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Decision-making tools for distribution networks in disaster relief

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Chapter 1 Project Overview

The devastation caused by the 2010 earthquake in Haiti was compounded by the significant logistical challenges of distributing relief to those in need. Unfortunately this is the case with many disasters. Rapid and efficient distribution of water, food, medication and other essential supplies is crucial to saving lives and rebuilding the region. Our research team at Northwestern University is leveraging our expertise in supply chain management and vehicle navigation under uncertainty to study design and operational improvements for humanitarian relief chains. This project will bring insights from this research to the relief community through the development of decision-making tools for supply distribution.

Distribution in commercial delivery services share some features with disaster relief; however, several critical attributes are not present. First, models and solution must be accessible and easy to implement by relief workers operating in extreme conditions. These end users often lack the technical background and support during their operations, and cannot implement complex optimization software used in industry. Second, information about the environment can be very limited following a disaster, to a degree not often encountered in commercial settings. Our analysis integrates this uncertainty in a dynamic approach that reflects the evolution of information. Third, the objectives in disaster relief have not been extensively studied in other sectors. We analyze relief systems with multiple (often conflicting) objectives to ensure efficient and effective distribution of relief supplies.

The project has three key activities: learning from agencies about their current relief operations (Chapter 2); developing prototype logistics models to improve operations (Chapter 3); and transitioning this research to Northwestern engineers, trained through this initiative (Chapter 4). In Chapter 5, we describe the next phase of research that builds on this project.

1. Needs Statement

Immediately after the 2010 earthquake in Haiti, Dr. Ralph Heckard redirected his mobile health care operations in Idaho to form Healing Wounds and Rehabilitation in Haiti, a grass roots operation to provide medical assistance and supplies to rural communities impacted by the disaster. As with all first-responders in Haiti, Dr. Heckard found that the logistics of moving supplies through Port-au-Prince was near impossible, and he looked at alternative options, including crossing from the Dominican Republic at Jimana, marked with an “A” in Figure 1. The next challenge for Dr. Heckard and his team was moving items from Jimana to those in need.

Figure 1: Difficulties in relief routing

Dr. Heckard's team is one of many grassroots efforts that emerged in the days and weeks after the earthquake, including Global D.I.R.T. (disaster immediate response team, www.globaldirt.org) and Material Management Relief Corps (mmrc-us.org). These groups all faced significant logistical challenges in distributing vital supplies such as water, food, and medication. However, the disaster often severely damages the transportation and other critical infrastructures in the affected region, leaving a large portion of the population displaced. Further, relief agencies are often unfamiliar with the region and must rely on limited technological support and incomplete information about the distribution area.

The urgency and magnitude of the need under these extreme conditions are matched only by the primitive nature of the methods and approaches used to meet these needs. Advances in information technologies, optimization techniques, networking power and the decision sciences have yet to be applied to the critical and most challenging problems that arise in disaster relief distribution operations. These problems further differ in substantial and substantive ways from those that are addressed under "normal" conditions—they are more chaotic, highly time-sensitive, constrained by incomplete or non-existent information in rapidly changing environment, require difficult and ethically challenging trade-offs, and must be deployed in an organizational void with uncoordinated decentralized and unsupervised agents.

The scope and mission of this project has been informed by our network of contacts from relief agencies. This network covers the broad range of organizations from small nongovernment organizations (NGOs) to large, international organizations and military/government operations, including the International Federation of Red Cross and Red Crescent Societies, the Federal Emergency Management Agency (FEMA), Feeding America, Mercy Corps, Friends of the Israeli Defense Force, United Methodist Committee on Relief, Arkansas Baptist State Convention, Material Management Relief Corps, as well as small grassroots organizations and individuals who have participated in the Haiti response such as Dr. Heckard and a number of doctors from Northwestern Feinberg School of Medicine. This close communication with a range of players in disaster relief response efforts has enriched our

understanding of relief distribution and strengthened the models and solution approaches we develop to assist the relief efforts.

2. Solution Approach

This initiative focuses on last-mile operations, after supplies have arrived at a regional warehouse, such as the situation faced by Dr. Heckard in Haiti, depicted in Figure 1. In this setting, a humanitarian agency identifies a relief strategy spanning a fixed time interval (on the order of a few days or weeks) to distribute aid to a set of geographically dispersed beneficiaries. Very limited information about the transportation network and the aid beneficiaries is available to the delivery agency and drivers. The network structure may be known prior to the disaster, but even that information could be highly unreliable given that what is considered a "road" in an undeveloped country might not be sufficient for a Red Cross truck to traverse. Further, the level of damage caused by the disaster is often unknown, particularly those links of the network that are impassable. As such, relief strategies must be robust and dynamic. For example, if a driver encounters an impassible link, the system must be capable of providing alternate plans. Major telecommunications carriers provided free access to their wireless services for the Haiti relief effort; therefore, the ability to communicate information was not the issue. Rather, getting the right information to the right people was a critical challenge. Our goal in this research is to develop models that can incorporate the ability to share information with models to make the best use of this information.

As mentioned earlier, the relief community is comprised of many diverse organizations, ranging from small non-government organizations (NGO's) such as Healing Wounds and Rehabilitation and Global DIRT to international organizations such as the Red Cross and Mercy Corp to government and military organizations such as the Federal Emergency Management Agency and the Israeli Defense Force. Working with organizations in each of these groups, we are developing a series of last mile distribution scenarios, categorized by organization type and the scope of the relief effort. Given that operations vary by the type of disaster, the location of disaster, the type of relief agency, and other factors, our approach is to develop base cases representative of the relief efforts of a particular group. Our initial models, described in Chapters 3 and 4, focus on our work with (1) small NGOs and (2) international organizations. In subsequent years, we will develop more general models to allow for more specific operating conditions of a particular organization within those two groups, and expand results to government and military operations.

3. Impact

The urgent need to improve the distribution networks for disaster relief is evident from continuing reports of excessive delays in delivering essential food, water and medical supplies in one disaster-stricken area after another. For example, in his April 2010 article about Haiti earthquake Vince Beiser writes "… there's no question that the global emergency relief system has significant shortcomings.

Governed for decades more by rules of thumb than research, it's still more art than science. Humanitarian supply chains are generally less efficient and the people running them less well trained than their commercial and military counterparts. They also suffer from a chronic lack of coordination. Dozens or even hundreds of groups swarm into disaster zones, tripping over one another, duplicating efforts, and competing for trucks, fuel, and food."

At the same time, this research has impacted the undergraduate and graduate students at Northwestern engaged in the project by exposing them to new applications of their operations research knowledge beyond commercial settings to non-profit organizations. Many students come to operations research with limited exposure to potential career opportunities: roughly 80% of graduating seniors in Industrial Engineering and Management Sciences at Northwestern pursue jobs in industry, with the majority of these students going to consulting or investment banking. As an example, one student who was involved in a capstone design project with a mobile asthma clinic, supervised by Prof. Smilowitz, commented that "as an asthmatic in my youth, I am familiar with the annoyance it bears on athletics, social life, and general comfort. What I am not familiar with, however, are the more serious effects on health and happiness it can have when undiagnosed or untreated…. I was startled by the seriousness of the issue of untreated asthma in Chicago….I am excited by the prospect of using my analytical problem solving skills to make an impact on their operations." This quote is a great example of what we hope to achieve through our work. As students experience first-hand the enormity of the operational/logistical challenges that non-profits face, we hope they will see the contributions they can make with their technical skills. As such, we hope to see more operations research students seek career opportunities in the non-profit sector. Chapter 4 describes a project that was performed by a team of undergraduates led by Professor Irina Dolinskaya and Ph.D. student Luis de la Torre.

4. Research Team

Karen Smilowitz is an Associate Professor of Industrial Engineering and Management Sciences, and holds the Junior William A. Patterson Chair in Transportation. Her research focuses on freight transportation systems and non-profit and humanitarian logistics. Recent projects have analyzed the opportunities and challenges of introducing operational flexibility in distribution systems. Dr. Smilowitz has worked with a range of collaborators from industry and non-profit organizations, including UPS, Coyote Logistics and the Mobile C.A.R.E. Foundation of Chicago.

Irina Dolinskaya is an Assistant Professor of Industrial Engineering and Management Sciences. Her research interests include optimal path finding in a direction, location and time dependent environments, and path planning with limited information about the region. Applications include vessel, autonomous vehicles and robot routing. Dr. Dolinskaya is currently working on a number of projects with the Office of Naval Research studying optimum vessel performance in evolving nonlinear wavefields and autonomous navigation for amphibious vehicles.

This research effort has included a number of graduate students, including current Northwestern students Luis de la Torre, Michael Huang, and Edwin (Zhenyu) Shi. The undergraduate students engaged in the enhanced search zone team are Ari Arevyan, Jireh Chua, Hogeun Jang, and Andrew Wald.

5. Report Organization

The report is organized as follows. Chapter 2 describes the survey funded by CCITT to better understand relief routing through interviews with aid organizations, reviews of their publications, and a literature review of operations research models in transportation of relief goods. We provide an analysis of the use of such models from the perspective of both practitioners and academics. Chapters 3 and 4 describe operations research models based on this work. Chapter 3 introduces the single-stop relief routing model and Chapter 4 details work in designing enhanced search zones for search and rescue operations. Finally, Chapter 5 presents an overview of future work.

Chapter 2 Disaster Relief Routing: Integrating Research and Practice

Just days after the 2010 earthquake in Haiti, the United Nations (UN) called the earthquake the worst it had encountered [1]. Six months later, UN Secretary General Ban Ki-Moon said the same about devastating floods in Pakistan, and called for half a billion dollars of support just for short-term relief [2]. In addition to these catastrophes, the past decade has seen many other large disasters including the 2004 Indian Ocean earthquake and tsunami, in 2005 Hurricane Katrina, the 2005 Pakistan earthquake, in 2008 Cyclone Nargis and the 2008 Sichuan earthquake. The destruction from disasters can leave populations without shelter, food and water, and in need of urgent medical care. In these situations, it can be necessary to supplement local capacity with regional or international aid. For example, within the first 30 days of the 2001 Gujarat, India earthquake, the International Federation of the Red Cross and Red Crescent (IFRC) arranged delivery of hundreds of thousands of blankets, tents and plastic sheets. Additionally, over 300 other non-governmental organizations (NGOs) and UN agencies provided assistance [3]. The Gujarat earthquake is just one of many large disasters that have required international assistance, and is far from the largest.

Disaster relief requires efforts on many fronts: providing rescue, health and medical assistance, water, food, shelter and long term recovery efforts. Much of successful and rapid relief relies on the logistical operations of supply delivery. In 2005, the United Nations established the Logistics Cluster as one of nine inter-agency coordination efforts in humanitarian assistance, recognizing the key importance of logistics in aid operations. The Pan American Health Organization (PAHO), a regional division of the World Health Organization (WHO), states in its publication Humanitarian Supply Management and Logistics in the Health Sector ([5]) that "countries and organizations must see [humanitarian supply logistics] as a cornerstone of emergency planning and preparedness efforts."

In this chapter, we focus on reviewing the problems related to routing of vehicles within disaster-affected regions to deliver goods and services to distribution points and beneficiaries. We analyze the representation of these problems in current operations research models for disaster relief, and identify outstanding related research questions. Mathematical models related to emergencies have a long history. In 1955, Valinsky [6] published one of the earliest papers in emergency assistance, on locating fire fighting resources. Work related to non-daily emergencies started in the 1980s, in assessing the risk of rare events such as large natural disasters (Sampson and Smith [7]) and simulations of traffic patterns to improve the flow of emergency evacuation (She et al. [8]). Disaster relief transportation also saw its start in the 1980s with a routing model developed by Knott in 1987 [9]. In order to better understand the ways in which operations research models are helping and can continue to help relief organizations, we have conducted a series of interviews with representatives from organizations involved in disaster relief. These include small and large NGOs, local, state and federal governmental relief organizations and commercial partners of relief organizations. In addition, we discuss findings from publications of relief organizations on logistical procedures for disaster relief. We have also conducted a comprehensive literature review of operations research models in disaster relief transportation and distribution. We review findings from these studies and discuss areas where models can continue to expand and capture

characteristics of relief distribution. Our literature review focuses on papers specifically in relief transportation and their modeling characteristics. Other surveys in humanitarian logistics have been published previously. [10] gives an overview of academic literature in disaster operations management, discussing work in disaster operations not limited to routing. Kovacs and Spens [11] provide a survey of both academic and practitioner literature in disaster operations. From their in-depth survey of practitioner literature, the authors find many challenges in disaster operations similar to what we found from our interviews: destabilized infrastructure; uncertainty in demand, supply, and the time and effort needed to distribute goods; a need for academic work that considers dynamics; and fundamental differences in goals and objectives between commercial and non-profit logistics. Simpson and Hancock [12] also provide a broad recent survey of work in all areas of emergency response, including disaster relief along with other categories such as daily fire and medical emergencies, evacuation, and search and rescue operations.

1. Information Collection Methodology

To collect papers on operations research models for this review, we searched journal search engines such as ISI Web of Science, the INFORMS journal database, Transportation Research Board publication database, Science Direct, Springer Journal Database and various individual journals' search engines. These were queried using the keywords "disaster", "emergency", "catastrophe", "humanitarian", and other forms of the words such as "disastrous". The search engines' filters were used to narrow results to operations research models for disaster relief. Within these results, papers were kept that specifically address the transportation and routing of goods. Finally, the reference sections of these papers were searched to find additional relevant papers. Many of the papers selected model additional characteristics, including asset pre-positioning, facility location, infrastructure repair following a disaster, or evacuation and rescue and evacuation, but all include transportation of goods as a significant component.

To learn about current practices and challenges in disaster relief transportation and distribution, we interviewed representatives from governmental organizations, NGOs, and commercial partners of organizations. We interviewed 32 representatives from 21 organizations over the phone or in person with follow-up questions by email. Interviewees were not all asked the same set of questions. All interviews began with similar initial questions and progressed based on the responses and expertise of the interviewee. From these interviews, we share responses that have an impact on modeling disaster relief transportation and distribution problems. To protect the confidentiality of interviewees, we use the conventions similar to those of Holguin-Veras et al.'s review [13] of logistics issues during Hurricane Katrina. Government agencies are referred to only as "state" or "federal" depending on their jurisdiction. Those from non-profit organizations not under the jurisdiction of a government are identified as volunteer organizations. Some of the organizations interviewed work primarily in countries other than the US, which we describe as international organizations. Those from commercial partners are referred to as "commercial partners". We interviewed three commercial partners, eight international volunteer organizations, four volunteer organizations working primarily in the US; three volunteer organizations that work in both the US and internationally; one US federal government organization and one US state

government organization. In addition to interviews, we include findings from the general media, trade publications and other publications in disaster relief and humanitarian logistics.

In the next sections, we review these papers concurrently with our findings from interviews and relief organization publications. We categorize papers by problem characteristics and discuss these characteristics with related findings.

2. Relief Transportation in Practice and Operations Research Models

2.1 Allocation Policies

A critical and challenging component of relief distribution is the allocation of goods to beneficiaries. In many situations, beneficiary needs exceed the available supply of goods and relief organizations must allocate limited goods. Published humanitarian guidelines do not provide standard procedures for allocation when demand exceeds supply. The Sphere Handbook is a collaborative effort between hundreds of NGOs to establish standards in humanitarian practice. It provides detailed minimum humanitarian standards to be met in relief, such as ensuring each person has 2100 daily calories of food [14]. The Sphere Handbook also states that agencies should provide aid impartially and according to need, but makes no mention of specific procedures when sufficient calories cannot be provided to all people in need. Florida and South Carolina, two U.S. states especially vulnerable to hurricanes, have detailed emergency management handbooks that describe quantities of goods to be distributed. However, they do not address how to allocate goods when these quantities cannot be met [15, 16].

A common trend we found in making allocation decisions is to prioritize the needs of the most vulnerable populations. In Sudan and Niger, Medecines Sans Frontieres (MSF, or Doctors Without Borders) and the UN, respectively, restricted food aid to the most malnourished children and their families [17, 18]. Two international volunteer organizations interviewed described making allocation decisions to beneficiaries by closely monitoring locations, targeting the people with the highest needs and ensuring they receive enough to satisfy Sphere standards. All policies described to us during interviews were egalitarian, requiring that an equal amount of need for all targeted populations are met.

In relief routing models, we find several types of egalitarian policies that maximize equality of a measure such as delivery quantity or speed. We also find examples of utilitarian policies that maximize the amount of demand satisfied without requiring equality in distribution of goods, or access to them in covering models. Hodgson et al. [19], Doerner et al. [20], Campbell et al. [21], Huang et al. [22], Nolz et al. [23], Van Hentenryck et al. [24], Mete and Zabinsky [25] measure equity and efficacy of aid distribution by minimizing the time to deliver goods to beneficiaries. Campbell et al. [21] studies the properties of vehicle routing problems that minimize the average or, alternatively, the latest arrival time of goods to beneficiaries. The authors find that these objectives result in faster delivery at a higher total transportation cost than with traditional cost minimizing objectives.

Huang et al. [22] extend these ideas by weighting arrival times by the amount of goods delivered. Mete and Zabinsky [25] minimize total costs of operating delivery warehouses along with minimizing total travel time of delivery. In all of these papers, all demand must be satisfied. In Nolz et al. [23] and Van Hentenryck et al. [24], latest arrival times are minimized along with minimizing the total amount of unsatisfied demand. This combines a utilitarian measure of delivery quantity with an egalitarian measure of delivery speed. Objectives that are egalitarian in delivery quantity are found in a number of papers. Jozefowiez et al. [26], Tzeng et al. [27], Lin et al. [28] take the opposite approach to Nolz et al. [23] and Van Hentenryck et al. [24], minimizing the maximum unsatisfied demand over all beneficiaries while minimizing total travel time. These papers use an egalitarian measure for delivery quantity and a utilitarian measure for delivery speed. Balcik et al. [29] also minimizes the maximum unsatisfied demand over all beneficiaries. In all papers mentioned so far except for Campbell et al. [21], cost minimization is included as an additional objective in multiobjective models. Ozdamar et al. [30], Doerner et al. [20], Yi and Kumar [31], Yi and Ozdamar [32], Shen et al. [33, 34] minimize total unsatisfied demand without considering equality of delivery.

Similarly, Clark and Culkin [35] and De Angelis et al. [36] minimize total unsatisfied demand but include constraints that all beneficiaries receive a minimum amount of goods. This may not lead to equitable solutions but can be used to enforce minimum standards such as those in the Sphere Handbook. Finally, Haghani and Oh [37], Oh and Haghani [38], Hachicha et al. [39], Barbarosoglu et al. [40], Barbarosoglu and Arda [41] minimize total cost of deliveries while satisfying all demands with no egalitarian or utilitarian component.

The above papers comprise a range of allocation policies. For each model type, there are realistic scenarios where a particular model is appropriate. Focusing on maximizing total or average speed of delivery while delivering the maximum quantity of goods possible is important in rapid and early response. With a large and urgent need, time may be better spent distributing supplies than evaluating needs. Equality in delivery is more suited to longer-term recovery and development aid where speed is less of a factor and political or social issues make equity in delivery important. While minimizing the cost of satisfying a specified level of demand is not explicitly egalitarian or utilitarian, the value of demand to be satisfied can reflect these goals. For example, the relief plans of the Federal Emergency Management Agency (FEMA), described in IS-26 Guide to Points of Distribution ([42]), specify quantities to distribute to beneficiaries. These plans also include guides for establishing contracts with suppliers to ensure these needs can be met. With these specifications and certain supply availability, a cost-minimization model for relief distribution would be appropriate.

2.2. Needs Assessment

Accurate needs assessment is crucial for achieving accurate models and maximizing the benefit of distributing relief goods. Needs assessment is much more challenging in the earlier phases of a disaster. As described earlier, some of the larger volunteer organizations we interviewed have dedicated staff that make periodic trips to affected locations to conduct assessment. Existing relief routing models can be adapted to model needs assessment rather than aid distribution. Demand at a location can represent the need to visit a location and assess need instead of demand for goods.

Needs assessment methods vary between organizations and change as the disaster situation evolves. When possible, organizations can use sources of information such as maps from the UN, World Food Programme (WFP) and WHO. Examples of available maps can be found at the website of the UN Geographic Information Working Group, which compiles maps from many organizations [43]. In addition, some volunteer organizations do not do needs assessment and instead focus on fulfilling needs identified by partner groups. One example is Mennonite Central Committee, an organization that works internationally and relies on partner organizations for needs assessment, as described in a case study by McLachlin et al. [44].

In our interviews, a number of volunteer organizations emphasized the amount of effort that goes into ensuring fair distribution. Monitoring a population to understand its needs and developing relationships with local leaders to ensure orderly and fair distribution takes significant resources. The organizations that described these challenges each have over thousands of staff members operating in many countries. For all but the largest organizations, needs assessment and incorporating complex allocation decisions may be impossible. Policies can be more sophisticated with wider availability of technology such as the UPS Trackpad used for tracking use and receipt of goods [45]. Another technology is Ushahidi [46], a website where the public can submit information through text message and email. Systems like these can help organizations perform needs assessment without sacrificing crucial resources. There are potential research questions when multiple data sources are available and provide conflicting information including the basic question of whether the effort to combine multiple and possibly conflicting sources is worth the effort.

An important issue to understand is the type and quantity of data collected by relief organizations. All organizations interviewed collect data for accountability to current donors and to show the impact of efforts for further fundraising. Data needed for accountability may not be at the same level of detail needed to test current models. Current relief distribution may not require the data necessary for model-based operations, and spending limited resources on data collection can impede the real goal of distributing goods. Understanding the advantage of using detailed models over methods requiring less intensive data collection is important with limited resources.

Data collection from past relief efforts can be extremely useful for researchers to test, validate, and compare models. Much of the current literature uses either historical data or data from disaster damage scenario modeling software (Hodgson et al. [19], Hachicha et al. [39], Barbarosoglu et al. [40], Ozdamar et al. [30], Barbarosoglu and Arda [41], Viswanath and Peeta [47], Clark and Culkin [35], Doerner et al. [20], De Angelis et al. [36], Jozefowiez et al. [26], Tzeng et al. [27], Yi and Ozdamar [32], Zhu et al. [48], Vitoriano et al. [49], Nolz et al. [23], Mete and Zabinsky [25], Rawls and Turnquist [50], Salmeron and Apte [51], Van Hentenryck et al. [24], Lin et al. [28]). Lin et al. [28] use FEMA's HAZUS infrastructure damage modeling software to generate damage scenarios; this software can be used for modeling damage in the U.S.. Some commonality exists in data sets. Hodgson et al. [19], [20] and Jozefowiez et al. [26] use data from the road network of the Suhum District of Ghana to test their models.

2.3. Uncertainty in Demand and Supply

Uncertainty is prevalent in the supply of relief goods. Every organization interviewed identified at least one level of the supply chain where supply delays and losses were a problem and many identified supply delays as a major impediment to goods distribution. A federal government interviewee emphasized the importance of properly prioritizing goods. In their experience, rapid delivery of goods was not delayed by lack of resources, but by using resources to deliver the wrong types of goods. Multiple volunteer organizations and commercial partners identified goods being held in customs as another significant problem. In a presentation on her medical work in Haiti following the 2010 Earthquake, Dr. Stacey Raviv of North Shore Hospital in Evanston, IL described significant time and efficiency lost because of disorganized warehouses [52]; this problem was also described by volunteer organizations interviewed. Several other volunteer organizations described the difficulty of finding transportation into a country for donated goods. A volunteer organization which stores and delivers the goods of partner organizations often had its partner organizations fail to deliver their goods in time for distribution. The overwhelming response of supply issues during our interviews highlights the potential for incorporating supply uncertainty into relief models.

Many models in the relief routing literature incorporate uncertainty in demand and supply. Several papers use two-stage stochastic programming to model the uncertainty of the damage caused by disasters and its effect on supply or demand. In Barbarosoglu and Arda [41], the first stage decision is to move goods between existing supply depots to preposition them. In the second stage, realization of the uncertain demand and supply are revealed and goods are transported to final beneficiaries. In Zhu et al. [48], Mete and Zabinsky [25], and Salmeron and Apte [51], demand, not supply, of goods is uncertain. In these papers, the first stage decisions made before a disaster are to open and stock warehouses with goods. In the second stage demand is fixed and goods must be routed from warehouses to final destinations. In Shen et al. [33], the first stage is also pre-disaster and demand is uncertain. In this paper, the first-stage decisions create routes for vehicles and the second stage allows adjustments in delivery quantities to each beneficiary after demands are revealed. In Rawls and Turnquist [50] and Van Hentenryck et al. [24], the pre-disaster first stage decisions are to locate and stock warehouses, which can be damaged during the disaster. In the second stage, demand and remaining supply is fixed, and the decision variables construct routes.

The papers discussed above model the uncertainty in physical damage caused by the disaster and the immediate post-disaster response, but there are many other potential sources of uncertainty and dynamic elements to incorporate. Uncertainty in supply can result from delays and losses of relief goods at multiple points in the relief supply chain. Demand can fluctuate unexpectedly due to many sources. These sources include people returning to greater self-sufficiency, beneficiaries moving between different areas to find greater relief, or unexpected challenges, such as disease epidemics resulting from the close quarters of relief shelters. Modeling this type of uncertainty can be extremely challenging. Two-stage stochastic programming models are already computationally difficult to solve and require more data than deterministic models. Computational and data challenges are only compounded by incorporating more uncertainty.

In addressing supply and demand issues in relief routing, there are many ways that current systems in both practice and models can be developed. Needs assessment in the early phases of a disaster requiring trips to beneficiaries can be integrated into models. Continued interagency collaboration, information sharing and technological improvement from practitioners can make time consuming trips less necessary. Researchers can continue to push the boundary of modeling uncertainty while practitioners address supply and demand problems and make the situation easier to model.

2.4 Vehicles and Routes

In this section, we discuss characteristics of vehicles and transportation networks in the current relief routing literature along with related findings from interviews and relief organizations. Models capture characteristics for a variety of relief organizations, and there are also many characteristics that can provide new areas for models to expand.

In Section 2.4.1 we discuss the how vehicles model supply depots and movement requirements of vehicles. In Section 2.4.2 we highlight some of the literature that models unique types of relief distribution, including air transportation and high-level strategic models of the relief supply chain. In Section 2.4.3 the effect of heterogeneity of delivery goods is reviewed. The last two sections, 2.4.4 and 2.4.5 respectively discuss vehicle fleet heterogeneity and uncertainty related to routes, such as travel time and vehicle reliability.

2.4.1 Modeling of Vehicle Depots

Traditional vehicle routing models assume that goods are distributed by a set of vehicles on routes beginning and ending at a single depot. Relief routing models can be classified into three groups: those with a single depot (Knott [9, 53], Hodgson et al. [19], Barbarosoglu and Arda [41], Doerner et al. [20], Jozefowiez et al. [26], Balcik et al. [29], Campbell et al. [21], Hsueh et al. [54], Ukkusuri and Yushimito [55], Shen et al. [33, 34], Huang et al. [22], Nolz et al. [23], Mete and Zabinsky [25], Lin et al. [28]); those where routes originate and end from multiple depots with all vehicles returning to their original depot (Barbarosoglu et al. [40], Yi and Kumar [31], Yi and Ozdamar [32], Zhu et al. [48], Vitoriano et al. [49], Van Hentenryck et al. [24]); and those that do not have the concept of a depot (Haghani and Oh [37], Oh and Haghani [38], Ozdamar et al. [30], Viswanath and Peeta [47], Clark and Culkin [35], De Angelis et al. [36], Rawls and Turnquist [50], Salmeron and Apte [51]). In those without depots, vehicles are not required to return to their starting points. Each of these types of models makes different assumptions about the structure of the relief organizations being modeled. Models with multiple starting and ending points are more applicable to organizations with greater resources than a single depot model. Some models that do not require vehicles to return to their starting points require the ability to communicate routing decisions to vehicles throughout a region. Communication at this level may not be possible, especially in the earliest post-disaster stages.

2.4.2 Specialized and Strategic-Level Models

Many papers present more specialized relief models. Two papers model the unique challenges of delivery by air. Barbarosoglu et al. [40] models helicopter logistics, considering pilots with specialized skills, sensitivity of fuel efficiency to cargo weight, and refueling requirements. De Angelis et al. [36]

models delivery of food by cargo plane, including landing schedules, parking capacity, and refueling schedules. Barbarosoglu et al. [40], Yi and Kumar [31], Yi and Ozdamar [32] consider the evacuation of beneficiaries while simultaneously making deliveries. With a limited number of vehicles, doing both at the same time can have an enormous potential to save costs and lives. Clark and Culkin [35], Tzeng et al. [27], Zhu et al. [48] take approaches with less operational detail than other models. In their models, commodities travel through several levels of nodes, from suppliers to beneficiaries. Nodes at each level have some quantity of supply and transportation capacity, but movement of individual vehicles is not tracked through the supply chain. As a decision variable, these models include the number of vehicles traveling between each node. The supply of vehicles available from each node is a parameter and not a function of the number of vehicles that have traveled between locations. Deliveries to recipients do not give routing information but give the number of vehicles that make deliveries and the quantity of goods delivered. These models require data at more levels of the supply chain than a last-mile distribution model, but require less detailed data at each level. These strategic-level models can be useful for finding bottlenecks in different levels of distribution and understanding the quantities of vehicles and goods needed throughout the supply chain.

2.4.3 Commodities and Delivery Locations

Several other route and vehicle characteristics are modeled in the literature. Commodities in disaster relief can be many different types of goods, such as food, medications, or tents. Most papers we review consider the delivery of multiple commodities, differentiating the transportation costs and demands of different types of goods. Balcik et al. [29] explicitly models the difference between single-use perishable items and multi-use non-perishable items, with demand backlogging allowed for non-perishable items and demand lost for perishable items. Government and volunteer relief organizations interviewed identified single-use perishable and multi-use non-perishable items as two major important categories. One federal government organization identified between seven and ten major relief commodities within those two types. An international volunteer organization noted that the safety of a vehicle differs based on the type of goods being carried. Easily re-sold goods such as food and water can be bigger targets for robbery than specialized medicine or medical equipment. Safety as a function of type of good carried has not yet been modeled.

One international volunteer organization identified providing safe drinking water as a unique challenge. Water purification tablets need to be delivered frequently and consistently in high volumes and tap stands for distributing water need to be placed where they can be accessible and safe. Nolz et al. [23] formulates the problem of routing and placement of water delivery systems. Rather than being transported directly to beneficiaries, potable water stations have to be delivered to central locations. This is modeled as a multi-vehicle covering tour problem that combines routing with the placement of tanks, constructing tours to place tanks at accessible points. Hodgson et al. [19], Doerner et al. [20] and Jozefowiez et al. [26] also model covering tour problems. Their problem setting is the routing of a mobile health facility that stops at locations and is visited by people in surrounding locations.

The covering tour model is applicable to many operational last mile delivery problems, as goods and services are often delivered to central locations visited by beneficiaries. For example, in the U.S. after a

disaster, as described in IS-26 Guide to Points of Distribution ([42]), FEMA sets up temporary points of distribution which beneficiaries visit to receive goods. A covering tour problem could be used for initial placement of these temporary points of distribution.

2.4.4 Vehicle Fleet Types and Technology

Some of the most ubiquitous assumptions of routing models are of a vehicle fleet with known capacity, known operating costs, known capabilities such as on which roads a vehicle can travel, and the ability to give these vehicles specific routing instructions. Many volunteer organizations interviewed stressed the difficulty of procuring and managing a fleet, which can affect these assumptions. A volunteer organization stated that even the largest organizations with a long term presence in a country do not generally own their vehicle fleets. This was echoed by others who do not own their own fleets, including a volunteer organization which works in over forty countries. The simplest solution may be to hire a commercial carrier to manage the details of most of the transportation, with the relief organization taking over at final destinations to distribute to beneficiaries. In its publication Humanitarian Supply Management and Logistics in the Health Sector ([5]) PAHO recommends contracting fleets and fleet management for transportation of relief goods when possible, but recognizes that fleet management companies may not be available. The document describes that it is much more common to hire multiple independent local drivers and vehicles and manage them internally. This was confirmed in interviews with several international organizations who stated that this management of heterogeneous fleets is a common challenge. Local drivers are sometimes hired for their knowledge of the region. When drivers know the region but the relief organization does not, there may not be enough information to make detailed routing plans for vehicles. With limited information and limited instructions to drivers, simpler models that do not assign vehicles detailed routing plans are more appropriate.

Another realistic assumption to consider is limited technology available in vehicles, especially when using local hired vehicles. Some of the current papers model the ability for vehicles to wait for further instructions at any stopping point in the transportation network (Ozdamar et al. [30], Tzeng et al. [27], Yi and Ozdamar [32], Hsueh et al. [54]). This has potential for significant cost savings as opposed to having to return to a depot, and assumes that communication with vehicles is always available. These models can help organizations to assess the value of tracking vehicles and maintaining constant communication before allocating limited funds for the technology to do so.

Many other routing related issues found during interviews and in relief organization documents point to modeling vehicles with restricted capabilities in movement. In Humanitarian Supply Management and Logistics in the Health Sector ([5]), PAHO recommends lightening the load of vehicles that have to cross rough terrain. One international volunteer organization described difficulties in making deliveries across rough terrains, and prefers using a combination of small capacity all-terrain vehicles and less flexible larger trucks to adapt to damaged infrastructure. Another international volunteer organization cited limitations in its routing because of both infrastructure damage and danger traveling in areas with conflict. In the OR literature, Knott [53] describes heuristics for relief routing which include rules to reduce vehicle payload by 20% if the road used is rough, and to give preference to different types of trucks on different types of roads.

Nearly every organization interviewed stressed the importance of awareness of cultural and political issues. In particular, these issues can affect the types of commodities that can be delivered and impact how vehicles make deliveries. One commercial shipping contractor stated that in order to maintain trust in some regions, delivery drivers needed to have an existing relationship with beneficiaries. This limits possible routes for each vehicle and makes routes driver-dependent. Limiting the region where each vehicle can travel is modeled in papers that model multi-modal travel (Haghani and Oh [37], Oh and Haghani [38], Ozdamar et al. [30], Barbarosoglu and Arda [41], Zhu et al. [48], Salmeron and Apte [51]), in which different vehicles have different parts of the network they can visit.

2.4.5 Uncertainty in Routes and Vehicle Fleets

As discussed in Section 2.3, many papers model uncertainty with two-stage stochastic programming models. In addition to modeling uncertainty in supply and demand of goods, Shen et al. [33], Mete and Zabinsky [25], Rawls and Turnquist [50], Salmeron and Apte [51], Van Hentenryck et al. [24] model uncertainty in travel time. In these papers, travel times are scenario-dependent and revealed in the second stage. In addition to modeling damage to transportation infrastructure, there are many possible sources of uncertainty to incorporate into models that we have learned about through interviews. An assumption of all current relief routing models is certainty of the size and composition of the vehicle fleet. Without this assumption, routing plans, especially multi-period routing plans, can become significantly more difficult to make. During relief efforts following Hurricane Rita, vehicles and drivers expected to distribute relief supplies abandoned New Orleans following reports of violence (Holguın-Veras et al. [13]). Several relief organizations reported problems while collaborating with organizations using volunteer drivers or vehicles. These groups may not be bound by contracts and monetary incentives and thus do not have the same incentives to uphold agreements as commercial carriers. Such a situation can cause uncertainty when determining the size of a fleet. Additionally, multiple volunteer organizations described the unreliability and necessary maintenance of older local rented vehicles as a problem. Reliability is modeled in Vitoriano et al. [49], in which vehicles have a road-dependent probability of breaking down while en route.

Even if vehicle fleets are known with certainty, unexpected events occur while on routes. An international volunteer organization that was interviewed stated that while delivering supplies in Haiti in 2010, accessibility of roads was changing constantly and unpredictably due to the movement of debris and government and military road blocks. They had no maps with updated information and had to discover the best routes by driving and exploring. In addition to uncertain travel times, one volunteer organization identified the time spent stopping at beneficiaries to distribute goods as a bottleneck, even with a dedicated staff at distribution points.

Safety of drivers was also a concern of many organizations. Safety was such a concern for one volunteer organization working in Haiti in early 2010 that it would sometimes not stop for any reason before reaching their destination. Other organizations agreed that safety was important and that robbery while delivering goods was a real concern. One volunteer organization described varying the path and dispatch times of routes to avoid establishing a pattern and making themselves obvious targets. Another volunteer organization obscures vehicles' identities when it is a potential target and prominently

displays logos identifying itself when people are sympathetic to its efforts. Some potential strategies for safety produce additional challenges and sometimes are against a relief organization's rules. In their analysis of aid operations in the Somali region of Ethiopia, Chander and Shear [56] note that WFP frequently used vehicle convoys for safety. Convoying would cause long delays in delivery while waiting for vehicles to group and limit travel speed significantly. Convoys and possibility of interdiction of vehicles are modeled by Vitoriano et al. [49]. In this model, vehicles have a probability of interdiction and at the expense of delivery speed they can form convoys to reduce this probability.

Some organizations, including IFRC, will not use armed escorts ([57]), while another volunteer organization will not make deliveries if it believes the situation would warrant an armed escort. In order to model the characteristics of vehicles and routes, a key issue is to understand the capabilities of relief organizations. For organizations where only simple instructions to independent drivers are possible, simpler models may be appropriate. Others may be able to make more complex decisions, especially those involving randomness or ambiguity.

For organizations of many different types, addressing the reliability of vehicles and drivers can improve planning delivery schedules. Some organizations may be able to adjust to uncertainty while vehicles are on routes and improve distribution quantities or safety of drivers.

3. Conclusions

Our interviews encompassed organizations of many different sizes, capabilities, and infrastructure that work in various regions worldwide. These interviews do not cover all of the possible problems of disasters or anticipate all potential issues resulting from future disasters. Most of the papers we review are the result of a collaboration with relief organizations. Researchers are collaborating with many different types of organizations: government and military organizations (Barbarosoglu et al. [40], Ozdamar et al. [30], Tzeng et al. [27], Zhu et al. [48], Salmeron and Apte [51], Van Hentenryck et al. [24]); non-governmental organizations (De Angelis et al. [36], Balcik et al. [29], Vitoriano et al. [49], Salmeron and Apte [51], Nolz et al. [23]); and experts in important related areas such as emergency medicine and seismology (Yi and Kumar [31], Yi and Ozdamar [32], Mete and Zabinsky [25]). Many of those that do not describe direct collaboration with organizations discuss using information from relief organizations to construct their models (Knott [9, 53], Haghani and Oh [37], Oh and Haghani [38], Clark and Culkin [35], Rawls and Turnquist [50], Lin et al. [28]). As well as improving relief distribution systems in practice, continuing to learn about unexpected challenges in disaster relief can continue to lead to innovative models and algorithms that can be of interest to the operations research community at large. Involvement beyond talking to organizations can be beneficial to give researchers real world experience. Organizations such as Volunteer Match (http://www.volunteermatch.org) list volunteer opportunities, including but not limited to disaster relief.

We have identified several areas where modeling can capture more characteristics of relief distribution. Most of the relief routing literature focuses on pre-positioning and initial distribution of goods and

services after a disaster. The early periods following a disaster are crucial for rapid recovery, but we learned about challenges involving more than the initial damage of disasters. We discussed multi-period delivery in interviews as beneficiaries may need support beyond the capacity of a single delivery. Multi-period routing has not been modeled in the relief routing literature. Along with multi-period routing are characteristics of routing beyond the initial damage. When planning future routes, ambiguity in the availability of vehicles, supplies and changing demand characteristics can be a challenge. These issues have only been incorporated in two-stage stochastic programming models for a single period of routing. Multi-period models incorporating these issues can give insight into simple rules of thumb and be useful for practitioners and help advance research in solving large multi-stage deterministic and stochastic models.

Risk-averse behavior in routing has not been studied in depth. Relief organizations are cautious in planning their routes because of the physical safety of drivers, variations in routing and distribution times and difficulty reaching remote and rural beneficiaries.

International volunteer organizations discussed variations in this risk aversion. Earlier in disasters, or when making initial deliveries organizations are more cautious. By hiring local commercial drivers rather than using employees of the organization, drivers are more familiar with the area and risk-aversion can be avoided at a cost. Exploring the trade-offs of different routing behaviors can help organizations improve delivery quantity while maintaining a high level of safety.

As models continue to be developed, more work can be done demonstrating the value of routing. This can help demonstrate to practitioners that models can help them save more lives. Many of the papers in the literature demonstrate the value of modeling relief routing. Campbell et al. [21] and Huang et al. [22] compare different types of relief objectives. Campbell et al. [21] prove several bounds on arrival times when using minsum and minmax arrival times instead of the total cost of travel. These bounds demonstrate that when using routing models, different objectives can have significant impacts on the speed delivery. Similarly, [22] shows similar results when comparing objectives maximizing the average speed of delivery, equitable service times, and minimum cost objectives. This paper also demonstrates on test cases that the shape of routes can change significantly depending on the objective. [24] implements a greedy method that models what is currently done in practice in the U.S. when delivering relief goods and compare it to their stochastic routing models and algorithms, showing reductions of 50.6% to 57.7% in delivery times over the status quo on benchmark problem instances. [36] compares its model's results to historical data from delivery of goods in Sudan and shows an increase of 9% to 22% in the number of deliveries made in the same time period.

The characteristics of different disasters and relief organizations will continue to provide opportunities and challenges for researchers. One of the most emphasized points in our interviews is that every disaster is unique and every relief organization has its own set of practices and policies. Over the course of a post-disaster response, the situation can evolve from chaos with limited information into a more orderly situation more amenable to models. Even the same type of disaster in the same region can present different challenges in two different years. The rain season is a threat to Haiti every year, but

after the damage caused by the 2010 Earthquake, damage from the rain season presented different challenges than in previous years [58]. In delivering solutions to relief organizations, limitations during a disaster situation such as data availability computing time and computing power can limit the scope and form of a model. These are issues when modeling any setting but can be especially limiting in a relief setting.

Disaster relief routing and distribution models have existed in the operations research literature for only a little over two decades, and there are many years of potential future work. We need to continue to understand the real problems faced by practitioners, especially as their practices evolve. Improved technology such as real-time tracking of goods and beneficiary demand, inventory management and supply chain software tailored for relief organizations, and computerized mapping can provide rich data sources for OR based decision support systems. Along with technology, organizational and collaborative structures are improving with interagency collaboration like the Logistics Cluster and the increased emphasis on logistics in relief efforts. For researchers, work in this area means advancing the ability to model highly chaotic and unpredictable distribution systems regardless of the modeling context. If models are to be flexible enough to address the high uncertainty of disasters, the framework can also be carried over into other areas with similar challenges.

4. Deliverables to date

Publications:

Luis E. de la Torre, Irina S. Dolinskaya, Karen R. Smilowitz (2011), "Disaster relief routing: Integrating research and practice", Socio-Economic Planning Sciences, Forthcoming.

Presentations:

Luis E. de la Torre, Irina S. Dolinskaya, Karen R. Smilowitz , Disaster Relief Routing: Integrating Research and Practice, Poster presentation at the 2011 Conference on Health and Humanitarian Logistics, Georgia Tech.

Luis E. de la Torre, Irina S. Dolinskaya, Karen R. Smilowitz, Disaster Relief Routing: Integrating Research and Practice INFORMS 2010, Austin, TX.

Chapter 3 Relief Routing Models

1. Challenges of Humanitarian Relief Routing and Modeling Implications

Based on the findings from the study described in Chapter 2, we have identified the following challenges of relief routing, which inform our relief routing models.

Beneficiary locations may be temporarily inaccessible. To achieve equity in aid, deliveries must be made to remote and difficult-to-reach locations. Rural locations may be especially difficult to reach because of weather and damaged transportation infrastructure. Many relief organizations will not go to locations deemed unsafe. Inaccessible locations require time-critical decisions about routing plans. Rather than just postpone deliveries, models should effectively use newly freed resources to make other deliveries earlier and mitigate the loss from inaccessible locations.

Uncertainty in travel and service times. In Haiti in early 2010, travel time between locations often varied significantly day-to-day, with little correlation across days. Long and uncertain service times to make deliveries also complicated operations. These delays can affect the number of stops that vehicles can make in settings where multiple visits per route are possible. The delays can be addressed by changing delivery plans mid-route, yet this dynamic option can be challenging methodologically. Route adjustments affect plans for the rest of the time horizon and must consider the effect on equity of distribution. Additionally, to be realistically implementable, route adjustments need to be simple yet effective decision rules.

Uncertainty in supply and vehicle availability. Relief distribution can be impacted by uncertainty in the availability of supplies and the vehicles needed to transport the goods. Supplies may be delayed while waiting for available space on cargo planes or boats or while clearing customs in international relief settings. Vehicles in disaster-affected areas may be unreliable and require frequent maintenance. Vehicle unavailability can also result from drivers being unwilling to make deliveries in dangerous conditions, as was the case in New Orleans during Hurricane Rita (Holguın-Veras et al. [13]). Plans for multi-period, multi-vehicle routes must be flexible to allow re-planning during the time horizon to accommodate uncertain delays and losses of supplies. With limited supplies, it may not be possible to meet all beneficiary needs and routing models must include decisions on how to distribute goods in such situations, taking equity into account.

Uncertainty in beneficiary needs. In the early phases of disaster relief, beneficiary needs can be uncertain because needs have not yet been accurately assessed. Relief organizations cannot wait for a thorough assessment of need to begin delivering supplies. Although there is a large body of literature on vehicle routing problems with stochastic demand, models traditionally address demand uncertainty by realizing demand immediately before vehicles leave on their routes or when vehicles arrive at locations, allowing immediate recourse decisions to satisfy demand. In this setting, it may be more appropriate to

address demand uncertainty by planning for recourse in later stages of the planning horizon rather than immediately.

Route structure impacts the options to mitigate uncertainty. Several of the above examples highlight the importance of the route structure dictated by the relief setting on uncertainty mitigation. Additionally, local cultural and political issues can affect how vehicles make deliveries. One commercial shipping contractor stated that in order to maintain trust in some regions, delivery drivers needed to have an existing relationship with beneficiaries. This limits possible routes for each vehicle and makes routes driver-dependent.

These factors represent several defining challenges in humanitarian relief routing. Not all factors are present or significant in all settings. In our research plan, we begin with the uncertainty in travel time and accessibility of beneficiaries and introduce other challenges in subsequent models, as applied to single stop routing problems, described next.

2. The Single-Stop Routing Problem

In rural settings, beneficiaries may be located far from a supply location (e.g., a seaport or an airport) and far from each other. Relief distribution in these settings is critical for remotely-located beneficiaries and challenging for the relief organizations. Given the geographic dispersion of beneficiaries, vehicles are often limited to only a single visit per day. From our interviews with organizations who work in such settings, we define the single-stop routing problem as follows.

The single-stop routing problem assigns vehicles to deliver to beneficiaries over a multi-day planning horizon, with each vehicle making at most one delivery per day. The objective is to maximize equity in the amount of aid satisfied among beneficiary locations. At the beginning of the planning horizon, each beneficiary is assigned to exactly one vehicle. Over the course of the planning horizon, goods are to be delivered respecting these assignments. Before a vehicle can be dispatched to a beneficiary, the route to the beneficiary must be declared accessible. Over the course of each day, the decision maker receives reports on the accessibility of routes and makes final dispatch decisions.

This problem shares many characteristics with dynamic fleet assignment, routing and dispatch. There has been extensive work in dynamic routing problems, yet our single-stop scenario differs from these problems because we consider only assignment and not routing decisions. In this way, the single-stop problem is similar to stochastic machine scheduling problems, although the objective in traditional scheduling problems is to complete a set of tasks with minimal time and/or cost. Our model presumes that we do not have sufficient resources or time to satisfy all the needs of beneficiaries, thus we maximize the utilization of these resources. Maximization of satisfied demand, sometimes incorporating an equity component, is found in non-profit models including but not limited to Balcik et al. [29], Lin et al. [28], Van Hentenryck et al. [31] and Yi and Kumar [24].

Given the uncertainty in beneficiary accessibility, we model the single-stop scenario as a multi-stage stochastic problem. To make the problem more tractable, we decompose the problem into two models: a planning model in which beneficiaries are assigned to vehicles and an operational model in which dispatch decisions are made throughout each day, as shown in Figure 2.

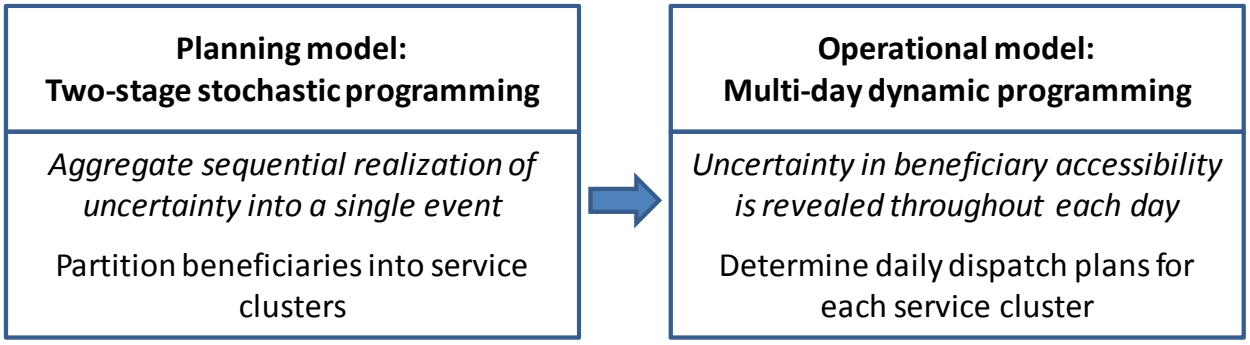

Figure 2: Decision models

We propose a two-stage stochastic programming model to partition beneficiaries into service clusters by vehicle in the planning stage. Unlike the more detailed operational model, this model aggregates the sequential realization of uncertainty within a day into a single event for that day. This representation of uncertainty balances approximating the true sequential realization of uncertainty with model tractability. We are in the process of developing and testing the models.

3. Deliverables to date

Presentations:

Luis E. de la Torre, Irina S. Dolinskaya, Karen R. Smilowitz , Dynamic Multi-Period Humanitarian Relief Routing, INFORMS 2011, Austin, TX.

Luis E. de la Torre, **Irina S. Dolinskaya**, Karen R. Smilowitz , Dynamic Multi-Period Humanitarian Relief Routing, IFORS 2011, Melbourne, Australia.

Luis E. de la Torre, **Irina S. Dolinskaya**, Karen R. Smilowitz , Dynamic Multi-Period Humanitarian Relief Routing, INFORMS 2011 Midwest Conference, Columbus, OH.

Chapter 4 Enhanced Search and Rescue

1. Introduction

Following a large scale disaster such as a hurricane, an earthquake, or an ice storm, search and rescue (SAR) at the local level is performed by SAR teams that are dispatched into the disaster-affected area. Currently, their operation adheres to rectangular grids that are drawn on a map arbitrarily. These grids do not take into account the road network and population density, which leads to ambiguous search routes and work distribution inequity. Therefore, we propose the formation of Enhanced Search Zones. Instead of the current grids, we make use of Emergency Service Number (ESN) zones which are predefined emergency response sectors recognized by multiple agencies including police and fire departments. We estimate the amount of work required in ESN zones via solving the Traveling Salesman Problem and develop a mathematical model that divides the area accordingly. As a result, we have a map that will allow SAR teams to be more effective and efficient in their search, reducing the maximum search time and achieving the equity of workload distribution.

2. Project details

The Enhanced Search Zones project was created in order to attend to the problem of search and rescue (SAR) teams not having an efficient strategy with which to carry out their missions in the wake of a countywide major disaster. The project focuses on Tipton County in Tennessee as a pilot region. The current procedure is to assign SAR teams to search regions and to require them to locate and ensure that the residents are safe and report the status for each region at the end of the search. The current division of search regions consists of rectangular grids arbitrarily drawn on the county map, without taking into consideration factors such as population density and road accessibility which may affect the difficulty and the speed of the search. This causes the unequal distribution of work among the SAR teams, which causes the whole search process to be inefficient.

Our team and our client determined the major problem with the current SAR strategy to be the inefficiency originating from the determination of search grids based on no analytical, systematic approach. The assignment of a densely populated area to a team and scarcely populated areas to other teams caused imbalances in the operation. The second major problem with the current method was the need for teams to leave their assigned search zones while trying to get to all the addresses in their zones due to the lack of road accessibility. This caused them to lose time and get held up at other regions which slowed down the whole operation.

The objective of this project is to derive a solution that assigns each team search zones that take into account factors such as population density and road accessibility while making sure that the teams are able to reach every node in the zone without leaving it. The proposed solution makes use of ESN (Emergency Service Number) zones that are predefined and used by multiple departments including

police and fire departments as response areas. This ensures that teams can reach every household in their search regions without leaving their region and improves the management of the whole SAR operation.

In the following section, we present the methodology which describes the ideas, formulation, and codes we used to reach our solution. Section 4 (Results) states the outcomes that were obtained by applying our method to the problem. The workload function for each ESN zone was used in 4 different ways to come up with 4 different solutions in order to compare the results and see the difference in solutions for different variations of the workload function. The discussion section mentions the assumptions that were made in coming up with our solution such as the SAR team search time per house and their average vehicle speeds. Using the Traveling Salesman Problem TSP as a method for integrating the road accessibility factor is also discussed in the section.

Section 6 (Next Steps) finally discusses the shortcomings of our solution in potential ways in which it could be improved. The sections focuses on issues such as the “Big City” case where an ESN has so much work that it is singled out as a search zone and that is has to be broken down. Other issues considered in the section are the integration of topographic and hydrographic data into the workload function. Another potential improvement to our solution is integrating our software with mobile devices so the SAR operation could be operated remotely.

3. Methodology

We first estimate the amount of work needed in each ESN zone via ArcGIS, a mapping and geographical data analysis software. An optimization model that minimizes maximum time is then developed in order to distribute the workload equally among the teams and minimize the time it takes to complete the whole operation.

3.1 Workload Estimation

There are a few metrics we can use to calculate the amount of "work" in each ESN zone: The amount of time it takes to search the houses is related to the number of houses there are in each ESN zone; the amount of time it takes to travel on the roads from one house to another; or the sum of the length of roads in each ESN zone. Due to common unit basis, we decided to use the time for search and time for traveling as work metrics.

The relevant statistics (address count and travel time per zone) are obtained in ArcGIS by using data management functions automated using Geoprocessing Toolboxes. These toolboxes allow data manipulation of map data. With these toolboxes, the user can simply load the shapefiles into the toolboxes and the numbers are produced. (See Figure 3.1)

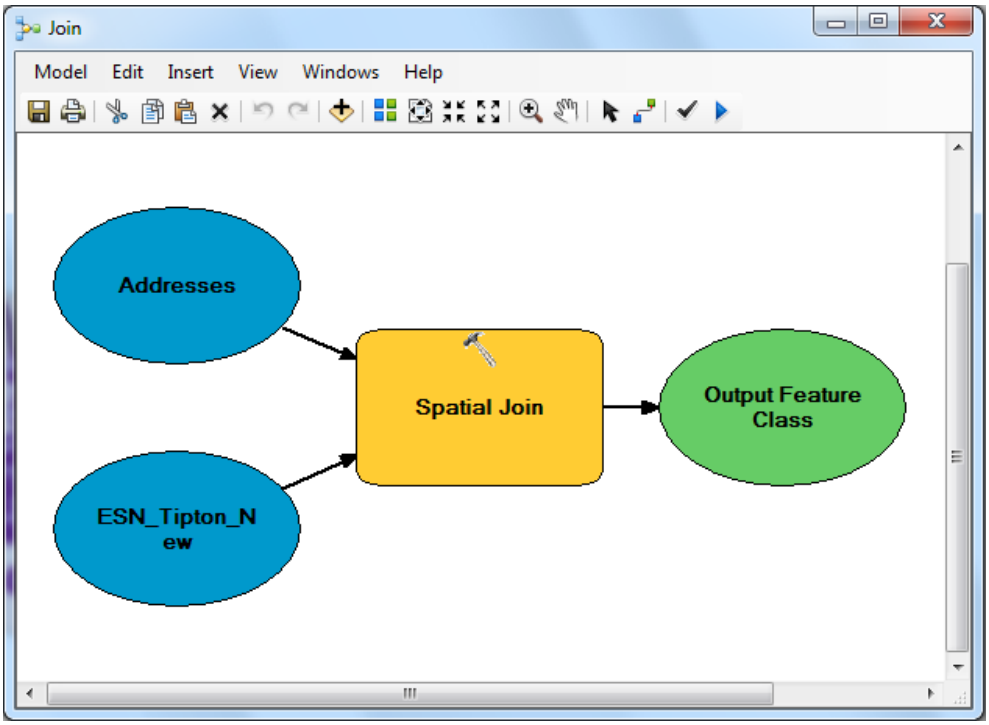

Figure 3.1 Joining shapefiles to obtain spatial statistics (Addresses per zone)

A spatial joining of the two shapefiles, Addresses and ESNs essentially combines the two datasets based on physical location and returns a new shapefile that contains the ESNs with a count of addresses within each ESN. (See Figure 3.2)

ESNadd

FID	Shape	Addresses_FID	OBJECTID	AREA	PERIMETER	ACRES	Index	Sqmiles	Count_
0	Polygon	0	1	660864275.502	141829.01	15171.356	V	2.37	731
1	Polygon	1	2	975470079.707	140960.7	22393.712	K	3.49	543
2	Polygon	2	3	557455774.249	122845.019	12797.424	J	1.99	321
3	Polygon	3	4	85333197.798	84151.607	1958.981	X	3.06	1110
4	Polygon	4	5	256036273.359	125591.999	5877.784	P	9.18	2501
5	Polygon	5	6	242119700.308	103363.397	5558.303	E	8.68	2410
6	Polygon	6	7	267275953.537	99925.58	6135.812	Q	9.59	817
7	Polygon	7	8	54202373.637	37633.547	1244.315	N	1.94	97
8	Polygon	8	9	897232383.53	121639.787	20597.621	S	3.21	646
9	Polygon	9	10	55938614.98	48213.787	1284.174	D	2.01	391
10	Polygon	10	11	415422647.908	128140.139	9536.792	M	1.49	818
11	Polygon	11	12	954852679.34	190417.869	21920.401	CC	3.42	534
12	Polygon	12	13	94343071.788	70238.273	2165.819	II	3.38	447
13	Polygon	13	14	54858203.065	46159.942	1259.371	I	1.97	448
14	Polygon	14	15	655817700.745	168481.848	15055.503	LL	2.35	597
15	Polygon	15	16	530242783.445	139333.976	12172.699	G	1.9	515
16	Polygon	16	17	543860625.702	111660.409	12485.322	A	1.95	733
17	Polygon	17	18	157506542.579	52817.729	3615.853	B	5.65	554
18	Polygon	18	19	228700252.804	70545.198	5250.235	R	8.2	585
19	Polygon	19	20	533377265.476	117992.122	12244.657	T	1.91	468
20	Polygon	20	21	197416918.6	72802.969	4532.069	U	7.08	356
21	Polygon	21	22	89458725.979	51568.663	2053.69	O	3.21	942
22	Polygon	22	23	473531324.392	115654.185	10870.783	F	1.69	1049
23	Polygon	23	24	465749635.094	130205.43	10692.14	H	1.67	258
24	Polygon	24	25	351835660.049	124117.015	8077.035	Y	1.26	553
25	Polygon	25	26	237712034.689	80501.63	5457.117	Z	8.53	605
26	Polygon	26	27	255679325.275	72592.628	5869.59	JJ	9.17	518
27	Polygon	27	28	498717960.533	158074.801	11448.989	KK	1.78	280
28	Polygon	28	29	491980440.563	108619.392	11294.317	L	1.76	516
29	Polygon	29	30	48460383.112	39916.866	1112.497	AA	1.74	649
30	Polygon	30	31	50832689.689	38101.121	1166.958	BB	1.82	259

Figure 3.2 Number of Addresses (Count_) in each ESN Zone

The following function was used to calculate the workload for each region:

$$W_i = \alpha \cdot A_i + \beta \cdot TSP_i,$$

where

W_i workload for ESN_i

A_i # of address nodes in ESN_i

TSP_i total distance for vising every node in ESN_i

α search time per Address node

β $(\text{average SAR team vehicle speed})^{-1}$.

The first part of the workload equation calculates the amount of time required to search all the address points in the ESN. By multiplying the search time per node estimate with the total amount of nodes, we calculate the total search time for the ESN.

The second part of the equation integrates the road accessibility factor in to the workload for each ESN. By assigning an average speed for each team, we can estimate how much time it is going to take the teams to reach each node in the ESN. By dividing the TSP, which is the total distance required to visit all the nodes, with average vehicle speed we obtain the total time it takes for teams to reach all the nodes. This equation estimates the workload of each ESN as the total time to search. The workload is increasing in A (population) and TSP (accessibility).

ArcGIS Network Analyst Extension was used to solve TSP for each ESN. We first split the main ESN shapefile (contains all regions) into separate regions. Then we again design a toolbox that first sections (Clip) the addresses and streets based on the boundaries of each ESN and solve a TSP within each ESN. (See Figure 3.4 and Figure 3.4)

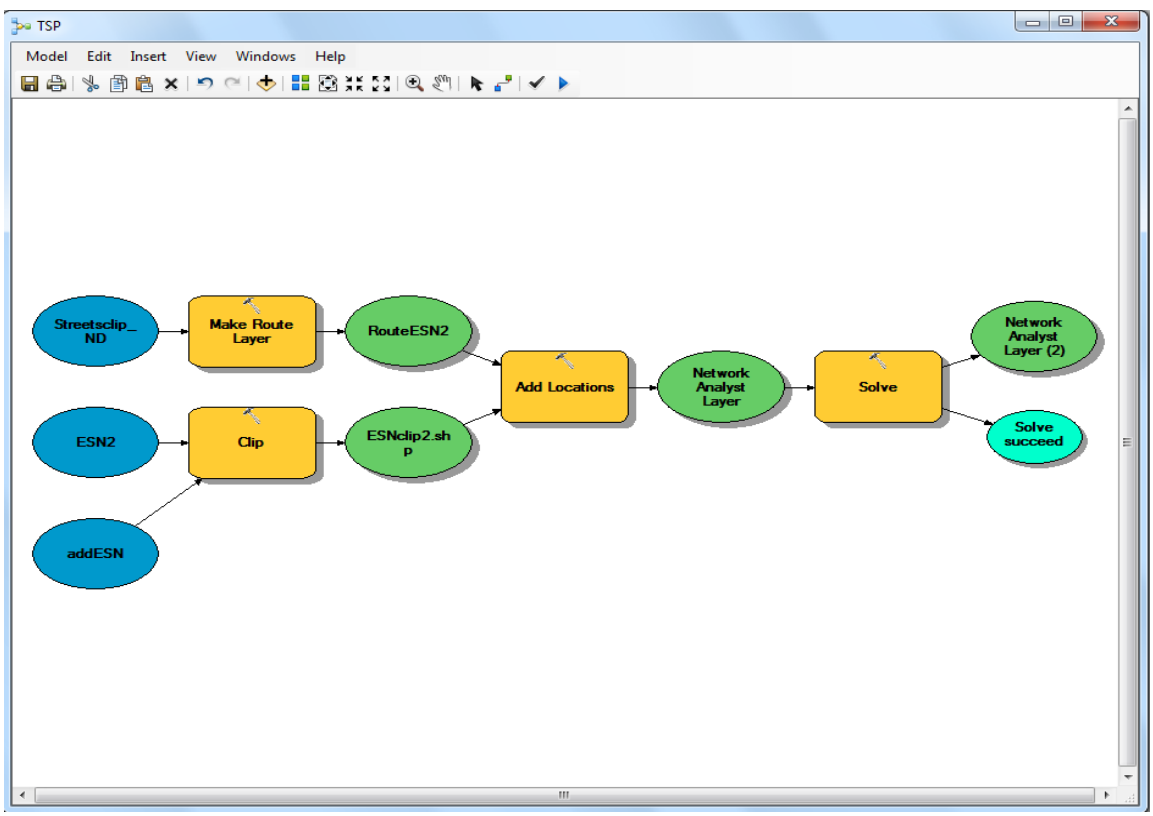

Figure 3.3 Toolbox that clips addresses and streets by ESNs and solves a TSP

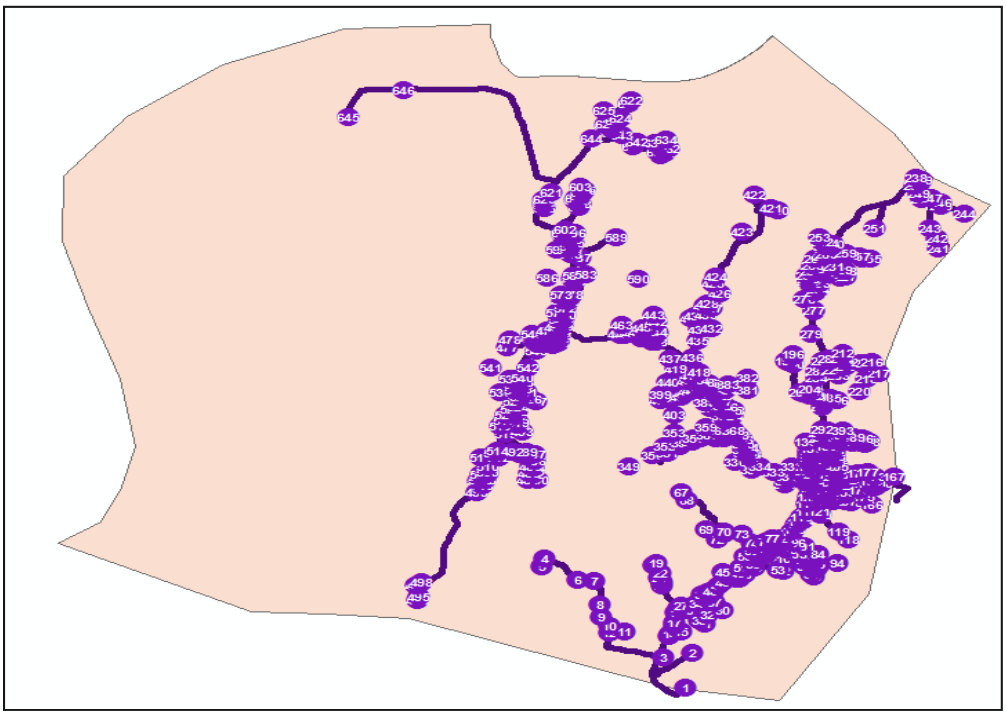

Figure 3.4 Solving a TSP within each ESN

The TSP solver in ArcGIS generates an origin-destination matrix and uses a heuristic to find the best sequence of visits. The solution is the total distance it takes to visit all address points. We calculate this route for each ESN zone. The TSP solver was effective for zones with smaller number of address points (less than 500), returning a solution in 15-20 minutes, taking 90 minutes for 1000 points. For denser zones, ArcGIS was unable to find a solution and an alternative method was used. We produced a shapefile containing points that locate all the road junctions in the ESN zone (See Fig. 3.5) and solve a TSP that visits these road junctions. The road junctions are be treated “address points” to be visited. This reduces the problem space while finding a solution that traverses the entire zone. This is an over-approximation, but a reasonable one based on the fair assumption that roads extend to building locations. An example is shown in Figure 3.5. For some ESN zones, there are locations disconnected from all other locations in the zone, due to connecting roads lying outside of the zone or missing data. Because these are so few of these isolated locations, we took an estimate of travel time without them.

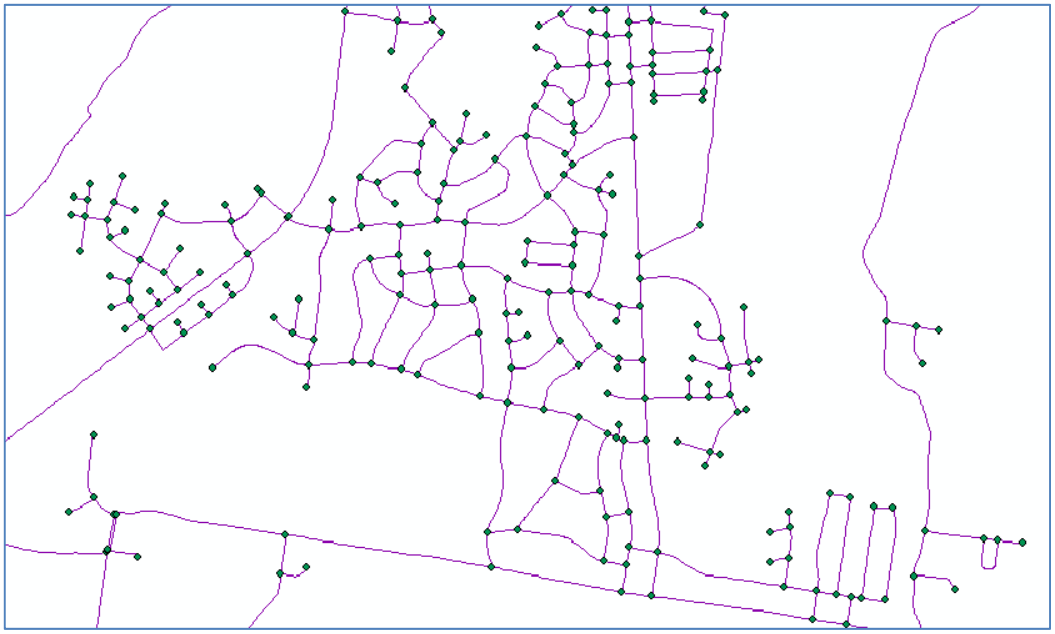

Figure 3.5 Road Junction as points to visit, used as an approximation of the TSP for dense ESNs

3.2 Map Partition

Now that we have estimated the amount of work required in each ESN zone, we develop a mathematical model that optimally partitions a disaster-affected area accordingly. Say we are given x search and rescue (SAR) teams. We want to divide the disaster-affected area, which comprises of ESN zones, into x regions to each of which a SAR team is assigned. The division has to minimize the largest workload among the teams while ensuring that the zones any team covers are contiguous to one another. The following notation is used to formulate the problem.

N set of ESN zones; $N = \{1, \dots, n\}$

N_0 $N \cup \{0\}$

K set of SAR teams

c_i amount of work required in zone i

a_{ij} $= \begin{cases} 1 & \text{if there is a direct path between zone i and zone j} \\ 0 & \text{otherwise} \end{cases}$

There are n ESN zones with 0 representing the starting point of a search and rescue operation. Parameter c_i is determined in the previous section; and parameter a_{ij} determines whether zone i and zone j are directly connected or not. We also introduce the following decision variables.

Z maximum workload among SAR teams

$$X_{ijk} = \begin{cases} 1 & \text{if team k travels from zone i to zone j} \\ 0 & \text{otherwise} \end{cases}$$

$$Y_{ik} = \begin{cases} 1 & \text{if zone i is visited by team k} \\ 0 & \text{otherwise} \end{cases}$$

$$A_{ik} = \begin{cases} d/n & \text{if node i is at distance d from the depot in a tree covered by team k} \\ 0 & \text{otherwise} \end{cases}$$

We are not interested in how each team travels among the zones. However, variable X is used along with A_{ik} in order to determine the contiguity of zones a team covers. See below for a brief graphical representation of the approach we follow.

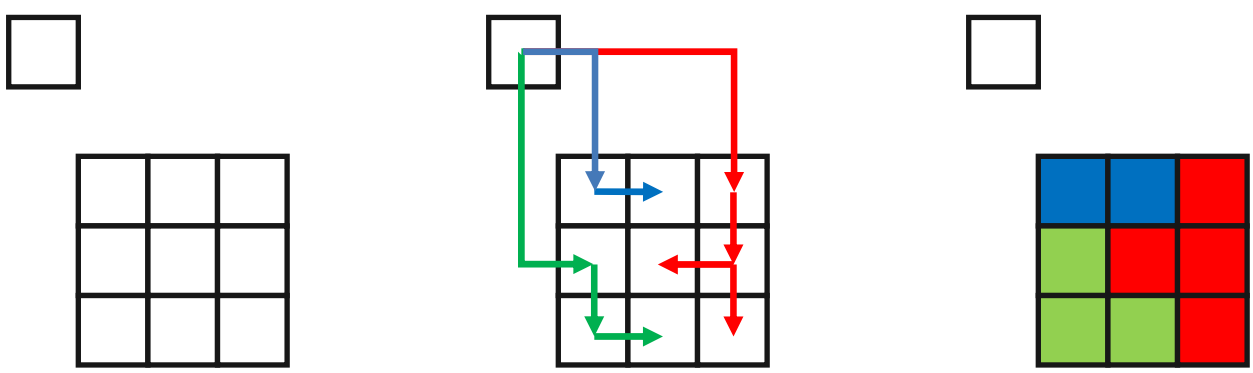

Figure 3.6 Graphical representation of the Map Partition Model

Say we are given 3 SAR teams and an area which comprises of 9 zones and an arbitrary starting point. Directed outward from the starting point, 3 distinctive trees are formed which exhaust all the zones. The set of zones a team will be assigned are the ones covered by the corresponding tree. Note that a tree has no disjoint component, thereby ensuring the contiguity of zones a team is assigned to.

The whole formulation is as follows:

minimize Z

subject to:

$$Z \geq \sum_{i \in N} c_i Y_{ik} \qquad \forall k \in K \qquad (1)$$

$$\sum_{j \in N} X_{0jk} = 1 \qquad \forall k \in K \qquad (2)$$

$$\sum_{k \in K} Y_{ik} = 1 \qquad \forall i \in N \qquad (3)$$

$$X_{ijk} \leq a_{ijk} \qquad \forall i \in N_0, \forall j \in N_0, \forall k \in K \qquad (4)$$

$$X_{ijk} + X_{jik} \leq 1 \qquad \forall i \in N_0, \forall j \in N_0, \forall k \in K \qquad (5)$$

$$A_{jk} \geq A_{ik} - \left(1 - X_{ijk}\right) + 1/(N+1) \qquad \forall i \in N_0, \forall j \in N_0, \forall k \in K \qquad (6)$$

$$\sum_{i \in N_0} X_{ijk} = Y_{jk} \qquad \forall j \in N, \forall k \in K \qquad (7)$$

$$X_{ijk} \leq Y_{ik} \qquad \forall i \in N_0, \forall j \in N_0, \forall k \in K \qquad (8)$$

$$X_{ijk} \in \{0,1\} \qquad \forall i \in N_0, \forall j \in N_0, \forall k \in K$$

$$Y_{ik} \in \{0,1\} \qquad \forall i \in N_0, \forall k \in K$$

Constraint (3) ensures that every region is covered by one of the SAR teams. (4) explicitly states that a SAR team can travel from zone i to zone j only if there is a direct path between them. Because of (5), no arc is bi-directed, and (6) prevents any cycle separate from the rest of the tree. (7) says that if zone j is visited by team k, team k must have travelled from some other region. Finally, (8) states that team k can only travel from i to j when the team is currently in zone i. Basically, constraints (2) through (8) are creating K distinct trees that stem from the depot, which all together exhaust all the ESN zones.

4. Results

The optimization formulation was tested using data from Tipton County, Tennessee. The US Census Bureau reported in 2000 that Tipton County had a population of 51,271 across its 475 square miles. Tipton County is broken into 38 distinct ESN zones. The map of Tipton County and its ESN zones is shown below, with the zones numbered arbitrarily (Figure 4.1).

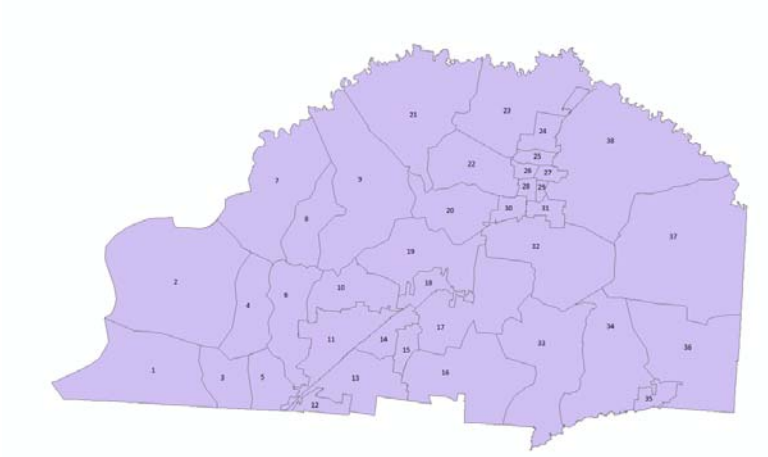

Figure 4.1 Tipton County and its ESN zones

4.1 Test Case

A data file was constructed based on the map of Tipton County. First, a matrix was constructed to reflect which zones share common barriers with one another. The client specified that typically seven teams would be assigned to search the ESNs, though this number could vary depending on disaster type and severity.

The final element to extract for the optimizer was the amount of work in each zone. The quantity of work in these types of search and rescue operations comes from two sources: the number of addresses and vehicle travel time. Because the number of addresses and the time required to traverse the road network could be proportionate, we experimented with two realistic measures of work for each ESN:

- Number of addresses
- TSP solution of the road network

4.2 Computation

All experiments were performed on a Linux server equipped with 3.5 64-bit processors at 2.4 GHz working in parallel, with 6 GB of RAM. The optimization formulation is written in AMPL, paired with CPLEX (an integer program solver). Runtime was lengthy; in most cases, the solver's progress was halted before it could prove it had found an optimal solution. CPLEX could often find a great solution very quickly, but this type of problem requires much time to prove optimality. Though some ESN assignments

are infeasible, CPLEX must explore (or rule out) 1.3x(10^32) unique solutions to the Tipton County problem, with its 38 ESNs and 7 teams.

All test cases were run for at least two hours. The percentage difference between the best-found feasible solution and the theoretical optimal solution is called the “gap.” All solutions presented in this paper are proven to have gaps between 1% and 4%. Generally the solver stopped finding better solutions to the problem after 15 minutes, and spent the remaining hours trying to prove optimality (slowly closing the gap.)

4.3 Test Case Results

The algorithm succeeded in minimizing the county's search time, as well as distributing the workload evenly amongst the seven search teams. Regardless of whether the work driver was the number of addresses or mileage in a given ESN, the work distribution improved over the status quo. Shown in Figures 4.2 and 4.3 below are maps based on address points and length of TSP tours, respectively.

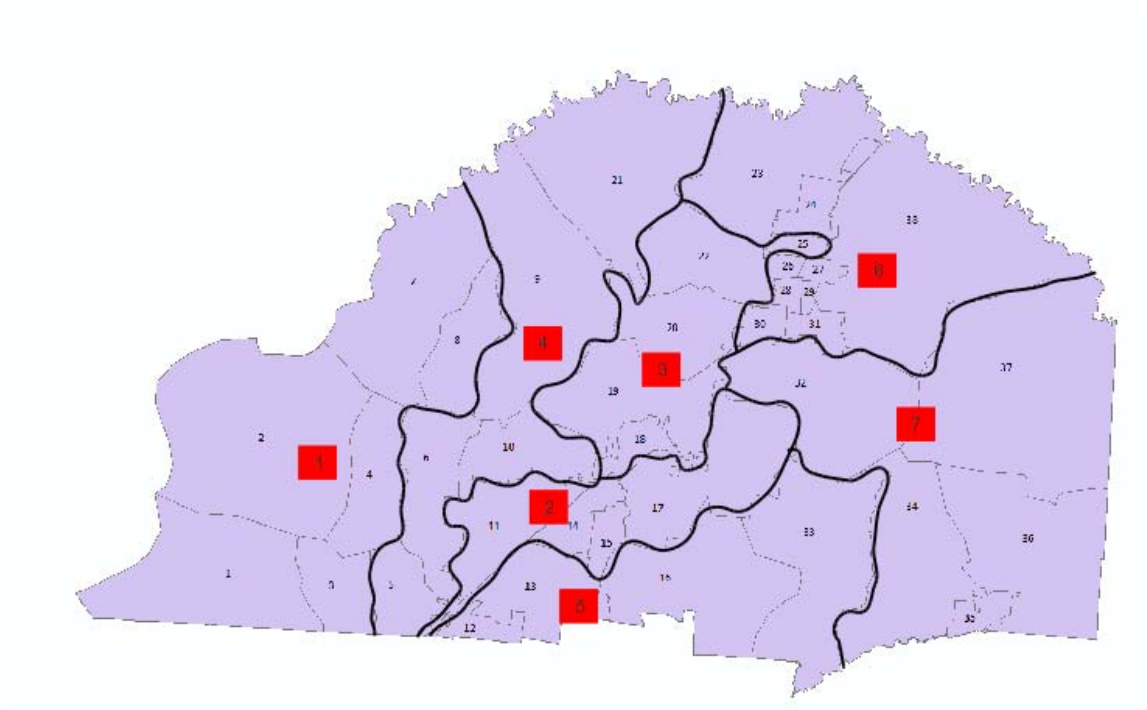

Figure 4.2: Search map for seven teams, based on length of TSP tour. Gap = 3.64%.

Team	Mileage of TSP Tour	Travel Time* (Hours)
Team1	207	6.9
Team2	202	6.7
Team3	201	6.7
Team4	213	7.1
Team5	215	7.2
Team6	205	6.8
Team7	209	7.0

*Assuming 200 addresses per hour.
Standard deviation of workload amongst the teams is 11 minutes.

Table 4.1: TSP Travel Time and Standard Deviation.

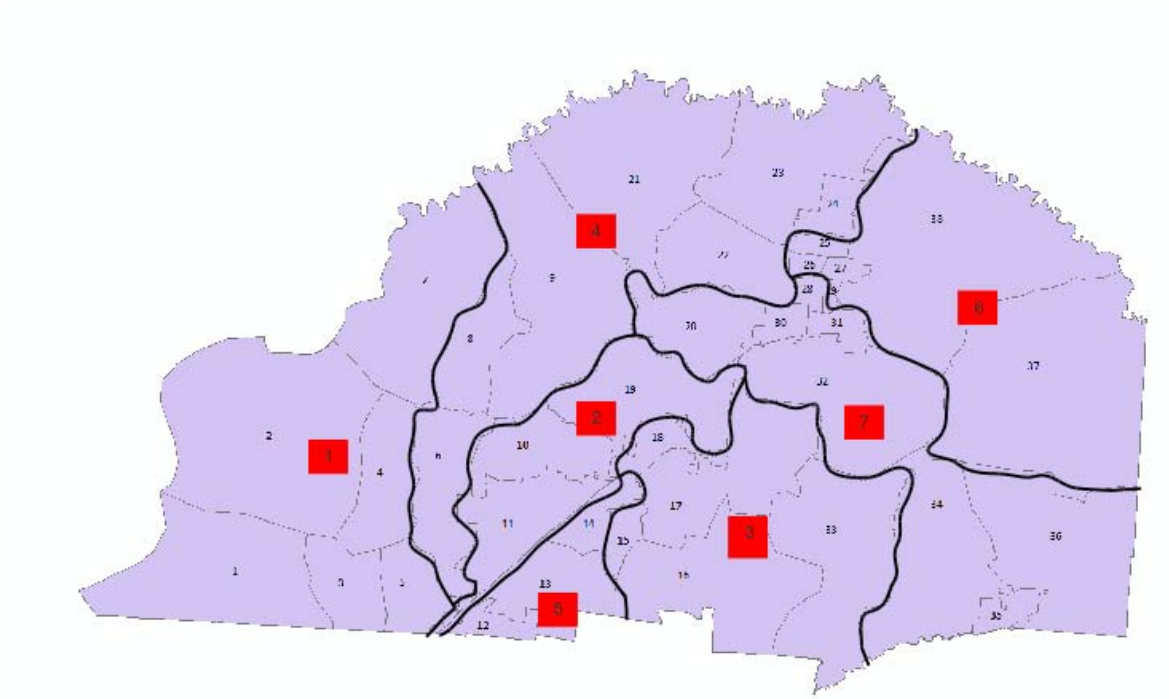

Figure 4.3: Search map for seven teams, based on number of addresses. Gap = 1.52%.

Team	Addresses in Search Zone	Time to Search* (Hours)
Team1	3740	18.7
Team2	3686	18.4
Team3	3589	17.9
Team4	3746	18.7
Team5	3743	18.7
Team6	3616	18.1
Team7	3700	18.5

*Assuming 200 addresses per hour.
Standard deviation of workload amongst the teams is 30 minutes.

Table 4.2: Search Time and Standard Deviation

We note that all teams have nearly the same amount of work in both scenarios. The standard

deviation is a good measure of the spread of work amongst the teams; we see that the standard deviation in both scenarios is low relative to search time. In fact, the work assignments are equal to the point that search time equity will probably depend more on differences amongst the search teams instead of the actual assignments. Because the number of response teams is much fewer than the number of ESNs in a county, it's likely that workload assignment will be equalized as a side effect of minimizing the total search time.

More importantly, however, we see that very different response maps were generated depending on how workload is measured for each ESN. If a response effort is focused mostly on searching each address in the county thoroughly, a map like Figure 4.2 would be appropriate; if the response were focused on visiting addresses, but not spending very much time at each address point, a map like Figure 4.3 would be optimal. Originally, the team suspected that the solution maps would be relatively insensitive to measures of work, since the amount of roads and the number of addresses should be proportionate. Though there may be a relationship between the number of addresses and the length of a TSP tour in a region, this relationship is non-linear – so both measures of work are important to consider when distributing workload to response teams. We conduct sensitivity analysis to explore the robustness of our model to any change in work parameters.

4.4 Performance Comparison with Current Grid Divisions

As mentioned earlier, currently, there is no fixed way in dividing up the county map into dedicated zones. As a working method, authorities will generally use the county tax grids as a guide for the assignment. (See Figure 4.4)

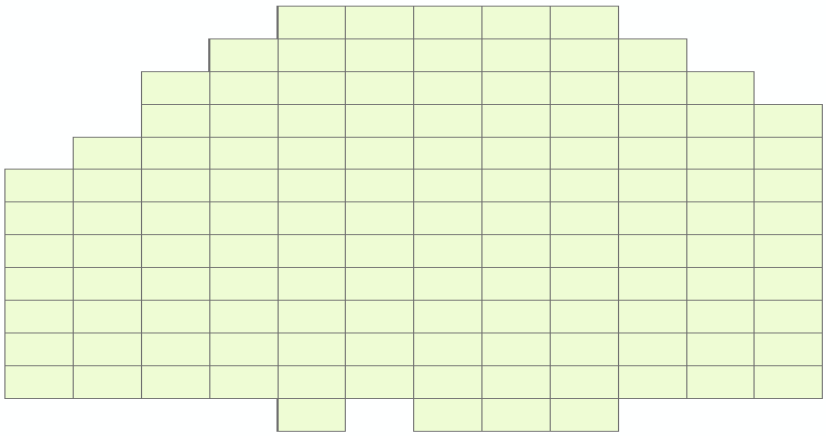

Figure 4.4 County Tax Grids as a guide to divide and assign regions.

These grids are generally divided into regions based on number of teams. As a basis of comparison with our model, we divide the region equally into 7 zones of similar area. (Figure 4.5) Since the actual division of the index grids are not fixed (there is no standard protocol on this), and information of that is not readily available, this division can only be considered one possibility of a current state. The point is to demonstrate the problem and provide a test case for comparison of current performance of search teams versus our Enhanced Search Zone performance.

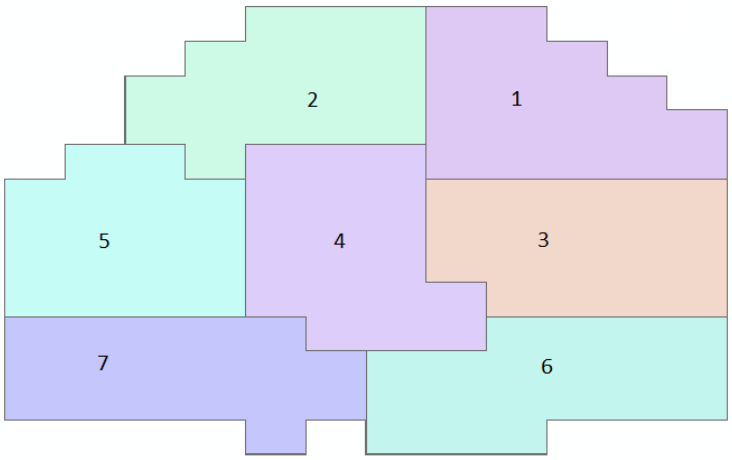

Figure 4.5 Equal Area Zones

As before, we calculate the number of addresses and TSP for each zone. Table 4.3 shows the results and corresponding standard deviations. As expected, compared to our ESN model results, the number of addresses differed greatly among regions and consequently their search time and TSP time as well. It is also noted that the maximum search time in our model is smaller than that in the current model. However, total system time is higher in our model. This can be due to teams in less dense regions having to travel further to reach addresses in their extended purview. Still, if the objective is to cover the entire county in the shortest possible time, then our model serves its purpose.

Team	Travel Time	Addresses	Search Time
Team 1	5.1	4240	21.2
Team 2	3.9	1207	6.0
Team 3	4.5	2022	10.1
Team 4	7.5	5470	27.4
Team 5	5.3	2720	13.6
Team 6	3.7	1732	8.7
Team 7	9.4	8432	42.2
Standard Deviation	2.1 hours		12.9 hours

Table 4.3 Current Index Grid Results

4.5 Sensitivity Analysis

To see how solution maps changed depending on work assumptions, we generated six maps to minimize:

- Search time, assuming one minute per address and a 20 m.p.h. travel velocity
- Search time, assuming one minute per address and a 10 m.p.h. travel velocity
- Search time, assuming one minute per address and a 5 m.p.h. travel velocity
- Search time, assuming 30 seconds per address and a 20 m.p.h. travel velocity
- Search time, assuming 30 seconds per address and a 10 mph travel velocity
- Search time, assuming 30 seconds per address and a 5 mph travel velocity

The results are attached in the appendix. We see that very different maps are generated depending on the measure of work for each ESN. The fundamental takeaway is that both work measures are important, and we recommend that multiple response maps are created. There is no "best map" that keeps appearing for this county, and it is unlikely that this would be the case for any other county. Different maps are needed for different disasters.

5. Discussion

We have considered the optimal partition of a disaster-affected area for the search and rescue operation. Our model is simple and intuitive, and it successfully takes into account both the road network and the number of houses. From our test case in Tipton Country, we see that our solution increases both the effectiveness and efficiency of the SAR operation. As compared to the existing tax index grid system, our solution results in an 89% improvement in search time. The workloads are evenly distributed among the SAR teams, thereby preventing logistics and communication problems; the overall search time is minimized; and by utilizing the predefined ESN zones, we expect to see an overall improvement in operations management.

We also recognize that our solution is sensitive to the fluctuation in parameter values—namely, the search time per house and the vehicle velocity. This suggests that the road condition and the capability of a SAR team need to be accurately identified prior to dispatching the teams to ensure the effectiveness and efficiency of the whole SAR operation. Also, a more robust model that takes into account parameter uncertainties and stochasticity should be considered in the future.

The model we used is based on a set of assumptions that need to be verified. First of all, we have assumed that the total travel time in an ESN zone corresponds to a TSP solution—the shortest length of a tour that visits all the houses. But we do not know how closely the TSP solution matches (or, is at least proportional to) the actual travel time; the path the SAR teams take may be far from the optimal one.

In addition, notice that we are excluding the travel time among the ESN zones in our model. If the time is relatively significant, it will be necessary to take the factorinto account. The simplest approach will be to use add the arc costs to the Map Partition model and modify the objective function accordingly. Also, we assumed for simplicity that the search time per house and the vehicle velocity stay the same throughout the whole operation. For a more realistic model, we need to differentiate the types of addresses and roads.

6. Next Steps

The solution of our project was sufficient in meeting the determined scope since it was able to take road structure and population as inputs and output enhanced search zones which divide the county into search regions based on the number of available teams with almost the equal amount of work assigned to each team. We could have improved our solution and take into account more factors if we had more time and data on parameter values. Besides the improvements suggested in the previous section, we propose the following that will lead to the next stage of our project.

6.1 The Big City Case

We foresee a limitation of our algorithm. There could be a case where one particular ESN in a county has a disproportionate amount of work relative to other ESNs. An example is shown below as Figure 6.1:

5	3	100
2	1	2
2	8	7

Figure 6.1: A county with disproportionate ESNs

If we were assigning three teams to these ESNs using our optimization formulation, an optimal solution would be that Team 1 works 100 hours, Team 2 works 15 hours, and Team 3 works 15 hours. For this case, we would need a way to either assign the large region to multiple teams, or break the large zone into multiple smaller regions and assign the sub-zones to the three teams.

We feel this case won't likely happen in the real world for two reasons. First, ESNs are already scaled to work drivers like population, number of addresses, and region size. ESNs are created based on emergency response standards, so it's unlikely an ESN would ever “stand out” like that. Second, it is the case that much fewer search teams are assigned to many more ESN zones. The time-intensive zones will be distributed relatively equally across the teams, and the smaller regions will be assigned to “even out” the work differences between the different teams. We will see a very equal work distribution if many, many ESN zones are assigned to few response teams. Nonetheless, this issue must be addressed in the future.

6.2 Integration of Hydrographic and Topographic Data

Currently the cost function that is used to calculate the total work for each ESN takes into account factors such as population and road accessibility. The total work for each team is minimized based on these factors. However it is evident that the amount of work it takes to search a region doesn’t only depend on the road structure and population. The elevation of the region as well as the water sources in the region also effect the time it takes for teams to search and rescue. Depending on the type of disaster, having a water source in the region may cause dramatic changes in the operation. A river may flood the region making roads in accessible and make it harder for teams to search the houses. Likewise a steep elevation within a region can cause critical problems in the case of an earthquake.
These difficulties can be accounted for if elevation and water sources are taken into account when assigning cost values to each region. In our opinion the best way to go about accomplishing this would be to estimate the negative effect of having elevation or water source on the total search time. The integration should be done so that it ensures the cost isn’t affected from water source or elevation when the disaster that took place is not related to them.

6.3 Compatibility with mobile devices

The solution of this project could be turned into a much more effective one if teams didn’t have to wait at the dispatch area in order to get instruction as for what their search zones are. If teams were provided with mobile devices that can receive and send real time data, the whole search and rescue process could be much faster.

The moment the disaster happens, teams would not have to come together at a station, their search zones could be sent to them based on their GPS location. Once they are notified of their search zones they can start the search right away. In addition to this, they can input any changes into the software which would adjust the cost accordingly. For example when teams are dispatched to their zones, and one team encounters a blocked road that renders the road inaccessible or poorly accessible, they can input that information into their devices. This information would be used by the software to update the cost parameters of each of the regions and to recalculate optimal search zones taking into account poor accessibility in one of the regions. Since all the teams are equipped with mobile devices, all of them would be notified of the new search zones and continue the process. This improvement to our solution would significantly increase the efficiency of the operation.

Another advantage of having mobile device compatible software would be to tell each team which route to take while searching within the region. The algorithm would be able to run TSP models for each region and come up with the most optimal routes the teams should take. If this information can be sent to the teams via their GPS in the form of checkpoints, the process of search and rescue could be done almost optimally.

Chapter 5 Project Extensions

As shown in this report, vehicle routing in humanitarian logistics, such as disaster relief distribution, involves many challenges that distinguish these problems from those in commercial settings, given the time sensitive and resource constrained nature of relief activities. While operations research approaches can improve the effectiveness of relief routing, these challenges must be addressed in routing models in order to realize the potential of the approaches. There have been many promising advances in the literature on relief routing, and aid organizations have been collaborating with academic researchers to increase the practicality of such models, as shown in Chapter 2. Further, increases in the availability and use of information technology in the wake of disasters can further the effectiveness of routing models for aid distribution. Presently, challenges still remain to make routing models more applicable to humanitarian aid delivery and more integrated with new streams of imagery, mapping, and crowdsourced real-time data. Dr. Jennifer Chan, from Northwestern's Medical School, has joined the research group in this effort. Dr. Chan has extensive experience in this area.

In our next phase of research, we focus on dynamic routing models for the distribution of relief supplies in humanitarian settings. We focus on the potential to improve these models, and thus improve the effectiveness of humanitarian relief, by using new mapping technologies and real-time information to mitigate the effects of dynamic changes during humanitarian crisis and disasters and the significant uncertainty that exists in these settings. Our proposed work will evaluate the improvements from these technologies for relief organizations in the field and develop a set of test cases for the research community to better design and test their routing models and solution approaches. To facilitate wide implementation and potential commercialization of our work, the developed test cases will be available online to practitioners and academicians, through a server dedicated to Humanitarian and Non-Profit Logistics at Northwestern University.

Recent years have seen rapid growth in the application of technology to humanitarian relief operations. Balcik et al. [29] detail recent increases in the use of technology in humanitarian response, from the use of telephones and radio-based communication methods in Somalia to more advanced technologies used by the United Nations Joint Logistics Centre (UNJLC) and the Federal Emergency Management Agency (FEMA). More recent events such as the 2010 Haiti earthquake and the 2011 Japan earthquake and tsunami have shown the value of increased adoption of technology. Updated orthogonal imagery is made freely available by government agencies and commercial sources, sometimes within hours of a disaster, so that damage to infrastructure can be quickly assessed. Geographical Information System (GIS) data layers on flood extents, earthquake damage, medical dispensaries, settlement camps, and other spatial data are made available for download and integrated into online map visualization tools. Mobile phones now play a central role in aid coordination thanks to the high penetration of mobile technology throughout the world, the inclusion of the Global Positioning System (GPS) in an estimated 80% of mobile phones in the next year, and the ease of using Short Message Service (SMS) technology for data transmission. Mobile units are used extensively to send georeferenced updates on road networks, movement of displaced persons, stocks of supplies, and other time-sensitive information.

While this new wealth of information greatly improves the ability of relief organizations to coordinate their efforts, the processes of data collection, management, and analysis must themselves be coordinated among a large number of agencies and individuals in order to be fully leveraged. Organizations such as Google.org, Crisis Commons, CrisisMappers, Ushahidi, and OpenStreetMap are working on this coordination effort by building online infrastructure and providing centralized repositories for "crowdsourced" data. In 2011, the United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) and the Stand By Task Force, a volunteer crisis mapping group, collaborated to produce real-time crowdsourced maps for UN operations in Libya.

However, the potential for technology implementation in humanitarian relief is still largely unmet. In 2011, UNOCHA and the Harvard Humanitarian Initiative investigated the humanitarian relief sector's struggle to accommodate the "information fire hoses" offered by new information sharing tools in the wake of the Haiti earthquake. The report recommended a framework for addressing this shortcoming, including increased attention to innovation, experimentation, academic evaluation, and coordination between the academic, technical, and practitioner communities (Harvard Humanitarian Initiative, 2011).

In the proposed work, we consider the incorporation of the above efforts as "inputs" for routing models to improve humanitarian relief routing. In a recent study, we investigate gaps in existing routing models through a review of operations research models for the transportation of relief goods and interviews with aid organizations, ranging from government agencies to non-government organizations (NGOs) and commercial partners engaged in disaster relief; see Chapter 2. Importantly, both the nature of uncertainty (e.g., the need for relief supplies, the availability of resources to address needs, and the impact of the disaster on infrastructure) and the mechanisms available to mitigate this uncertainty are very different from what is found in commercial settings. For example, travel times may vary in a commercial setting due to congestion; however, one can model this uncertainty reasonably well with a bounded distribution of travel times. In a disaster setting, the very existence of a path between locations may not be known, or the lack of security of the path may restrict its use by response agencies. Our group is researching ways to develop dynamic models of humanitarian relief routing that explicitly address the unique nature of uncertainty in disaster relief and the feasible recourse mechanisms to respond to uncertainty (Northwestern University Humanitarian and Non-Profit Logistics, 2011).

In the proposed research, which is receiving cost-share from a grant through the Google Research Awards Program, we focus on a related question: how can operations research models exploit advances in mapping technologies and real-time information to improve the distribution of humanitarian relief? Specifically, we will investigate how the identified sources of uncertainty in relief routing can be mitigated through available real-time information about the affected region, provided by sources such as Google Earth and Google Crisis Response. To answer this question, we propose a research plan to:

1. develop a testbed of routing problems designed specifically for humanitarian relief routing, to be used by the research community to evaluate new modeling and solution approaches;

2. quantify the benefits of technology for agencies engaged in humanitarian relief through improved operations research models that incorporate this technology; and

3. launch an online server housing the developed testbeds with the capabilities for other academicians and practitioners to use as well as contribute to the database.

Given the experience of our research team in related routing problems and knowledge of crisis mapping tools and real-time information sources, we can offer quantitative measures of improved humanitarian relief effectiveness through enhanced information using operations research models. This requires advances to our current models of relief routing to evaluate a range of available information. This, in turn, increases the need for a set of test cases, which is lacking in humanitarian relief routing literature; creating such a testbed will be an important contribution of this work. We plan to use the technologies identified above to assist in creating the testbed and evaluating the benefits of available information technology to humanitarian aid distribution.

The contributions of this proposed research lie in the interface of operations research modeling and the application of mapping technologies and real-time information to disaster relief operations. We believe that this work, by further integrating these two streams, can play a key role in improving the distribution of humanitarian relief. We hope to bring together resources related to mapping technology and real-time information to address the significant uncertainty that exists in so many aspects of disaster relief.

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Appendix

1 Sensitivity Analysis Results for Enhanced Search Zones

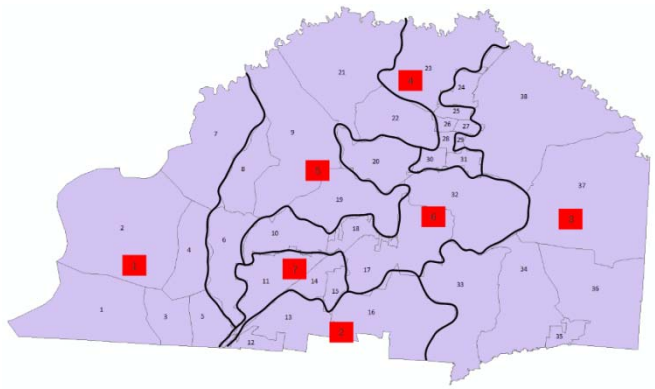

Figure a. Assuming one minute per house and a 20mph search vehicle. Gap = 1.80%.

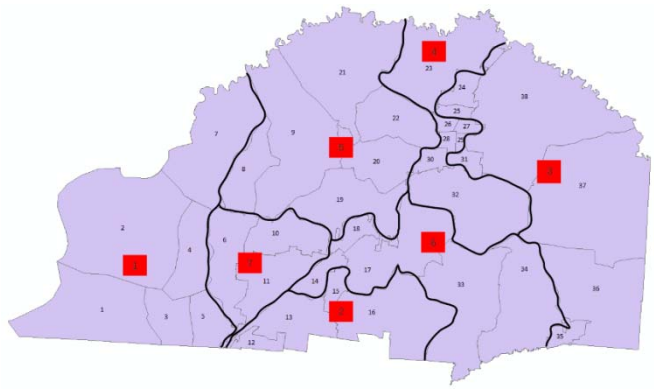

Figure b. Assuming one minute per house and a 10mph search vehicle. Gap = 1.86%.

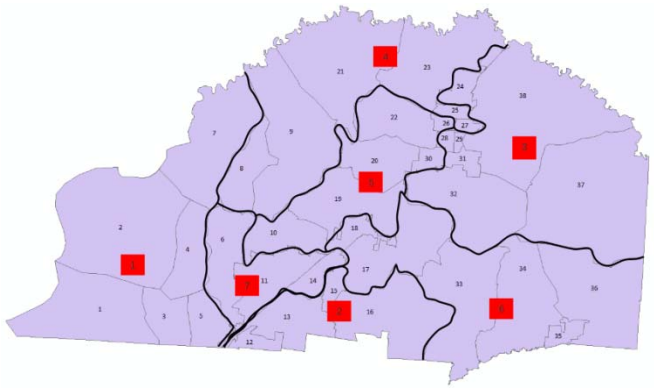

Figure c. Assuming one minute per house and a 5mph search vehicle. Gap = 1.41%.

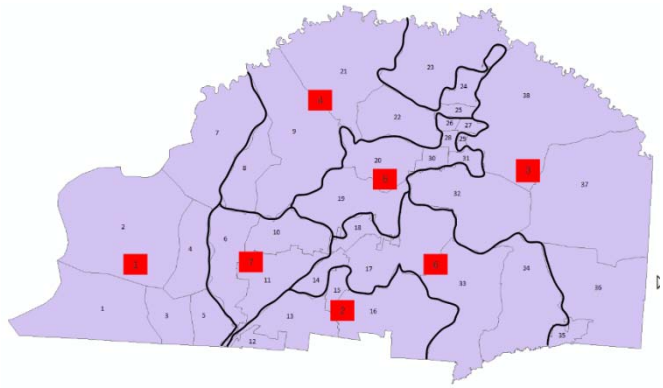

Figure d. Assuming 30 seconds per house and a 20mph search vehicle. Gap = 2.00%.

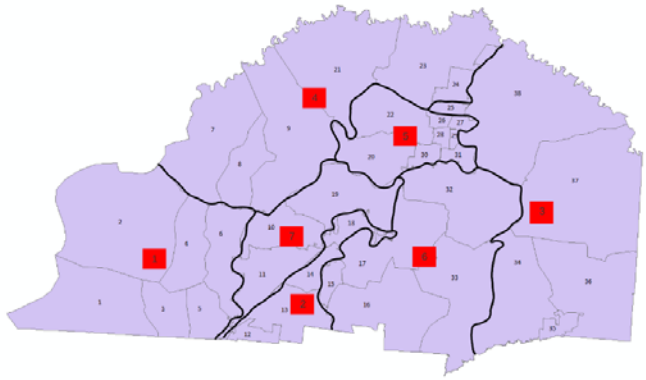

Figure e. Assuming one minute per house and a 10mph search vehicle. Gap = 2.00%.

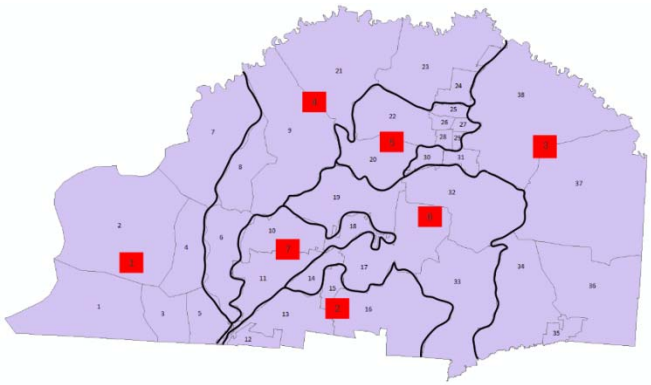

Figure8f. Assuming one minute per house and a 5mph search vehicle. Gap = 3.81%.