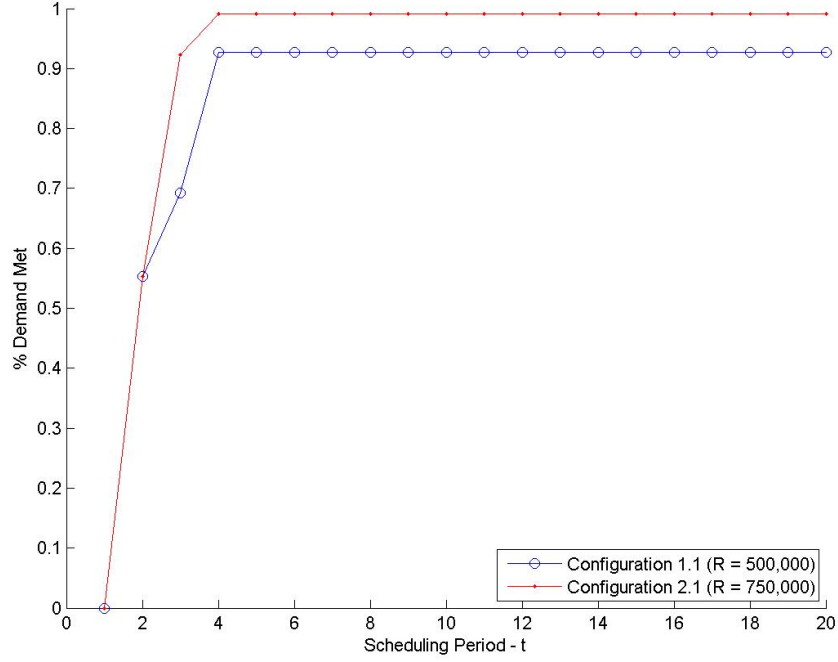


Figure 2. Percentage of demand met by scheduling period with increased communication capabilities. Configuration 1.1 depicts base case parameter settings (communication radii are set to 500,000 GIS coordinate units). Configuration 2.1 differs from Configuration 1.1 only in communication radii; specifically, communication radii are increased to 750,000 GIS coordinate units.

Figure 2 illustrates the percentage of demand met at each scheduling period with both standard and increased communication capabilities. We note that, with the increased communication radius, it is possible to meet the total demand for relief items within the scheduling horizon. This highlights the value of having the capacity to build more powerful communication systems. In situations where network damage makes it infeasible to repair all communication entities, having increased communication capabilities preserves the ability for communication to flow to all demand nodes. Figure 2 also shows that, for some instances, increased communication capabilities allow for the delivery of more relief items, sooner. Since each communication entity provides communication coverage to a larger subset of demand nodes, the repair of a communication entity results in the ability to meet a higher percentage of demand

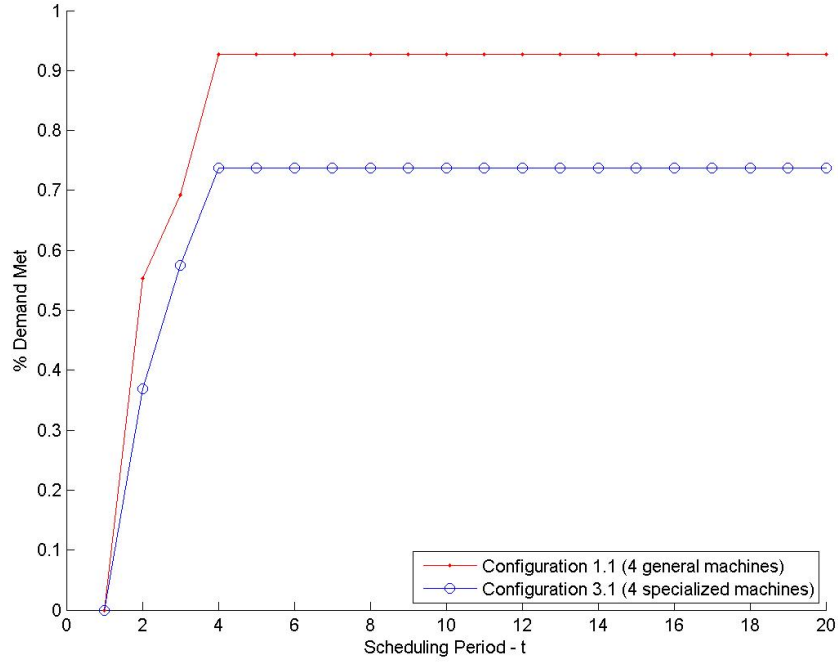


Figure 3. Percentage of demand met by scheduling period with selected machine configurations. Configuration 1.1 depicts base case parameter settings (4 general machines are dispatched to make repairs). Configuration 3.1 differs from Configuration 1.1 only in machine type; specifically, 2 machines work only on the communication network, and 2 machines work only on the transportation network.

in less time.

4.2.3 Machine Limitations.

In addition to increased communication coverage, emergency planners may want to understand how changes in machine capability affect their potential to meet demand for relief items. Of particular interest is the added benefit of utilizing machines that are capable of accomplishing a variety of tasks, rather than utilizing machines that are specialized. Figure 3 compares test results of two network configurations. In Configuration 1.1, repairs are made using four machines that can work on both the transportation and communication networks (general machines). In Configuration 3.1, repairs are made using four specialized machines, where two of the machines

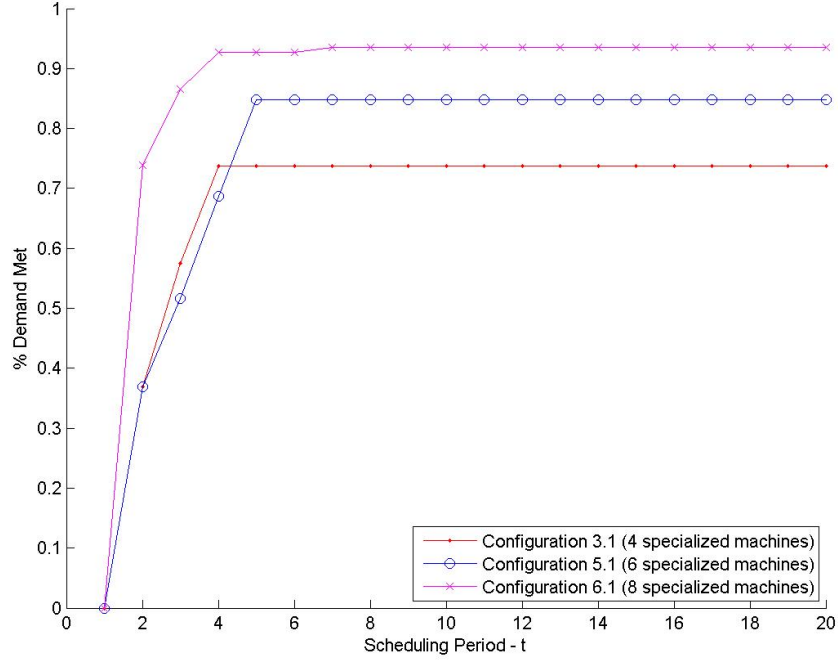


Figure 4. Percentage of demand met by scheduling period with increased numbers of machines. Configurations 3.1, 5.1, and 6.1 differ only in the number of machines dispatched to make repairs. These configurations, utilize 4, 6, and 8 specialized machines, respectively.

can work only on the communication network and the other two machines can work only on the transportation network. We observe that solution values are significantly higher for instances with four general machines rather than four specialized machines, even though a_μ values in Configuration 3.1 are less than a_μ values in Configuration 1.1. While the TCRD problem accounts for differences in size between machines of varying capabilities, emergency planners may have to consider other unique features of general machines such as higher training requirements, increased coordination between infrastructure systems in the delegation of machines to tasks, and increased economic costs. These unique features could offset the projected benefit of utilizing general machines.

Different emergency scenarios will call for varying work force sizes. Figure 4 compares test results from network configurations in which four, six and eight specialized

machines are dispatched to make repairs. These results highlight the increased ability to meet demand for relief items when more machines are available to work on restoration tasks. We note that while increasing the work force does increase overall ability to meet demand for this scenario, it does not necessarily improve the rate at which percentage of total demand met increases during the initial repair phase. This indicates that there may exist a tradeoff between meeting demand quickly and trying to maximize total demand met. Figure 4 depicts a scenario in which a decision maker who is primarily concerned with meeting 70% of total demand as quickly as possible may prefer to dispatch only four specialized machines, rather than six specialized machines, during the initial repair phase.

4.2.4 Policy Restrictions.

Emergency scenarios that require cooperation from a host nation or that severely limit the amount of resources that can be delivered to the affected region may be prohibitive with respect to the capacity to meet demand for relief items. Moroney *et al.* [25] discuss how the strong resistance to international aid exerted by the autocratic regime in Burma after Cyclone Nargis in 2008 made United States DoD relief operations exceptionally challenging. This represents a scenario in which the capacity to deliver relief items and machines into the affected region is initially limited but improves over time. Emergency planners in different scenarios may observe the opposite effect. Holguín-Veras *et al.* [17] explain how the delivery of unsolicited donations poses a huge obstacle to relief operations. In response to requests for particular relief items, such as blankets or bottled water, made by the host nation immediately following a natural disaster, donations containing large volumes of these items will be delivered to the affected region long after they are needed. This results in congestion at supply depots, and it may limit the ability of emergency planners to deliver

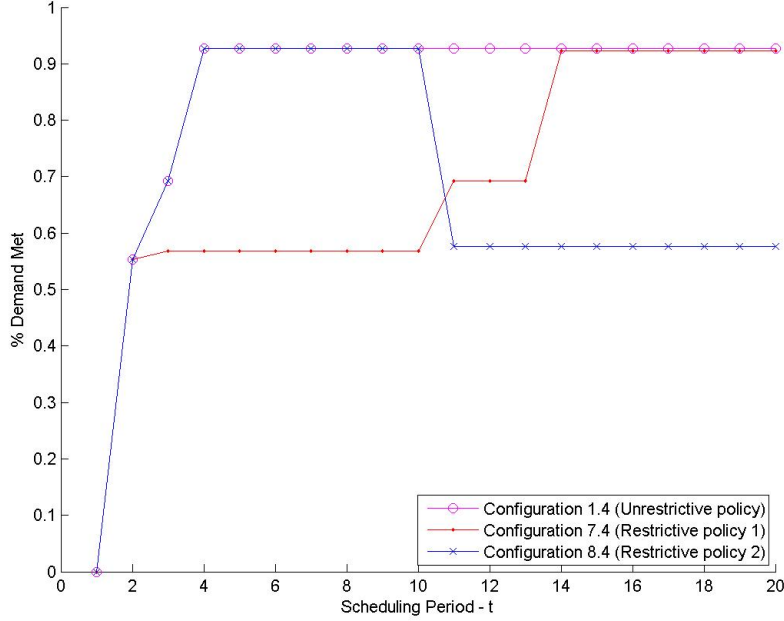


Figure 5. Percentage of demand met by scheduling period under policy constraints. Under an unrestrictive policy, $u_t = 5000, \forall t \in T$. Under restrictive policy 1, u_t is reduced to 2500 during the first half of the scheduling horizon. Under restrictive policy 2, u_t is reduced to 2500 during the second half of the scheduling horizon.

what is actually needed to affected regions after the initial repair phase. We consider three policies based on these considerations. The first policy imposes no restrictions, and $u_t = 5000, \forall t \in T$. The second policy (i.e., restrictive policy 1) limits the flow of relief items and machines into the affected region by reducing u_t to 2500 during the first half of the scheduling horizon. The third policy (i.e., restrictive policy 2) restricts the flow of relief items and machines into the affected region by reducing u_t to 2500 during the second half of the scheduling horizon. Figure 5 illustrates how the implementation of these policies influences the flow of relief items and machines into the affected region and limit the ability to meet demand over time.

Overall, objective function values are relatively close (within 5.5%) for test instance pairs that differ only in when policy restrictions are implemented. However, as indicated by the test instances depicted in Figure 5, policy restrictions imple-

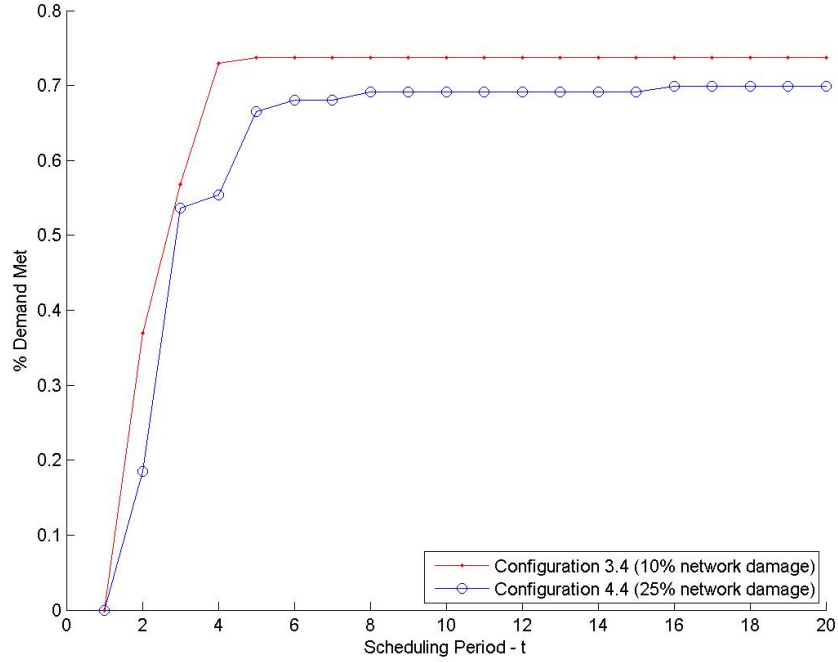


Figure 6. Percentage of demand met by scheduling period with increased network damage.

mented at the beginning of the scheduling horizon can be more debilitating than those implemented at a different time. This may be because policy restrictions reduce the rate at which machines can begin working on arcs in the network, so restrictions implemented during the first half of the scheduling horizon limit the cumulative time over which machines can work on damaged arcs.

4.2.5 Network Damage.

Figure 6 compares solution values for instances with 10% and 25% damage to the transportation network. As one would expect, networks with increased damage require more time to accomplish the repairs necessary to meet demand for relief items for the majority of demand nodes. This results in a more gradual increase in the percentage of demand met over the scheduling horizon. We also note that the relative increase in unmet demand is disproportional to the increase in network damage.

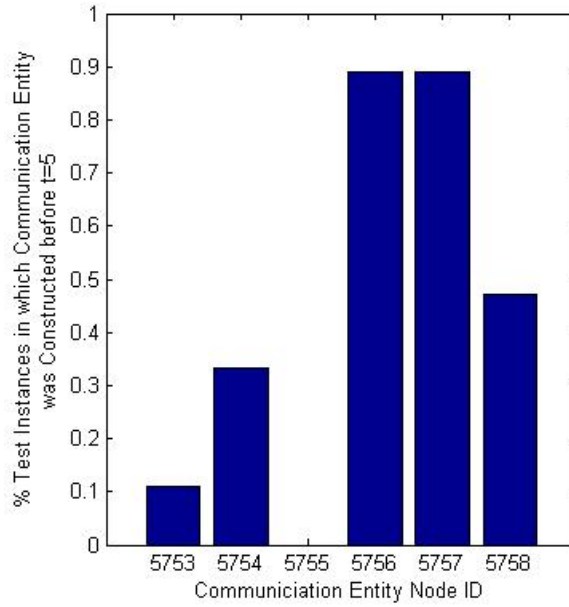


Figure 7. Percentage of test instances in which a communication entity was constructed in the initial scheduling phase (before $t = 5$).

For problem instances with four specialized machines, a 15% increase in number of damaged arcs results in, on average, a 3.3% increase in total unmet demand. Future testing could be conducted to determine how changes to other model parameters, such as communication radii, machine configurations, and policy restrictions affect solution values for test instances with increased network damage.

4.2.6 Critical Facilities.

Emergency planners may benefit from knowing which facilities, once constructed or repaired, result in the greatest increase in fulfilled demand during the initial repair phase. Figure 6 reveals that even for test instances with 25% network damage, only 3 time periods are necessary to meet approximately 55% of demand. This indicates that there exist critical facilities which after being repaired enable the fulfillment of much demand. the establishment of certain communication entities and distribution centers is critical to the relief operation. Figure 7 provides a visual approximation

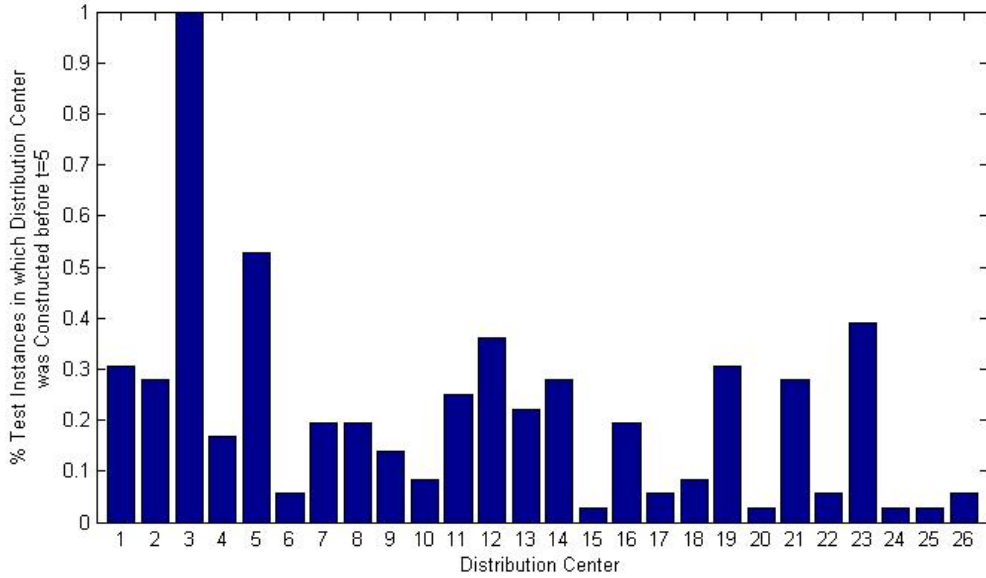


Figure 8. Percentage of test instances in which a distribution center was constructed in the initial scheduling phase (before $t = 5$), where Distribution Centers (1 – 26) correspond to Node ID’s (5779 – 5804).

of the importance of each communication entity during the initial repair phase, relative to the other communication entities. We note that communication entity nodes 5756 and 5757, which provide the greatest communication coverage to demand nodes (see Table 2), are constructed during the initial repair phase in nearly 90% of our test instances². Likewise, communication entity node 5755, which provides the least communication coverage to demand nodes, is not constructed during the initial repair phase in any of our test instances.

Figure 8 provides a visual approximation of the importance of each of the twenty-six distribution centers during the initial repair phase, relative to the other distribution centers. We note that Distribution Center 3 is constructed during the initial repair phase for every network configuration tested. This strongly supports the hypothesis that the establishment of certain facilities is critical to increasing fulfillment

²Percentage calculated based upon the 36 test instances for which a positive optimal solution was found.

of demand during the initial repair phase. Future testing could be conducted to determine the effect of removing these critical facilities from the network.

4.3 Summary

Test results over all configurations of selected model and network parameters exhibited general trends. Assuming that relief efforts are not restricted due to policy constraints, emergency planners should dispatch machines to begin making repairs as soon as possible in order to achieve optimal distribution of relief items. Emergency planners should expect an initial repair phase during which flow of relief items will be limited. After the initial repair phase, the emergency planner can expect that higher percentages of demand points will be able to receive relief items. Increasing communication capabilities can improve the emergency planner's ability to meet affected regions' demand for relief items. Additionally, gaining access to machines that are not limited with respect to what jobs they can process improves repair efforts. Test instances in which four general machines were dispatched resulted in about an 18% increase in total demand fulfillment relative to test instances in which four specialized machines were dispatched. Emergency planners may face a tradeoff between relief operation speed and overall demand fulfillment when deciding how many machines to dispatch. We found that there exist certain key communication entities and distribution centers whose construction is critical during the initial repair phase for most network configurations. Emergency planners should identify these critical facilities and prioritize their repairs. Future testing could be conducted to confirm that with increased communication capabilities, available machines, and/or scheduling periods, one would be able to meet 100% of the demand for relief items by the end of the scheduling horizon.

V. Conclusions and Future Research

5.1 Conclusions

In this thesis we formulated a mixed-integer linear program to solve the TCRD problem. Our formulation captures interdependencies exhibited between the transportation and communication networks, accounts for resource policies that constrain the delivery of relief items and machines into the affected region, and ensures that machine movement is feasible given the transportation network status when scheduling machines to tasks. Our model helps emergency planners determine how to dispatch machines to set up distribution centers and communication entities in order to optimally disseminate relief items to demand points.

We implement our formulation in Visual Studio 2008 invoking CPLEX 12.6. We modify a data set representing the transportation, power and other interdependent infrastructure systems covering an artificial county to use for testing. Tests were conducted on different instances of the TCRD problem based on changes to selected network and model parameters, including communication radii, machine number and types, policy constraints, and network damage.

Our test results offer insights into effective emergency planning strategies after an extreme event. Solution values for most test instances reflect a general trend in which key repairs are made during an initial repair phase of the scheduling horizon. We found that the establishment of particular communication entities and distribution centers during this initial repair phase is critical to the rapid increase in demand fulfillment during the beginning of the relief operation.

Dispatching machines that are limited in which tasks they can perform can severely limit the ability to meet demand for relief items over time. Decision makers should consider using machines with broader capability sets, so long as the economic costs,

training requirements, and other unique features associated with these machines does not offset their intended benefit. In general, the utilization of more machines entails increased demand fulfillment. However, when considering how many machines to dispatch, emergency planners may face a trade-off between total demand fulfillment and the time required to meet certain demand thresholds, since dispatching fewer machines sometimes allows for higher demand fulfillment during the initial repair phase.

Communication capabilities are very important to the success of restoration efforts. Increases in the communication coverage of demand points by communication entities can significantly improve the overall ability to meet demand for relief items. Furthermore, increasing communication capabilities can help to more quickly achieve fulfillment of demand during the initial repair phase.

Policy constraints caused by resistance from an uncooperative host nation or resulting from an overflow of unsolicited humanitarian supplies can severely limit the ability to meet demand for relief items over time. All else equal, policy constraints implemented towards the beginning of the scheduling horizon may be more prohibitive than those implemented sometime afterwards, since they delay the ability of machines to begin working on the damaged network. This incentivizes emergency planners to find ways to maximize the amount of machines they can send into the affected region during the initial repair phase.

Finally, we found that for scenarios with greater network damage, emergency planners should expect a less defined initial repair phase; increases in demand fulfillment are gradual and require more time. We also note that increased network damage does not dramatically reduce the ability to meet total demand. The increase in percentage of unmet demand over the entire scheduling horizon is disproportionately less than the increased percentage of network damage.

5.2 Future Research

We believe that our formulation successfully accounts for many of the unique parameters and challenges associated with the TCRD problem. Future research could be conducted to validate our findings and to improve our formulation and solution method. Herein, we discuss future research possibilities from which our current research could benefit.

First, we recommend the development of a heuristic solution method that improves the ability to solve large problem instances in a tractable amount of time. This could benefit emergency managers working in impacted regions that are significantly larger than a single major city or county.

Future research should consider time-weighting of maximum flows. All instances tested for this thesis assume that demand fulfillment is equally important over all time periods. We suspect that applying increased weights to maximum flows at the beginning of the scheduling horizon may result in different solution patterns.

The implementation of alternate objective functions could provide emergency planners with more equitable solutions. Currently, we seek to maximize the sum of the maximum flows of relief items over all time periods. Other objective functions could better account for social costs often associated with relief operations. For example, we could develop a max-min objective function that maximizes the minimum amount of demand fulfilled over all demand nodes. This would ensure that no demand points are discluded from the relief effort. Furthermore, we could apply preemptive weighting on earlier periods of the scheduling horizon so that priority is placed on relief distribution during the critical periods immediately following an extreme event. The implementation of these objective functions could improve equity of the relief effort.

Testing could be extended to include more network configurations and parameter

settings. For example, test instances could be conducted with higher levels of network damage in order to inform emergency planners dealing with regions that have sustained greater damage than the test instances represented in this thesis. Additionally, test networks could be adjusted to allow machines greater freedom of maneuverability on the network so that machines are always able to continue network repairs.

Finally, we propose extending our formulation to account for additional interdependent infrastructure systems (e.g., a power system which must be established in order for the communication network to operate). Accounting for additional interdependent infrastructure systems could help provide emergency managers with more robust solutions after an extreme event.

Appendix A. Tables

Table 3. Parameter settings for each network configuration

Network Configuration	Integer Seed	% Damaged Arcs	Communication Radius	# Machines	Machine Configuration	u_t for $t \in \{1, \dots, 10\}$	u_t for $t \in \{11, \dots, 20\}$
1.1	1	10%	500000	4	General	5000	5000
1.2	2	10%	500000	4	General	5000	5000
1.3	3	10%	500000	4	General	5000	5000
1.4	4	10%	500000	4	General	5000	5000
1.5	5	10%	500000	4	General	5000	5000
2.1	1	10%	750000	4	General	5000	5000
2.2	2	10%	750000	4	General	5000	5000
2.3	3	10%	750000	4	General	5000	5000
2.4	4	10%	750000	4	General	5000	5000
2.5	5	10%	750000	4	General	5000	5000
3.1	1	10%	500000	4	Specialized	5000	5000
3.2	2	10%	500000	4	Specialized	5000	5000
3.3	3	10%	500000	4	Specialized	5000	5000
3.4	4	10%	500000	4	Specialized	5000	5000
3.5	5	10%	500000	4	Specialized	5000	5000
4.1	1	25%	500000	4	Specialized	5000	5000
4.2	2	25%	500000	4	Specialized	5000	5000
4.3	3	25%	500000	4	Specialized	5000	5000
4.4	4	25%	500000	4	Specialized	5000	5000
4.5	5	25%	500000	4	Specialized	5000	5000
5.1	1	10%	500000	6	Specialized	5000	5000
5.2	2	10%	500000	6	Specialized	5000	5000
5.3	3	10%	500000	6	Specialized	5000	5000
5.4	4	10%	500000	6	Specialized	5000	5000
5.5	5	10%	500000	6	Specialized	5000	5000
6.1	1	10%	500000	8	Specialized	5000	5000
6.2	2	10%	500000	8	Specialized	5000	5000
6.3	3	10%	500000	8	Specialized	5000	5000
6.4	4	10%	500000	8	Specialized	5000	5000
6.5	5	10%	500000	8	Specialized	5000	5000
7.1	1	10%	500000	4	General	2500	5000
7.2	2	10%	500000	4	General	2500	5000
7.3	3	10%	500000	4	General	2500	5000
7.4	4	10%	500000	4	General	2500	5000
7.5	5	10%	500000	4	General	2500	5000
8.1	1	10%	500000	4	General	5000	2500
8.2	2	10%	500000	4	General	5000	2500
8.3	3	10%	500000	4	General	5000	2500
8.4	4	10%	500000	4	General	5000	2500
8.5	5	10%	500000	4	General	5000	2500

Table 4. Experimental Test Results. Reported value ‘N/A’ indicates that a positive objective function value was not found in the allotted solution time for the respective network configuration.

Network Configuration	Optimal Solution Value	Optimality Gap	Solver Time (secs)
1.1	73655	0.3%	683
1.2	74239	0.5%	1317
1.3	74284	0.2%	2700
1.4	73723	1.2%	653
1.5	71355	0.7%	593
2.1	79449	0.7%	2700
2.2	79078	1.6%	1552
2.3	80078	0.2%	2241
2.4	79012	1.5%	1473
2.5	77803	2.0%	1701
3.1	58409	0.0%	517
3.2	59110	0.0%	76
3.3	58409	0.0%	199
3.4	58343	0.0%	461
3.5	57447	0.0%	198
4.1	56699	2.1%	648
4.2	54645	2.1%	2700
4.3	57237	0.9%	1134
4.4	53424	6.7%	1696
4.5	55525	0.1%	2051
5.1	65643	1.3%	2700
5.2	58400	15.0%	2138
5.3	66604	0.0%	1372
5.4	N/A	N/A	N/A
5.5	56659	12.5%	2700
6.1	75723	0.2%	2276
6.2	75834	0.2%	2700
6.3	N/A	N/A	N/A
6.4	N/A	N/A	N/A
6.5	N/A	N/A	N/A
7.1	56150	6.4%	2700
7.2	59214	1.5%	2700
7.3	58916	1.8%	2700
7.4	59088	1.5%	2700
7.5	53303	11.5%	2700
8.1	58505	0.2%	938
8.2	58400	1.2%	903
8.3	58636	0.5%	2700
8.4	58533	0.9%	2700
8.5	56246	1.1%	547

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14. ABSTRACT Among the devastating consequences of extreme events, whether natural or manmade, is the disruption of transportation, communication, and other critical infrastructure systems. The restoration of these systems can be especially challenging due to the fact that damaged infrastructures are often characterized by complex interdependencies. Given a region with interdependent transportation and communication networks, both of which have sustained some damage due to an extreme event, we seek to maximize the satisfaction of geographically distributed demands for relief items over time by scheduling work crews to selected restoration tasks and routing the delivery of resources. We develop a mixed-integer linear programming formulation that captures the interdependencies exhibited by the transportation and communication networks, accounts for policy constraints that limit the delivery of resources into the affected region, and ensures that machine movement is feasible given the transportation network status when scheduling machines to tasks. After conducting tests on a variety of model instances, we establish the importance of relief operations during the initial phase of the scheduling horizon, demonstrate how changes in selected network parameters affect optimal scheduling decisions, and identify several key facilities whose construction is vital to the fulfillment of demand for relief items.						
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